Disruptive Technologies and Digital Transformations for Society 5.0

Pradeep Kumar Garg · Nitin K. Tripathi · Martin Kappas · Loveleen Gaur *Editors*

Geospatial Data Science in Healthcare for Society 5.0

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Disruptive Technologies and Digital Transformations for Society 5.0

Disruptive technologies and digital transformations for Society 5.0 aims to report innovations to enable a futuristic society in which new values and services are created continuously, making people's lives more conformable and sustainable. It aims to present how problems can be solved in different areas, including mobility, health, agriculture, food, manufacturing, disaster prevention, and energy to name a few. Society 5.0 framework is based on data captured by real-world sensors and sent to the virtual cloud world for Artificial intelligence (AI)-based analysis, which in turn will return to the real world in physical form through robots, machines, and motor vehicles. People, objects, and systems are all connected in Society 5.0 and converge in cyber and physical space to collect a large amount of data from a variety of sources using sensors and devices. In Society 5.0, new values created by social innovation eliminate regional, age, gender, and language disparities and enable the delivery of personalized products and services that meet many individuals and potential needs. Digital transformation marks a radical rethinking of how an organization uses technology, people, and processes to fundamentally change business performance. Disruptive technologies including AI, affective computing, Blockchain, biological computing, cloud computing, emotion theory, human-computer interaction, Internet of Things (IoT) predictive analysis, probabilistic methods, swarm intelligence, socio-cognitive neuroscience, quantum computing, web intelligence have monumental roles to play in digital reality and Society 5.0. These technologies are shifting the economic landscape and the time has come to imbibe these technologies and empower organizations to exploit them now and in the future. The Series accepts research monographs, introductory and advanced textbooks, professional books, and reference works.

Aim and Scope

- The series is focused to explore how disruptive technologies are helping in digital transformation and how organizations are changing the way they do business, concerning innovation processes and business model transformations.
- This series is focused on how various disruptive technologies are creating opportunities across the business landscape.
- This series provides a comprehensive guide to Industry 4.0 applications, not only introducing implementation aspects but also presenting conceptual frameworks to the design principles of Society 5.0. Besides, it discusses such effects in new business models and workforce transformation.
- Changing dynamics of global production, its complexities, high end automated processes, high-level competitiveness, and emerging technologies for new generation goods, products, and services.
- Special focus on AI, affective computing, Blockchain, biological computing, cloud computing, cognitive intelligence, digital business transformation, decision sciences, e-health services, emotion theory, Futuristic digital society, habitat Innovation, human-computer interaction, Internet of Things (IoT), Internet of Humans (IoH), IoT-oriented Infrastructure, mobile computing, neural computing, predictive analysis, probabilistic methods, resilience in cyber-physical systems, robotics and automation for futuristic applications, swarm intelligence, synergies, and tradeoffs of food, energy, and water (F-E-W) nexus, socio-cognitive neuroscience, smart homes, and smart buildings, smart mobility and transportation, smart factories, embedded devices, quantum computing, and web intelligence to name a few.

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ISSN 2730-9061 ISSN 2730-907X (electronic)
Disruptive Technologies and Digital Transformations for Society 5.0
ISBN 978-981-16-9475-2 ISBN 978-981-16-9476-9 (eBook)
https://doi.org/10.1007/978-981-16-9476-9

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

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Chapter 1
Potential of Geospatial Data in Healthcare for Society 5.0

P. K. Garg

1 Introduction

Human welfare is defined as "*the health and well-being of all humans*". Human welfare is dependent on several factors, such as human and ecosystem health, resource availability, and social and economic setup. It also depends on food availability, environmental health hazards, contagious and infectious diseases, chronic health issues, healthcare delivery, and many more. The population of a country still suffers from many diseases in spite of availability of various healthcare programs. This is particularly true in developing/under-developed countries due to lack of management of facilities, inadequate hospitals and medical professionals, presence of large slum areas, lack of hygiene, delay in treatment, non-availability of advanced healthcare systems, lack of technological development, etc. It is presumed that a healthy society can contribute more to social and economic development, as people will be more productive due to their good mental and physical ability and high social well-beings.

Health is vital for everyone, and it requires understanding of the determinants of a disease and its spread. The World Health Organization (WHO) defined health as "*a state of complete physical, mental and social well-being, and not merely the absence of disease or infirmity*". Winslow, one of the leading scientists in public health, has defined public health in 1920 as "*the science and art of preventing disease, prolonging life and promoting health and efficiency through organized community effort for the sanitation of the environment, the control of communicable infections, the education of the individual in personal hygiene, the organization of medical and nursing services for the early diagnosis and preventive treatment of disease, and for the development of the social machinery to insure everyone a standard of living*

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_1

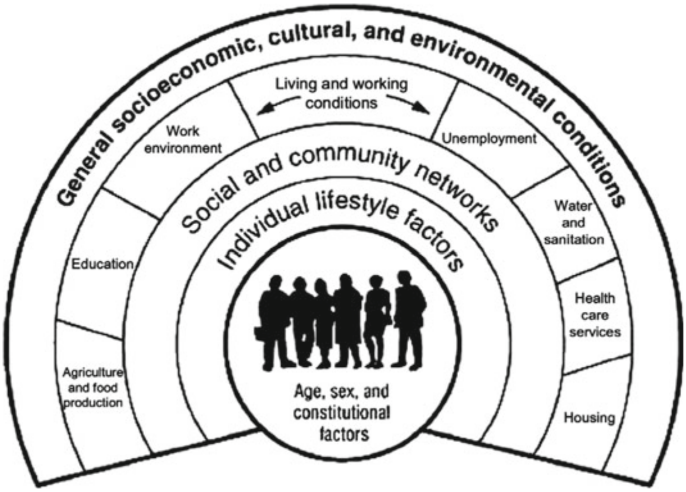

Fig. 1 Dahlgren–Whitehead model showing factors responsible for the worldwide emergence of diseases [16]

adequate for the maintenance of health, so organizing these benefits as to enable every citizen to realize his birthright of health and longevity" [31].

Figure 1 shows a model, called the Dahlgren–Whitehead model, which shows that a large number of factors, such as climate, environment, water quality and management, education, air pollution, natural disasters, and social, are responsible for the emergence of diseases [16]. The characteristics of these parameters, including socio-demographic and environmental conditions, provide a valuable information on health and diseases. Public health resources, specific diseases, social infrastructures, and other health-related data can be mapped in relation to their surrounding environment. Maps can play an important role as it is considered to be an excellent means of communication. The representation and analysis of maps showing disease incidence data are basic tools in the analysis of regional variation in public health.

All healthcare issues have an inherent geospatial location attached to them [18]. Health geography can provide a spatial information on population's health, distribution of disease in an area, environmental effect on health and diseases, accessibility to healthcare, and spatial distribution of healthcare facilities. Health geography is an emerging discipline that may require geospatial data, such as satellite images, global positioning system (GPS), unmanned aerial vehicles (UAVs)/drones, LiDAR, to investigate the health-related issues. Geospatial data, such as population of a district, weather of a region, pollution levels, and geo-tagged social media data, which consist of a geographic component to identify their locations (e.g., coordinates, addresses, and post-codes), can be effectively analyzed using geospatial technology, such as image processing software and geographic information system (GIS). More recently, Internet of Things (IoT)-based sensors and devices deployed in health establishments, smart cities, and highways continuously generate the geo-tagged data, called big data [13].

There are several applications of data science in healthcare. Data science has the potential to locate all the patients' data quickly as per the requirements and provides stakeholders of the healthcare sector a precise data pool for better health management of a region. The developments in the patient's health can be monitored through usage of data science so that the suitable treatment can be provided to individual patient. With cloud-based storage and modern analytical tools, all stakeholders in healthcare system, such as organizations, patients, medical staff, and drug manufacturers, can derive a large number of benefits [35]. For example, the patients can recover faster, doctors can significantly enhance the medical outcomes, organizations can save costs and improve the efficiency of operations, and drug manufacturers and other healthcare providers can make better decisions.

2 Historical Developments

Medical GIS has its foundation in medical geography, which can be found in the literature of several ancient civilizations, including China, Greece, and India, with perhaps the earliest coming from the work of the first physician, Hippocrates in the fifth Century BCE. Several developmental concepts in the field of medical geography have been documented by Aristotle, Plato, and Hippocrates who first published their observations regarding geography and human or animal medical problems. The relationship between health and area has already been discovered in the past, and it began with Hippocrates, the father of medicines [18]. In his treatise, which is about air, water, and places, he described the different characteristics of cities that influence the public health of people and found that people who live on lowlands near waterways are more likely to develop malaria. Almost 1500 years ago, Al-Razi, the Persian physician and spatial thinker, used spatial decision method by placing pieces of meat in wooden columns in different places of Baghdad city to find the best location of hospitals [14]. The first spatial health map of plague disease spread was produced in Bari, Italy, 1694, as the plague was considered one of the most dreadful diseases. Later, Samuel Mitchell [23] and Henry Marshall [22] brought the two topics together to a single medical philosophy and system.

The GIS in the field of spatial health began in 1854 by Dr John Snow when the cholera epidemic hit the city of London, England, killing at a rate of 500 people per week [4]. Dr Snow, who is known as the father of modern epidemiology, used mapping concepts to find the source of cholera in London and drew the spatial maps which showed a number of features relevant to the disease (e.g., outbreak locations, roads, property boundaries, and water lines). Through spatial analysis, he discovered that cholera cases existed mostly along water lines, with a significant number of deaths (black dots on the map) centered around the water pump (Fig. 2). Dr Snow emphasized that there was a relationship between the place and health, and

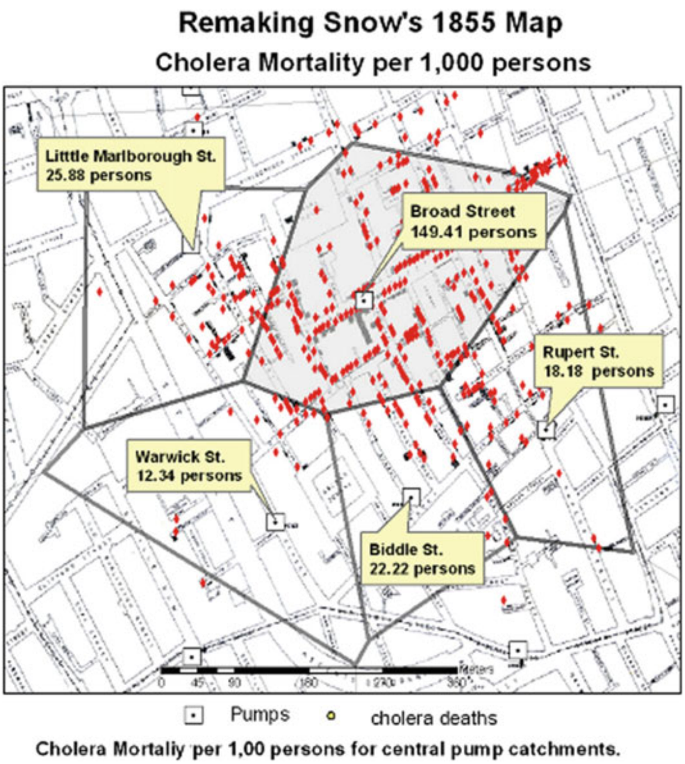

Fig. 2 Map showing locations of Cholera outbreak in Soho, London [4]

spatial map proved that cholera cases were spreading through water. This map is considered to be the beginning of the spatial analysis that later supported the field of epidemiology, specifically in studying the spread of diseases as well as public health planning involving quantitative techniques of geographical analysis [13].

Another major focus of medical geography relates to the spatial analysis of population-based measures of access, healthcare delivery, and resource allocation. These issues are particularly relevant to policymakers, health services researchers, and planners. Historically, one of the leading works in the history of GIS and health was published in 1875 when Alfred Haviland produced the first atlas of colored maps to locate areas with a high cancer rate in the counties of England and Wales [1]. He used the maps to establish correlation between environmental risk factors of the disease, of which the most important was mineral production. A timeline of other major events in medical geography is given in Table 1.

Table 1 Timeline of major activities in medical geography

	Activity
1700	1694 map of plague in Bari, Italy
	1792 Finke's Medical Geography
	1798 map of yellow fever in New York city
1800	1819 map of yellow fever in New York city
	1820s map-makers add demographic data to map surface to determine the nature of disease outbreak
	1821 map of typhoid fever in New York city
	1832 map of progress of cholera around the world and map of cholera in Exeter
	1836 map of cholera in Hamburg, Germany
	1840 map of hernias in France (good example of medico-statistical mapping)
	1841 map of sanitation in Dublin, Ireland
	1850 map of cholera in London
	1854–55 numerous maps of cholera in Soho, London
	1856 world map of health and disease
	1875 maps of cholera in New Orleans, Memphis, Nashville, and USA. Alfred Haviland produced the first colored maps in atlas for cancer disease in England and Wales
	1876 map of cholera in East Africa
	1878 map of offensive odors in Boston, MA
	1885 maps of typhoid in Plymouth, PA and map of sever outlets in Harrisburg, PA
	1886 map showing distribution of population in State of Pennsylvania
	1892 map of smallpox epidemic in Western Australia and map of the distribution of cancer in British counties
1900	1901 maps from Sedgwick's Principles of Sanitary Science and the Public Health
	1925 map of sandfly fever in Peshawar, India
	1950s maps from the Welt Seuchen Atlas
	1960 map of cancer in Horrabridge, England
	1960s maps of the death rate in England
	1961 maps from May's Studies in Disease Ecology (including world distribution of important malaria vectors, and a worldwide schematic of plaque foci)
	1962 map of Burkitt lymphoma in Africa
	1969 map of schistosomiasis in South America
	1971 maps of influenza in England
	1972 map of bronchitis in Leeds
	1977 map of hepatitis in Tasmania
	1986 map of influenza in the United States
	1988 map of malaria in India and map of leukemia in India
	1980s–1990s maps of outbreaks of AIDS in Ohio and USA

(continued)

Table 1 (continued)

	Activity
	1989 map of HIV in Eastern Tennessee
2000	2000 CDC releases EpiMap to display data from EpiInfo as maps
	2002 map of AIDS in Thailand and map of dengue fever in Pennathur, India
	2004 map of AIDS in the United States

3 Need for Data Science in Healthcare

Data science is rapidly growing to occupy all the industries of the world today, including health industry. The utilization of data science strategy has many benefits to healthcare companies, as shown in Fig. 3. The main aim of any healthcare organization is to provide quality treatment at a lower cost as well as to maintain high standards to take the right medical decisions. However, the vast amount of unstructured healthcare data may often complicate the decision-making process [18]. All medical centers' records, doctors' prescriptions, patients' reports, lab tests' results, discharge summary, etc., need to be safely stored digitally so that these may be quickly retrieved and used with ease.

The advancements in computers and in particular data science have made it possible now to obtain and verify accurate diagnostic process. The computer vision is also being used widely in diagnostic processes. With the help of big data and data analytics approaches, a disease can be quickly and accurately diagnosed. Big data provides a smarter way to diagnose the patients, while suitable algorithm may

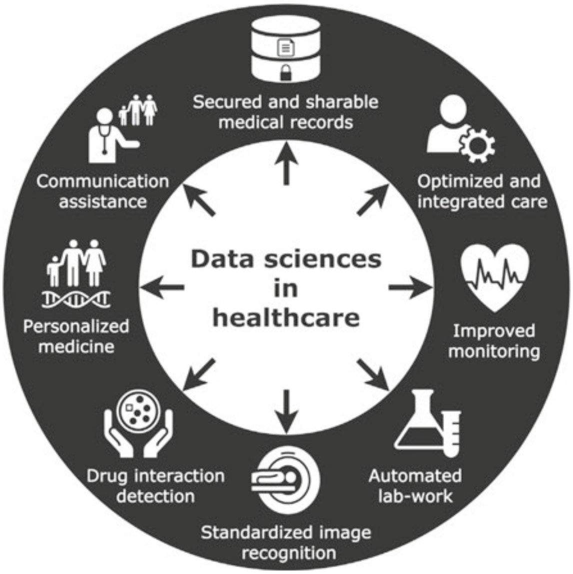

Fig. 3 Various uses of data science in healthcare

suggest the necessary tests and therefore reduce the overuse of tests. In addition, doctors can feed the patients' data into an algorithm that can suggest the most likely diagnoses required. But the irony is that despite of availability of huge amount of health data, the diagnostic failure rates are still relatively high. According to a study, each year in the USA, over 12 million adults who seek outpatient medical care receive a misdiagnosis, including about 5% adults [5]. Data science and predictive analytics are valuable tools which can help significantly reduce the death rate and lead to predictable medical outcomes as well as optimize the way hospital operations can be managed.

The data science and machine learning (ML) can be used to optimize the clinic staff scheduling and reduce the waiting time, manage supplies and accounting, and even build efficient action programs for epidemics, such as seasonal flu outbreaks [15]. Deep learning (DL) methods employ the data science and analyze imaging data, such as X-rays and CT scans and check the derived results against large database of clinical reports and laboratory studies to enhance the accuracy and efficiency of diagnostics. Mobile apps, supported by data science technologies, offer a significant opportunity for better diagnosis and more efficient disease monitoring. With rapid increase in data science and sensors generating medical data, it has become possible to lower the costs of treatment, improve patient care, make better policy, and make improved medical decisions based on a patients' history. Analytics-based preventative medicine can contribute indirectly to an overall reduction in healthcare costs. In addition, the use of data processing and analysis tools allows health professionals to make better decisions.

4 Society 5.0 and Open Data

In 2016, the Japan Business Federation "Keidanren" proposed a new smart society of twenty-first century, called "Society 5.0" that would be responding to new economy needs with Industry 4.0 [17]. The new society was described as a super-smart and human-centered society which would incorporate latest innovations, such as robots, big data and artificial intelligence (AI), advanced analytics, and predictive decision support systems to tackle various social and economic challenges [28]. Society 5.0 is also named as a "Society of imagination" [10]. It will provide transparency and active participation in social issues, with equal opportunities for all people, and an integration between cyberspace and physical space of people and government. It would create an environment which will use high-end information and communication technology (ICT) in Industry 4.0 and provide the opportunity to develop the human resources as well.

The open data greatly supports the idea of greater openness and accountability in business and administration governance. The openness of data, both public and private, is considered as one of the most crucial drivers for a sustainable economy in developing a new ecosystem in society. Open government data (OGD) provides access to create added value in Industry 4.0 and Society 5.0 [26]. It is considered

Table 2 Key terms describing Society 5.0 and Industry 4.0

Key terms describing Society 5.0	Key terms describing Industry 4.0
Human-centered society, society of imagination, and super smart society	Actuators
Sustainable development: sustainable development goals (SDGs), dimensions of sustainability	Automated guided vehicles, adaptive robotics
Artificial intelligence, robotics, Internet of things	Digital factory, smart factory, additive manufacturing, and hybrid production
Cyber-physical systems: intelligent transportation, smart manufacturing, regional care, and smart food-chain	Big data analytics, cloud technologies, cyber industry network
Data: digitization, data formats and interfaces standardization, utilization of standard data	Cybersecurity, cyber-physical infrastructure embedded systems
Expanding transparency and active participation in social issues	Industrial Internet-communication and networking
Equal opportunities for all people, integration of innovative technologies and society	Internet of things and mobile technologies
Imagination and creativity of people	Radio-frequency identification (RFID), real-time locating system (RTLS) technologies, and sensors
Information platforms	Simulations
Open innovation and innovation as a driving force for new business and services	Value creation due to technological transformation
Regulatory of laws toward implementation of new technologies	Visualization technologies, such as virtual reality and augmented reality

as a driving force for new businesses and services that would ensure the sustainable development of a human-centric society with open innovations. Open (government) data equality and free access to data is an important resource for their transformation into new services and solutions for all stakeholders. This can be achieved using AI, big data, and modern technologies, implemented through systems with open standards. The literature shows that open data and open innovations are the key factors in the sustainable environment, of Industry 4.0 and Society 5.0, as shown in Table 2 [28].

5 Healthcare Data Collection from Various Sensors

The healthcare is an industry that includes hospitals, doctors, clinics, and other medical establishments [18]. In developing countries, however, the demand for health services outpaces the available resources, and therefore, defining the priority is one of the most challenging issues faced by health policymakers. At present, the infrastructure for networking among various healthcare service providers is not adequate to use geospatial data and technologies. Doctors also need to understand their surrounding communities where their patients are located. Although the geospatial data and technologies have been used since long in public health organizations, its use was relatively recent by health groups for health service planning. A properly designed geospatial-based technology system for healthcare can outreach to patients globally which physically is an impossible task. Such systems are required to be developed, installed, and maintained to improve the quality and to standardize and individualize the quality of care provided to global patient-base.

Geospatial data that support health research can be categorized into four broad types, as follows.

(i) Data about healthcare capacities, such as health facilities, employment, and administration. (ii) Data about the population and their health conditions and healthcare needs. The demographic health survey data, which are surveyed in many countries describing disease outbreak rates and other health indicators of the population, are often published with map coordinates of surveyed clusters. Five of the global population datasets are (a) Gridded Population of the World—GPW v3, (b) United Nations Population Information Network (POPIN), (c) Home HYDE—the Netherlands Environmental Assessment Agency (PBL), (d) LandScan, and (e) International Data Base—U.S. Census Bureau.

(iii) Data about the environment, both natural and social, which affects people's health. For example, the long standing water may affect the dispersion of malaria, which in turn affects the surrounding residents' health.

(iv) Data about transportation and the address location of patients is essential in understanding the accessibility for care, dissemination of medical supply, traffic routing, connectivity among street/road segments, transmission of infectious diseases, distribution of patients, best route and travel time, and locating a place with its postal address or longitude and latitude coordinates.

5.1 Remote Sensing Sensors

Maps have always helped the medical and public health professional to understand the role of geography in outbreaks and pandemics of plague, cholera, typhoid, malaria, and several other infectious diseases. Atlases and maps relevant to health can serve as reference sources and guides for policymaking and planning health services [13]. These maps have also provided useful information to analyze and understand the pattern and density of chronic diseases, such as cancer and heart disease, which is more prevalent in under-developed nations. The medical image analysis is closely linked with the geospatial discipline of image sensing and processing. Effective cartography and map interpretation and analysis through image processing and GIS are important for spatial analysis of diseases as well as evolution of modern medical geography. Remotely sensed images are being used frequently for the change analysis, climatic studies, demarcating transport routes, identifying the stagnant water, and deriving the pandemic patterns. Based on spatial and temporal analysis of maps, public health and medical professionals can effectively use the information to correlate the geography with their healthcare data.

The use of remotely sensed data for taking decisions on human welfare and health can be categorized into four processes: observing, explaining, projecting (forecasting), and applying in practice. Remote sensing-based analysis is usually associated with observing, explaining, and projecting [11]. Temporal remote sensing data are used to observe the patterns or changes, which then informs the explanations of causal relationships and processes. Future projections can be made based on past observations, understanding of processes, and assumptions made. Models thus developed for making the projections are tested and refined by further observations. These modeling tools can then be used to aid the decision makers and planners. Creating a strong linking between observations, explanation, and projection to application is vital to providing appropriate information to the decision makers.

In 70s, the aerial photography was used by some epidemiologists for demographic purposes, or selection of population samples, and to describe the characteristics of study areas. The launch of first commercial remote sensing satellite, ERTS-1 (Earth Resource Technology Satellite, later renamed as LANDSAT) by the NASA, USA, in 1972 provided global coverage of remote sensing data at 80 m spatial resolution [11]. Through the 1970s and 1980s, a large number of satellites were launched by other countries which provided improved resolution images that were utilized to map land surface features and investigate the epidemiology of diseases. Later, the use of image processing methods and GIS technology has increased in the field of medical sciences, particularly in health sector. With the availability of increased resources, health departments and epidemiologists used robust ICT to support public health preparedness and response.

Satellite data can be used to study spatially and seasonally varying impacts of infectious diseases on humans. Data obtained through various remote sensing satellites provide a means of linking environment (such as resources and infrastructure), diseases (such as malaria or cholera), and poverty (such as nutrition). Medium-resolution LANDSAT and SPOT satellite data have traditionally been used to examine the details of land and environment from space. The coarser resolution satellite data (e.g., NOAA-AVHRR and INSAT) is useful in understanding the seasonal events associated with the transmission of many diseases. Such data are used to identify the regions of environmental similarity (spatial clusters of similar climate, soil, or topography) and thus provide a unique view of the environmental context of human activities over broader regions [13]. In general, satellite data with coarser spatial resolution have higher temporal resolution, which allows efficient tracking of changing environmental conditions. Table 3 presents the observations and benefits that can be derived from various remote sensing images for land and environmental monitoring.

Large-scale mapping of spatial features, such as houses, water ponds, hospitals, healthcare facilities, and transportation network, requires very high-resolution satellite imagery (ranging from <1 m to 5 m), which can be acquired by various commercial satellites, such as IKONOS, GeoEye, and WorldView [11]. A considerable amount of very high-resolution images is also publicly available via online

Table 3 Land and environmental conditions monitoring by various remote sensing images [25]

Condition	Observations	Benefits	Remote sensing images
Water	Water quality, water availability, and water locations and types, rainfall	Monitor conditions conducive to water-borne disease growth or migration (worms, flu, meningitis, cholera, malaria, West Nile virus, and AIDS); wetland mapping	Radar, multi-spectral, optical (Landsat)
Air and atmosphere	Ozone measurements, particulates, heat and temperature, UV measurements, and wind dynamics	Air quality, atmospheric chemistry, monitoring climate change allows for indirect measurement of diseases, such as asthma	Thermal reflectances (MOPITT)
Soil and vegetation	Soil moisture, vegetation types, and vegetation productivity	Habitats for disease vectors	Multi-temporal, multi-spectral optical (MODIS, Landsat)
Land use and land cover	Land cover, livestock, NDVI, and cropland extent	Soil, water, and livestock interactions; land-sea interface; detection of floodplains and ice cover	Multi-temporal, multi-spectral optical (MODIS, Landsat)
Infrastructure	Roads and transportation, water access, sewers, communications, waste disposal, urban population distributions at high resolution	Disease vector tracking; improving health service response in times of emergency; developing GIS data layers for modeling housing, land cover, etc.; high-resolution population distributions can assist in health issues associated with infrastructure (i.e., obesity as related to infrastructure); understanding of teleconnections	Very high-resolution optical (IKONOS, QuickBird)

Note MODIS—Moderate Resolution Imaging Spectroradiometer, MOPITT—Measurement of Pollution in the Troposphere, NDVI—Normalized Difference Vegetation Index platforms, such as Google Earth, Google Maps, BHUVAN, and Bing Maps. These images are compressed natural color composites (red, green, and blue) that are suitable for visual interpretation. With Google Earth, it is possible to access the historical images of an area. However, the high cost of recent images (as separate bands) and technical challenges of working with commercial very high-resolution images to classify each small feature accurately have restricted their uses for healthcare applications. In addition to the cost of image acquisition, manipulating and analyzing large volumes of very high-resolution imagery require considerable storage space and processing power. The ‘Smallsats’ that are compact and relatively inexpensive satellites have been developed to be deployed in large numbers. The PlanetScope mission, which began in 2016, consists of more than 120 Smallsats that collect daily 3 m very high-resolution satellite images for entire globe [13]. With PlanetScope satellites, seasonal and inter-annual environmental variability can be tracked and mapped.

The Sentinel-1 satellite was launched by the European Space Agency (ESA) in 2014 which has free global access to synthetic aperture radar (SAR) data. It provides 10 m spatial resolution C-band data for the entire globe on a 12-day repeat cycle. The SAR collects data at longer wavelengths that can penetrate cloud cover and therefore has been used effectively to map landscape features, such as irrigated agriculture, open water, and wetlands that provide habitats for mosquito larvae. These data can also be used to estimate the soil moisture and identify saturated soils where water is likely to store and create larval habitats. The Sentinel-2 mission, launched in 2015, acquires global data weekly at 10–20 m spatial resolution. Although these resolutions are not suitable for detecting individual larval habitats or dwellings, but Sentinel-2 data are freely available with higher radiometric quality as well as middle-infrared band that is useful for mapping vegetation and water accurately.

In addition to satellite data, the emergence of other sensor platforms, such as UAV/drones, global positioning system (GPS) and mobile phones, can be used to monitor the movements of people carrying infectious diseases [13]. There is a great potential for integrating these technologies with satellite remote sensing, such as using drones to collect very high-resolution data on larval habitats and training the algorithms to classify larger areas and make predictions over longer time periods. It is well known that the distribution of healthcare services around the world is uneven. In addition, challenging terrain and variations in infrastructural facilities are common. Drones provide a potential solution to such logistic problems. For example, drones have successfully delivered small-aid packages after the Haitian earthquake in 2012. In a developing country, like India where estimated 500,000 people are in need of organ transplantations every year, drones could prove to be big lifesavers. Currently, the drones are not being used in India for medical services, but with improvement in technology and reliability, these can provide a major support in delivery of healthcare services for fast delivery in cases, like transport of an organ, life-saving drugs, specific group blood, devices, etc. Newer technologies even make it possible for smart drones to deliver emergency resuscitation equipment to heart attack patients using spatial intelligence technology [12].

Location-based information and intelligence is critical to healthcare planning. Everything happens ‘somewhere’ at ‘some location’. The information on ‘where’ is required for quick access to healthcare, which provides quality of care services. Location-enabled devices are also life-saver for people suffering from memory loss or disorientation, particularly dementias, like Alzheimer’s or Parkinson, and Autism. Real-time locating systems deliver contextual awareness and operational intelligence to the IoT system to increase efficiency, improve quality management, and reduce cost. There are many other examples, from simple calculations of travel time to get to a clinic, to more unique uses, such as setting up a geo-fence to keep individuals safe suffering from Alzheimer’s disease. Intelligent medical devices can remotely monitor a patient’s health parameters and enable health service providers to make an informed decision on diagnosis, prognosis, and medicine prescriptions for the ailing patient. They can even ensure that emergency personnel can be deployed before the patient even knows that there is likely to be a problem. Using GPS tracking, wearable sensors allow senior citizens to be found quickly and safely. The complete knowledge of patients, equipment, or staff location and status can significantly decrease the average length of stay, procedure completion time, or bed turnover time.

5.2 Wireless Sensors

The introduction of ICT provided an increased opportunity to access healthcare providers, do more efficient tasks and processes, and provide a higher quality of healthcare services [29]. A large number of healthcare providers now use hand-held and mobile devices networked by wireless LANs or wide area public wireless networks to connect to the patients and have access to digital medical information and records, in order to provide a range of healthcare services. Pervasive healthcare may be considered as a possible solution to many of these problems and a possible future of healthcare services. In simple terms, pervasive healthcare can be defined as, “*healthcare to anyone, anytime, and anywhere by removing locational, time and other restraints while increasing both the coverage and quality of healthcare*” [32]. The pre-mature and untimely deaths and injuries could be minimized by having anytime-anywhere access to patients’ records. Although many high-end and complex healthcare procedures and processes cannot be well served by using mobile and wireless technologies, but some benefits in terms of anytime-anywhere information can still be derived.

The healthcare services in rural and remote areas of a country are a major challenge [30]. Another challenge is to provide better healthcare services to an increasing number of people using limited financial and human resources, which is particularly true in under-developed countries. Mobile telemedicine has been in use for more than thirty years now, which has expanded the reach and coverage [32]. Mobile telemedicine could remove the constraints on both location and time. With an increasing bit rate of wireless networks, such as 5G networks with support for video-conferencing, mobile telemedicine could be widely deployed economically.

Handheld devices are required to be improved further that will meet the resolution requirements of medical imaging applications in the telemedicine environment.

The IoT offers the opportunity to connect equipment and sensors and aggregate data over multiple devices. Real-time monitoring from anywhere improves the quality of life of patients. Exceptions can be addressed in real-time, minimizing waste, improving equipment utilization and lowering the production costs. Healthier pharmaceutical operations can ensure that drugs are more affordable for patients. The advances in sensor, connectivity devices, Internet, cloud, mobility, and big data technologies have the potential to influence further changes with the support of IoT [35].

Location management in healthcare can be effectively carried out using several components, including GPS, cellular networks, wireless local area networks (WLANs), and radio frequency identification (RFID) for location tracking of people, devices, and services with reasonably good accuracy. The patients in a pervasive healthcare environment may have sensors on their bodies, thereby creating intra-body and inter-body networks of sensors. The cellular, personal communications systems (PCS), and global system for mobile communications (GSM) can be used for location tracking and updating the locations of patients [32]. The cellular/PCS along with smaller WLANs and PCS can also be used in indoor location tracking, providing higher location accuracy. A cellular/PCS system or a satellite-based system may provide the outdoor tracking support for healthcare applications. Even WLANs and RFID-based systems can also provide support to applications requiring outdoor location management. Healthcare applications can derive benefits from location tracking of patients and healthcare providers, devices, and supplies. For example, it will be easy to find people with matching blood groups, locating organ donors, providing post-operation care for people, helping old and mentally challenged people in hospitals, and nursing centers and own homes.

Figure 4 shows an integrated wireless architecture for pervasive healthcare applications [32]. The architecture is designed to be independent of a single wireless technology while allowing the use of several diverse mobile and wireless networks to support the requirements of healthcare applications. The architecture uses several unique capabilities and functionalities of the current and emerging mobile and wireless devices, networks, and middleware. These capabilities include access to multiple and diverse wireless networks, a range of location tracking, and ad-hoc networking for increasing the access and quality of healthcare service. These functions can support several new healthcare applications, location tracking of patients and devices, intelligent emergency response system, and mobile telemedicine.

Healthcare professionals have though started using hand-held devices to access the patient records, write electronic prescriptions and diagnosis, send reminders to patients, and billing codes for healthcare services, but many people have problems to adapt hand-held devices with their complex inputs, difficult and unreliable applications, unfamiliarity with the digital technology, and fear of information loss. In addition, many hospitals and service providers restrict the use of wireless devices (through jammers) within their premises in fear of interference with more sophisticated medical instrumentations. Although most hospitals and service providers

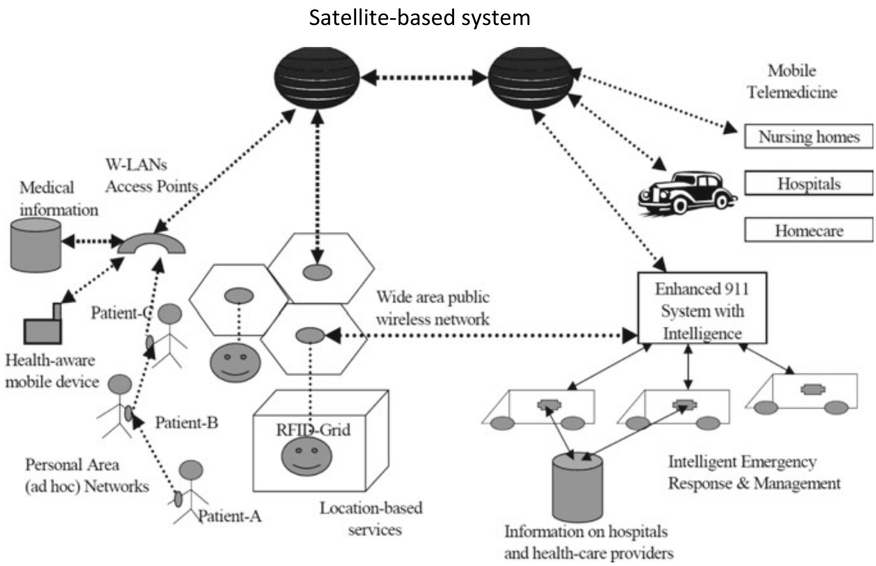

Fig. 4 Integrated wireless network architecture for healthcare environment [32]

understand the potential of mobile and wireless technologies, even then presently the use of wireless technologies in healthcare is very limited. Some of the limitations are (i) lack of comprehensive coverage of wireless and mobile networks, (ii) reliability of wireless infrastructure, and (iii) limitations of hand-held devices, (iv) providing patient monitoring in diverse environments (indoor, outdoor, hospitals, nursing homes, etc.), (v) transmission using cellular networks and WLANs, (vi) formation of ad-hoc wireless networks for enhanced monitoring of patients, and (vii) routing and network support for mobile telemedicine. Many of these patients also suffer from psychiatric disorders, such as paranoia resulting in a suspicion toward wireless technologies, especially those requiring a patient to wear a locator or other device.

Nonetheless, the current and emerging wireless technologies [33] would further improve the overall quality of service for patients in both cities and rural areas, reducing the stress and strain on healthcare providers, while enhancing their productivity and quality of life, and reducing the overall cost of healthcare services in the long run. The mobile and wireless technologies can be used effectively by matching infrastructure capabilities to healthcare needs. These include (i) the use of location tracking, intelligent devices, user interfaces, body sensors, and short-range wireless communications for patient monitoring, (ii) the use of instant, flexible and universal wireless access to increase the accessibility of healthcare providers, and (iii) reliable communication among medical devices, patients, healthcare providers, and vehicles for effective emergency management.

6 Big Data

One of the latest advancements in the fields of medical science is the ability to collect and analyze large amount of information, called big data. Big data refers to *datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze.* Big data in healthcare can be developed from a variety of sources, starting from electronic health records to server logs of search engines and wearable devices and offering several opportunities, as shown in Fig. 5. A big challenge, however, is to analyze this big data to its effective use. It is therefore necessary to apply robust geospatial technologies to process, analyze the spatial big data, and predict the outcome in real time [24]. The growing sizes of datasets and increasing availability of software tools capable of processing them are enhancing the applications in health sector.

The cloud computing environments have also facilitated broader use of remote sensing data [35]. Google Earth Engine includes a browser-based interactive development environment and a JavaScript application programming interface that provides access to a wide range of satellite data products. Computations may be carried out via parallel processing in the Google Cloud, facilitating the analysis over large areas over long-time periods. The cloud-based implementation allows access for end users with limited computational resources in low-bandwidth environments. Commercial computing service providers, such as Google Cloud and Amazon Web Services, have also provided access to extensive satellite data archives via their platforms. Other emerging platforms for cloud-based analysis of Earth observation datasets that could be useful for health applications include Sentinel Hub, Open Data Cube (ODC), and the System for Earth Observation Data Access, Processing and Analysis for Land Monitoring (SEPAL).

The medical uses of big data remain limited, mainly for research, aiming to provide information about patients' conditions and to assist in decision making [34]. Within

Fig. 5 Sources of big data in healthcare

hospitals, some data-driven software is used to identify patients at high risk, while other software can predict the patient affluence and/or waiting time in emergency departments. The data-driven applications in various fields include tele-monitoring systems, implementing advanced prediction of diseases, etc.

7 Data Science Applications in Health Sector

Medicine and healthcare are two of the most important parts of human lives. There are several fields in healthcare, such as medical imaging, drug discovery, genetics, predictive diagnosis, trend analysis, planning healthcare facilities, and several others that make use of data science. Figure 6 shows some example areas of data science applications. It is observed that treatments that are generally given to a majority of the patients are the ones which are currently being practiced by the doctors, as specific treatment to one patient does not exist in medicines. In general, doctors examine the patients, talk to them about their ailments, and compare their symptoms with the diseases they know and prescribe the common medicines. In complex cases, they would research the literature and consult with the experts. Traditionally, medicines solely rely on the advice of doctors based on patients' symptoms. However, this may not always be correct and prone to human errors.

There are several innovations involving data science that will lead to improve and personalize the healthcare, as discussed below. Data science plays a major role in creating a better understanding of the relationship between treatments, outcomes, patients, and costs.

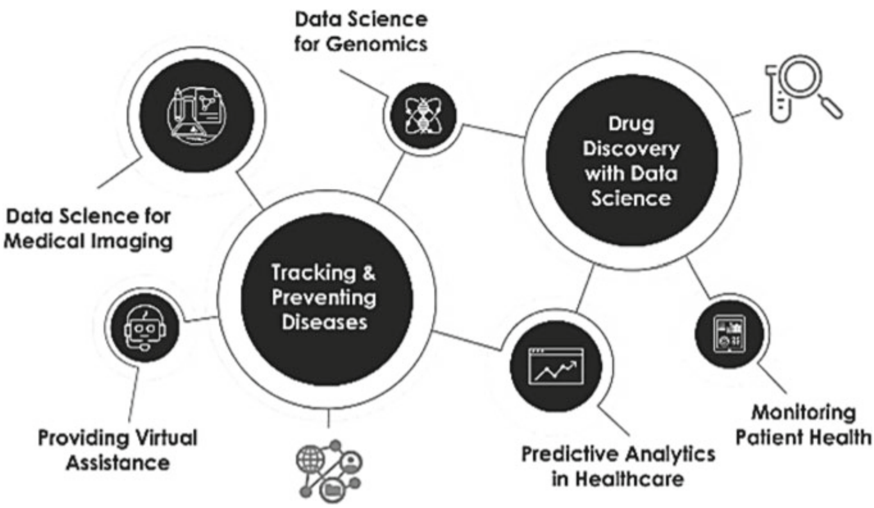

Fig. 6 Various applications of data sciences in healthcare

7.1 Geographic Information System (GIS)

A GIS can be described as an information system that *stores, edits, analyzes, integrates, displays, and shares geographic information in a decision-making context* [4]. The GIS methods are used in the field of public health research to present the data that are linked to geographical locations. The graphical visualization and dynamic simulation capabilities of GIS can be employed as powerful tool to reveal underlying relationships or process using geostatistical analysis and geodatabases. An understanding of the spatial occurrences of various diseases in an area is required for proper planning and management where some characteristics of the diseases can be derived from remote sensing and GIS technologies [8]. All GIS systems provide basic mapping and spatial analysis tools, such as creating maps by overlaying geospatial data by points, lines or polygons, or raster datasets, and non-spatial data stored as tables and spreadsheets [13]. Various types of spatial data referenced spatially in a GIS system are often referred to as "layers". These layers work much like a set of clear transparent overlays that allow the analyst to establish the relationships between layers (Fig. 7), for example, the relation between diseases and transportation networks, healthcare facilities, population characteristics, disease distribution, socioeconomic status, and other characteristics.

The GIS-based spatial analysis utilizing large datasets could provide accurate and updated information on medical and social trends. In addition to population health, GIS can be used to explore the dynamic links between people, their health and well-being, and changing physical and social environments. Although only a limited online social media activities are geo-located, but by mining health-related geo-located tweets, space–time analyses of these tweets can provide spatial–temporal patterns of disease transmission. Big data can also help determining the urban mobility in case of an emergency, e.g., earthquake. Health organizations have the opportunity to utilize the medical GIS with their large sets of medical records and other information [8]. This information can be used to increase the accessibility of health services to people in need, as well as to analyze the illness patterns. Additionally, health organizations can visualize, interpret, and display geo-location data through the use of GIS tools, mapping applications, and big data. Continuing innovations in GIS and big data will witness how new technologies, analytical techniques, and data sources will shape the future of the health GIS [13].

7.2 Genomics

Modern genomics is a relatively new field in medical science. It focuses on the study of genes to estimate the need of medical interventions to avoid with fatal or genetic diseases. Genomics is "*the study of sequencing and analysis of genomes, and the health of a human depends on his/her genes and environmental factors*". A genome consists of the DNA and all the genes of the organisms. A term called,

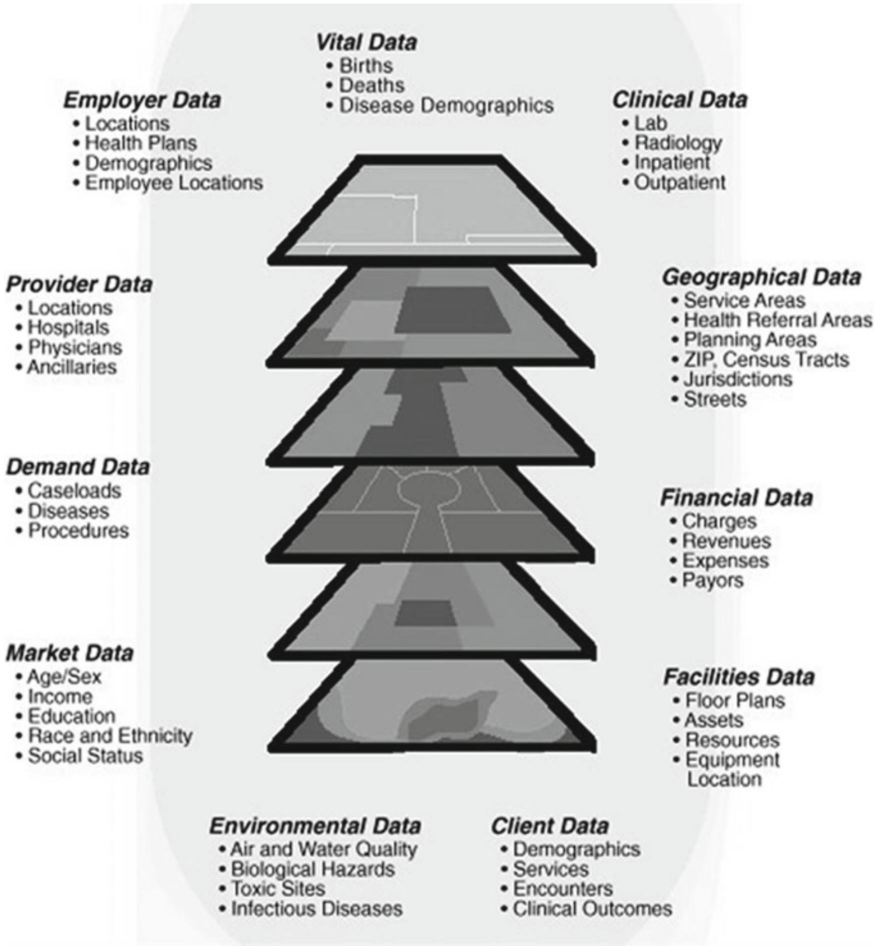

Fig. 7 Various layers in GIS required for health-related studies

bioinformatics, is used that combines the data science and genetics. It deals with the analysis of genomic strands and search for irregularities and defects in it, which helps finding the connections between genetics and health of the person. Timely steps can be taken to cure many patients from these genetic diseases. With the development of data science application in medical, it is now possible to analyze and derive insights from the human genes in a relatively shorter period of time with lower cost.

Research in genomics involves finding the right drug which provides a deeper insight the way a drug reacts to a particular genetic issue. The AI with the use of several data science tools, such as MapReduce, SQL, Galaxy, Bioconductor, etc., can help the genomic experts take specific action to improve the patient health. The MapReduce processes the genetic data and reduces the time to process the genetic sequences. The SQL is a relational database language that is used in GIS to perform querying and retrieving data from genomic databases. Galaxy is an open-source, GUI-based biomedical research application that can be used to perform various operations on genomes. The bioconductor is an open-source software developed for the analysis and comprehension of genomic data.

Data about genetic behavior are generally highly variable, creating a situation of ambiguity. Advances in genomics can determine the entire DNA sequence of a human and understand how a specific genome sequence can better manage the health of individuals. It is also possible to measure the components in blood to understand the molecular structure of persons during healthy and disease conditions. Next-generation genomic technologies will allow data scientists to drastically increase the amount of genomic data collected on large population. Integration of new informatics approaches with genomic data in disease research will improve understanding about the genetic bases of drug response and disease. The research, such as genetic risk prediction and gene expression prediction, still remains to be carried out in future.

7.3 Body Sensors

Wearable technology plays a prominent role in today's healthcare transformation. The wearable sensors are closely interwoven and are becoming smaller and more mobile, opening new pathways to interact with patients, perform tests, collect data, and deliver the treatments. With an evolving healthcare delivery model, the healthcare companies now produce the wearables and other IoT devices which are among key healthcare technology. Wearable body sensors, such as heart rate monitors, blood monitors, lactate acid sensors, testosterone and estrogen sensors, are already in use in many countries though at primitive stage. These sensors provide useful data to better manage the health, as they can automatically collect health metrics, such as heart rate, pulse, blood pressure, body water level, temperature, oxygen concentration, and blood sugar level. Thus, they eliminate the need for patients to collect the data themselves and travel to the data analysts for providing the output data. A number of potentially dangerous chronic conditions, such as diabetes and hypertension, can be monitored through wearable sensors/devices as these diseases require routine observations in chronic disease management. These devices generate large amount valuable data that can further help doctors with diagnostics and treatment. The proliferation of sensors providing personal health data and increased computational power helps providing better healthcare for individual at lower costs.

Healthcare cloud-based framework is considered as one of the most recent methodologies in cloud applications, which can be used for enhancing the patient's safety and monitoring a patient from a remote location to provide quality of services. Post-operational data is extremely important for medical professionals to access patient's information remotely through network. It requires developing a reliable healthcare system, which can be used for real-time recording and sending notification of vital signs of the patients. With the advancement of modern bio-instrumentation and ICT, the healthcare system can acquire data and records and transmit it anytime to any remote location. The servers can be connected to an open communication network via TCP/IP protocol. A healthcare system based on wireless sensor network (WSN) and radio frequency identification (RFID) is capable of monitoring the patient's medical status using RFID body sensor and wirelessly transmitting all clinical data to a local workstation before transmitting it to the central cloud database server via IP address. It can also be shared with the physician any time for medical advice. In cases of emergency, the patient can be informed about altered treatment through their wearable devices or messages through their smart phones. The main issue in such system, however, is the privacy and security of patient's health information to protect such information from unauthorized people or organizations. Controlled distribution of passwords is one such option (Fig. 8).

The amount of data that a human body generates daily is about two terabytes. Due to advances in technology, most of these data, including information about heart rate,

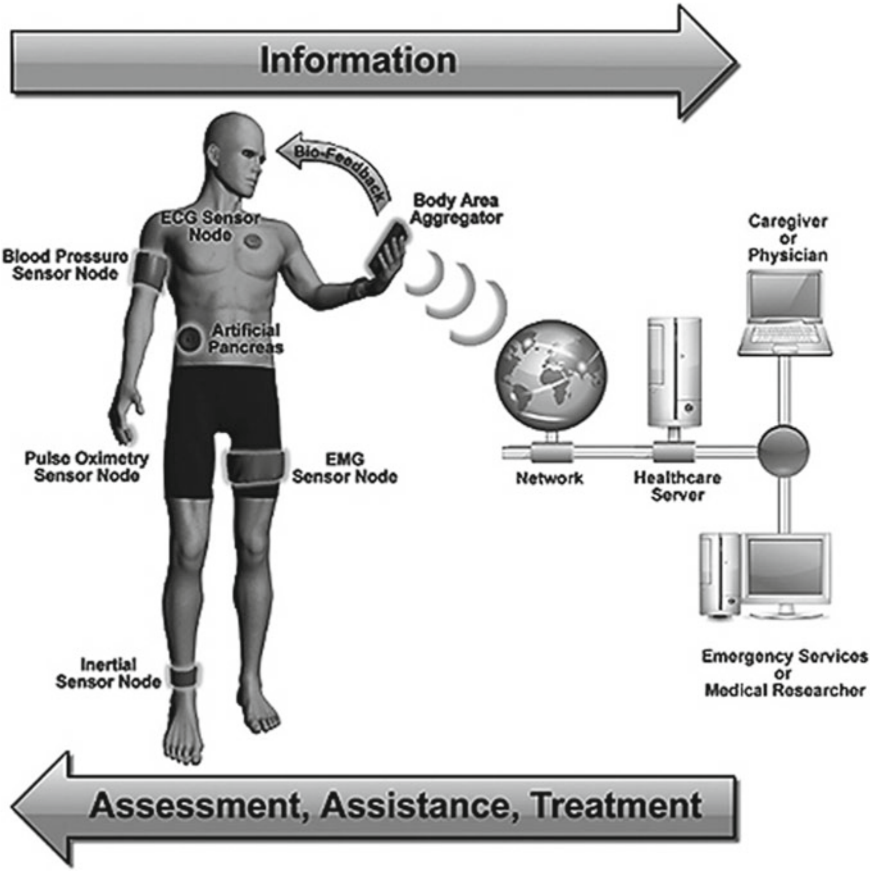

Fig. 8 Wearable sensors and communication approaches in healthcare

sleep pattern, blood glucose, stress levels, and even brain activity, can be collected, and health of the person monitored. World's leading technology companies, such as IBM, Apple and Qualcomm, have been in the forefront in health innovations. By collecting and analyzing heart rate and breathing patterns, machine learning algorithms can be used to detect the slightest changes in the patient's health indicators and predict the possible disorders. It is estimated that about 600,000 people suffer by sudden heart stoppages in the USA every year, the above system can be used to anticipate the problem and send out timely alerts that may save thousands of lives. While adoption levels are growing, the wearables market is still in the early phases of expansion.

The global wearable healthcare devices market is projected to reach USD 46.6 billion by 2025 from USD 18.4 billion in 2020, at a CAGR (compound annual growth rate) of 20.5% from 2020 to 2025. Emerging economies, such as India, China, and Brazil, are expected to provide a wide range of opportunities for players in the health industry. Furthermore, the growing adoption of mobile platforms, increasing adoption of AI and 5G, and the growing awareness and preference for home healthcare will also boost the growth of this market [21].

7.4 Electronic Medical Records

The electronic medical records (EMRs) are now required to be stored by law in most of the developed nations. Data become very powerful, particularly when it is combined with other data sources. Hospitals and increasing use of body sensors are creating large amount of health data which can be stored in digital form and analyzed and transformed into new forms of health knowledge and understanding. This information can help the patients identifying the tests and treatments that are irrelevant and help the doctors and hospitals to design a system where the patients are charged only for the outcomes. Data science allows accurate prediction of treatments which will be more effective for the individual patient, thus lowering the healthcare costs. The availability of EMRs data will help study whether treatments are effective or not. Also, the improved techniques for analyzing the data for personalized medicine would lower the costs. In addition, it will provide a proper legal regulatory scheme.

7.5 Medical Imaging

Another important use of data science in the health industry is through medical imaging, such as X-ray, MRI, and CT scans, as these techniques capture the images of inner parts of human body. The doctors examine these images and assess the causes of illness visible to them. However, at times, it is difficult to find the microscopic deformities, which might lead to improper diagnosis. With image enhancement, image segmentation, and machine learning/deep learning techniques, it is now possible to find such microscopic deformities precisely on these images [3]. Other image processing techniques, like object recognition using object-based image analysis (OBIA), support vector machines (SVMs), image enhancement and reconstruction, spatial filters, edge detection etc., can also improve the accuracy of detection of deformities/abnormalities from images. Big data platforms, like Hadoop, apply MapReduce to find the parameters that can be used for various tasks. There are several open datasets of brain imaging, such as BrainWeb, IXI dataset, fastMRI, and OASIS, that can be utilized to gain a learning experience for image enhancement.

7.6 Preventive Care

One of the major uses of data science in healthcare is the pre-treatment diagnostic phase to take preventive care against major diseases. Often the entire treatment schedule and recovery of the patient are heavily dependent upon the accuracy of the initial physiological and symptom of data collected, so achieving very high accuracy is very important in the field of medicine. Data science is directly connected to AI which is the foundation for the collection of patient's specific data. Such specific data would help the doctors to prescribe customized treatment/medicine as per the need of the ailing patient. For example, in case of a pregnancy or a tumor, it is extremely helpful, as non-intrusive medicine-based treatment may be important for such patients. Thus, it makes the medical efforts pro-active and contributes immensely to the treatment.

7.7 Drug Discovery

Data science in the healthcare sector is useful for the innovation of new and effective drugs. Drug discovery is a highly complicated discipline and is a time-consuming process that requires heavy testing and large expenditures. The data science algorithms can help to simulate how the drugs will react in human body, thus eliminating the need of long laboratory tests. While the historical data can assist in the drug development process, machine learning/deep learning algorithms can help optimizing and increasing the success rate of predictions. Machine learning/deep learning algorithms can find the probability of the development of disease in the human system [3]. These algorithms can be used to develop models that determine the prediction from the given variables.

Large number of drug companies are heavily dependent on data science for doing their research to develop better drugs in the future. These companies use the patients' information and metadata, which are helpful to develop models and determine statistical relationships between the attributes. For example, the companies can develop the drugs that address the key mutations in the genetic sequences. Further, chemical compounds can be analyzed and tested against a combination of different cells, genetic mutations, etc., using data science. With a combination of genetics and drug-protein binding databases, it is now possible to develop new innovations in drug discovery field.

7.8 Personalized Medicines

The personalized medicine may be defined as a "*comprehensive, prospective approach to preventing, diagnosing, treating and monitoring disease in ways that achieve optimal individual health care decisions*". It involves customization of healthcare treatment tailored to meet individual patient's requirements [20]. Data science supported by technology, however, allows for completely different approach to the treatment, which might be entirely specific to the individual with personalized treatment and care. Data scientists can now work effectively on big datasets, combining these with clinical trials and direct observations by the practicing physicians, to provide customized treatment for individual. Doctors with the help of data science can track the clinical diagnosis of the patients with confirmed diagnosis. A smarter and economical healthcare system includes (i) the treatments that area tailored to suit the individual biology, (ii) the treatments that are administered effectively, (iii) the services of doctors and hospitals that are used in a cost-effective manner, and (iv) the patients pay for the outcomes, and not for the procedures.

7.9 Virtual Assistance

Data science is of immense value to provide virtual assistance to the patients in need, particularly in emergency. Examples include pre-mature baby delivery or erratic and untimely seizers or people caught in a fire or have undergone a tragedy, like a rape, or burglary or a break, which may require immediate attention to save the life of affected persons. The virtual assistance is also important in places that are inhabited but have no/limited medical infrastructures. Most importantly, virtual medical care saves the lives of the people.

7.10 Neuro Care

Data science has a big role to play in the field of neuro care. The brain is a delicate organ and perhaps the most vital to the existence of a human being. Even the microscopic disorder in the sensory or nerves in the brain can be life threatening for the people who suffer from these neuro disorder. The data science can accurately find the desired results if it is quality data in sufficient quantity. It can generate insights into the future course of action to bring about effective and efficient neuro care. Major brain surgeries can be done effectively if the doctors have precise data with them as a result of data science interventions. The AI tool can be used to derive data to improve the neurological health of the patients.

7.11 Effective Dieting

The latest developments in data science add value to the efforts of dieting. The data collected from several sources about the lifestyle of people can be useful for developing the need-specific diet routines for different kinds of people belonging to different groups. It is thus possible for doctors to prescribe accurate diets as per the analyzed data of individual patient's history or a group of people who have suffered a similar problem in the past.

7.12 Predictive Analytics

Large amount of medical data in data science can help in ascertaining that specific diseases affect people in a certain age group or in a certain environmental conditions. However, the trends observed may not be the same universally, but there are certain indicators which help doctors to find out the relation of a specific disease with a particular group of people. Data analytics of the past history of cases and a profiling of the current patient can help the doctors create awareness among the public at large for caring their health themselves to a certain extent.

The healthcare predictive analytics is changing as more organizations harness the potential of big data to implement the right infrastructure for generating actionable insights. Individual patient carries with him/her a lot of data, including terrabytes of imagery associated with MRIs, CT scans, and X-rays. The doctors and healthcare administrators may be able to analyze these data in a repeatable, efficient, and intuitive way using a number of analytical processes and present them on a dashboard for communicating complex information in a much simpler way.

The medical data are normally stored in a spreadsheet or report, but predictive analytics can provide better outcomes for patients. The GIS data can establish the relationships and patterns that traditional healthcare IT systems cannot detect. Considering the variance of the unstructured medical data, which at present is difficult task to understand, strong predictive analytics software will be difficult to create, but software to structure and analyze medical data will be extremely helpful to healthcare providers to assess and understand the patient problems and profile, which subsequently will improve the quality of healthcare provided.

8 Conclusion

Healthcare is a tremendously dynamic field. The medical data are required to be continually updated, and the analytics need to reflect the change. GIS could be used effectively to get a dynamic answer with its tools for mapping, visualizing, and analyzing the time-series health data. Because of the changing nature of health and disease at different locations and at different times, there is a need for health planners and policymakers to use data analytics software more effectively to meet the needs of people [2]. From the past and present data, a better future prediction can be made. The future work could investigate problems related to data quality, the impacts and consequences of spatial scale on data relationships, and the development and use of appropriate spatially statistical and modeling techniques in data analytics.

Satellite remote sensing is now routinely used in health-related research to measure the environmental conditions that influence population, human vulnerability, and transmission cycles of diseases. Very high-resolution satellite data can be used for detailed mapping of habitations, water bodies, estimate human population density, and identify land use practices that affect human to some diseases. Despite the prospects, satellite observations are still not routinely incorporated into health decision support system. To alleviate this gap, there is a need to develop and test new tools that use remotely sensed data for specific disease applications.

As the relationship between location and healthcare continues to receive attention, health service providers need ways to integrate social determinants and community-specific information into their health management strategies. With the rise of IoT devices, a unique opportunity exists to get a better understanding of healthcare-related issues. It not only requires a faster response to outbreaks, but also a better understanding of the needs to have the proper healthcare personnel, materials, pharmaceuticals, and infrastructure. Faster, simpler, and more sophisticated tools for analyzing and visualizing patterns in data would be needed to make better decisions in a meaningful way. The challenge, however, is to use and analyze big geospatial data that the IoT-enabled diagnostics will create.

With an increasing number of devices being added to hand-held devices, including cell phones and PDAs (Personal Digital Assistants), it is expected that in near future, these devices will be able to sense/observe one or more vital signs and transmit alert messages to hospitals, ambulances, and healthcare providers for getting emergency services for their users. In addition to the use of wireless technologies in detecting the emergencies quickly, more efficient vehicular routing and detailed information on nearby hospitals can be used to treat the patients immediately and save them.

Data science has immense contribution from predicting treatment outcomes to curing diseases and making patient care more effective. While data science provides tools and methods to extract real value from unstructured patient information, it eventually contributes to making healthcare more efficient, accessible, and personalized. The number of healthcare institutions making data-driven decisions is increasing slowly but steadily. In future, the boost in health innovation would be driven by the three main factors: (i) advances in technology, (iii) growth of digital consumers, and (iii) reduced costs of healthcare.

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Chapter 2
Geospatial Health Data Analytics for Society 5.0

P. K. Garg

1 Introduction

Access to healthcare is one of the most important facilities for healthy population of a country. Healthcare access is a major concern for policy makers globally. Geospatial data and associated techniques can be used for improving the access and eliminating the disparity in the region for healthcare facilities. Accessibility ensures that all the sectors of the society have equal and adequate access to primary healthcare, regardless of their socio-economic and geographic factors. Human health always has spatial and temporal dimensions which can be very important as the spatial patterns of distribution of diseases can help understanding the dynamics of transmission and spatial determinants of the diseases.

Recent advances in geographical information and mapping technologies have created new opportunities for public health administrators and planners for planning, analysis, monitoring, and management of health systems. The application of geographic analytic techniques to understand the distribution of disease and determinants of health is the key issue in public health research. Analyses of remotely sensed data provide useful information about changes on the Earth's surface, changes in land cover, sea surfaces, temperatures, and climatic parameters. The land use and land cover maps derived from remote sensing data when integrated with the affected population, can lead to provide a correlation with the disease. These maps are then subsequently analyzed to model the disease risk and provide new insights in epidemiology [1]. The spatial and temporal remote sensing data can be combined with other data types for taking decisions related to society's health and well-being. Weather forecasting from satellite images is an excellent example of such application. Inspite of the great potential, remotely sensed observations of the land surface are not commonly applied to decisions about human health welfare.

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*, Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_2

Technology and healthcare go hand in hand. The technological advances have made it possible to examine the spatial and temporal trends in large scale epidemiological data, and save lives of patients. Geospatial technologies and IoT are becoming important tools for modern healthcare sector. While public healthcare has adopted geospatial technologies much earlier, their use in the health sector has grown substantially only in the last decade. The healthcare sector is now using these technologies to improve the quality of services and cut down the healthcare costs, while maintaining the operational efficiency. The government, administration, planners and other public healthcare organizations place emphasis on mapping of health centers, pharmacies, hospitals, etc., and creating databases using recent technologies for finding out the solutions of health-related problems, and taking appropriate decisions. The government has started to recognize the importance of GIS (Geographic Information System) in developing innovative methods for healthcare management and formulating healthcare programs [2].

The computerization and interconnection of a wide variety of services and devices have greatly facilitated the collection, storage, and analysis of vast amount of data. As these data management and analysis have become key components to many businesses, efficient tools and techniques for extracting the knowledge from huge structured and unstructured databases are required to be developed. Thus, a paradigm shift is observed in data analysis as more and more data is made available. Machine Learning (ML) and Deep Learning (DL), and data-driven approaches now-a-days have been used for various tasks, including medical diagnosis [3]. With the growth of high-performance and cloud computing capabilities, Artificial Intelligence (AI) and ML/DL, have been increasingly used in healthcare. Research in the healthcare field now focuses on the development of methodology to maximize the access to healthcare.

2 Geospatial Techniques

Geospatial technique is an emerging scientific discipline that combines the spatial data science, remote sensing, UAV/Drone data, GPS, GIS, AI, ML, DL, Big Data mining, visualization, and high-performance computing tools to extract useful information (Fig. 1) [4]. The use of geospatial technologies and spatio-temporal tools is increasing around the world as a means to understand the dynamics of infectious disease transmission and non-communicable disease distribution. Geospatial techniques are increasingly being used to model the environmental parameters with demographic data to assess health outcomes, hypothesis generation, conducting new data linkages and predicting disease occurrence [5].

With the development of GPS technology, the user's location can be determined even by mobile phones, and used to track the movement. Location analytics provide useful tools to model behaviors for informed actions. The disease prevention and control organizations can analyze travel movement information of close contact

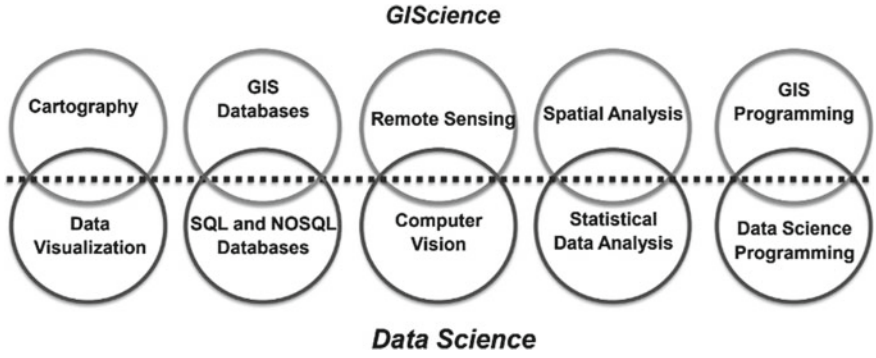

Fig. 1 Various forms of spatial data science

groups for quickly identifying the suspected patients to provide them timely diagnoses. The geospatial technology has been used in infectious disease modeling or prediction of disease occurrence and for disease surveillance [6].

In past few years, the wearables and connected devices have emerged that can collect large amount of individual health information through IoT (Internet of Things), such as heart rate patterns, blood pressure, sleeping patterns, etc. This data integrated with GIS technology helps discovering long-term geographic health trends in certain populations or certain regions, thus providing new opportunities in healthcare research [2]. In recent years, advancements in AI are also growing interest in real-time syndromic surveillance based on social media data. The DL algorithms can be applied to Twitter data to detect illness outbreaks, and subsequently build up and display information about such outbreaks to provide situational awareness. Innovative statistical methods and computational tools can be used for public health surveillance, including spatio-temporal models, for disease risk prediction, cluster detection, and travel-related spread of disease, to devise strategic policy in reducing the effect of diseases.

There are two broad ways to involve the use of remotely sensed data in human health studies: (i) in process-based models, and (ii) in pattern-based models. The process-based models simulate the underlying biological processes of disease transmission and spread, and are applied to predict the future outcome of different land use, environmental, or policy scenarios. For most diseases, since the current understanding of the processes is insufficient, thus, the use of pattern-based or statistical approaches improves the understanding about the working of processes [7]. Statistical approaches can be used to establish the relations among different variables, and as such do not determine the cause-and-effect relationships required to build the process-based models. The pattern-based approaches thus can provide useful relations between environmental drivers (including climate) and demographic processes (birth, death, infection, recovery). These relations can then be used in a process-based modeling approach. The pattern-based technique is extremely flexible and achieves good accuracy with consistency. Satellite data, available at various spatial and temporal resolutions, is very useful to develop the pattern-based approach for infectious disease modeling by providing environmental data over large areas [8]. By analyzing these relationships and understanding past trends, it is possible to better predict and anticipate future disease patterns and movements.

Health is considered as a geographical phenomenon, and therefore GIS can be employed by public health administrators and professionals, policy makers, statisticians, and medical officers. It serves as a platform for integration of multi-parameters for disease monitoring activities, and plays a vital role in information management, monitoring, analysis and prediction. Some applications of GIS in public health includes [9]: (i) geographical distribution and variation of diseases, (ii) analysis of spatial and temporal trends, (iii) identifying gaps in immunizations, (iv) mapping populations at risk and stratifying risk factors, (v) documenting healthcare needs of a community and assessing resource allocations, (vi) forecasting epidemics, (vii) planning and targeting interventions, (viii) monitoring diseases and interventions over time, (ix) managing patient care environments, materials, supplies and human resources, (x) monitoring the utilization of health centers, (xi) route health workers, equipment and supplies to service locations, and (xii) publishing health information using maps, etc.

3 GIS as an Enabling Tool

The GIS methods are used mainly to capture, store, analyze, manage, and visualize data that are linked to locations (Fig. 2). GIS brings together fields of geography and statistics in a wide range of applications such as, urban planning, water resource mapping, landuse mapping, and, more recently, in the field of public health research [7]. GIS could also be used to analyze large quantity of data and identify the areas

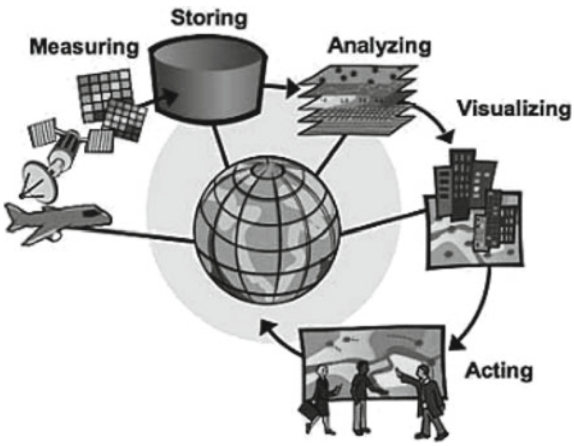

Fig. 2 Various functionalities of a GIS

where health facility is lacking at different levels. It can map and assess the geographical variation in required health services and developing innovative approaches of healthcare needs.

A GIS consist of five major components, as shown in Fig. 3; (i) the spatially referenced data that are collected and stored in a relational geodatabase, i.e., an information system from which data can be retrieved by logical queries, (ii) the hardware that stores the data and processing tools, (iii) the software/algorithms by which users have access to database, make query and analyze the data, (iv) the procedures for analysis and management of data, and (v) the people, both the developers and users of spatial data. In dealing with zoonotic diseases, affecting mostly developing countries, these challenges (shown in right pentagon) represent obstacles in building efficient and effective GIS architectures [10]. Each of these components play an important role and incorporates varying levels of complexity, depending on the application for which GIS is used. GIS can be used to integrate large amounts of geographical information from different sources, programs and sectors; including epidemiological surveillance, census, environment and others [2]. GIS tools have been widely used in health and human services, including epidemiologists, biostatisticians, vector control professionals, environmental health professionals, hospital planners, and human services professionals, among others.

GIS applications in public health may include tracking of immunizations, identifying health service areas, and developing health policies. The GIS technology has been used in public healthcare for tracking the sources of epidemiologic diseases and their spread in the communities. This information is vital for the authorities to respond more effectively to outbreaks of diseases as well as taking appropriate measures for the population at risk. GIS-based maps can help them understand disease diffusion as well as overall public health status to make decisions regarding the resources required to be deployed.

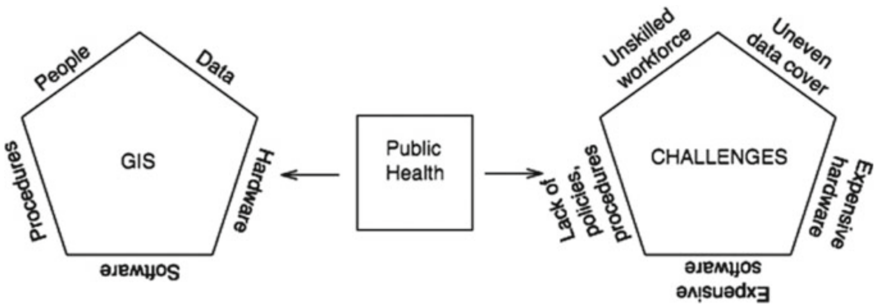

Fig. 3 Components of a GIS shown at the edges of a pentagon (left pentagon) and associated challenges (right pentagon) when data are collected unevenly or unrepresentatively, when the layers of information are handled by an unskilled workforce, in the absence of proper data handling and storage procedures, and if adequate hardware and software cannot be obtained [10]

GIS can also be used to create health profiles that describe demographic, economic, and lifestyle characteristics of the population as well as possible environmental health hazards in the area. Such data can be geotagged with coordinate system to individual's address to identify geographic variation in health needs. The spatial analysis in GIS can assess the healthcare needs for areas by facilitating the spatial linkage of diverse health, social, and environmental data sets [11]. GIS not only offers a platform for spatial interaction analysis, but also a means for developing models that describe geographical context.

The GIS is an enabling technology that integrates and analyzes multiple spatial data sources to provide answers of various queries. It is being recognized as an effective tool to answer complex questions related to health promotion, medicine, and epidemiology [7]. It allows visual representations of complex patterns, and the application of various spatial techniques to derive useful results. The GIS can provide powerful tools for linkage (through relational databases), analysis of spatial, quantitative, and qualitative data from various sources, and visualization of spatial data. As digital information on demographics and utilization becomes more widely available, health data will be incorporated in GIS-based decision support tools that allow communities and decision-makers to examine healthcare needs, access, and availability. The policy makers can explore inequalities in access to healthcare with the help of GIS tools.

4 Global Health

As countries strive to meet global development goals, the efficient use of resources as well as efforts to address geographic inequity becomes critical. The healthcare system consists of organizations, institutions, and resources aimed primarily at improving public health, and providing services that meet existing and future needs of all individuals. During the 1970s, the WHO and UNICEF adopted the "Health for All" strategy globally, mainly due to deteriorating health levels of people caused by a number of factors; such as poverty, and poor living conditions and malnutrition [12]. This strategy aims to achieve the highest possible level of health for people, according to five basic principles: (i) adopting several sectoral programs, (ii) preventing an outbreak of disease, (iii) making decisions by the community, (iv) using suitable latest technologies, and (v) achieving equitable accessibility and spatial distribution of healthcare services.

Geospatial data has been used for years by global health organizations to support population health and community initiatives. The health sector world-wide has been using geospatial technologies in their planning and marketing. The availability of large quantity of open source health data offers further new opportunities to analyze and monitor the trends in disease. It also provides new insights to assess the effectiveness of health systems, addressing these trends. GIS can be used for the analysis and display of complex information in a simple way so as to discover the patterns that are not apparent from the raw data. The poverty maps of many countries have been developed by the United Nations Development Program (UNDP), the World Bank and other international agencies, which are used to prioritize the health services as per the needs of the populations. The incorporation of multiple sources of geospatial information on human health and demographics determines the hotspots for disease transmission, and the use of predictive risk charts and maps to inform public health interventions [13]. Understanding the determinants of a disease and its spread from person to person has become increasingly global [14].

Spatial equality in access to healthcare for all can be achieved by spatial planning in GIS. It requires spatial distribution of population density for estimating the distribution of healthcare services in a geographical area. In addition to mapping the locations of pharmacies, community clinics, health centres, and hospitals, it is possible to identify the areas that lack such facilities. GIS can also be used to locate the areas, such as; (i) with patients having high concentrations of asthma, diabetes, cancer, heart failure, etc., and (ii) that lack health facilities for addressing the illnesses, such as obesity, diabetes, mental health issues, and respiratory illnesses.

GIS can also be used by hospitals and health systems to develop and monitor location-based population for health strategies, inside or outside a hospital or doctor's clinic. Both spatial and temporal analytic tools also require robust data management, such as the frequency of data updation [2]. The healthcare providers can use GIS as the platform for integrating and analyzing the clinical data, along with the environmental, behavioral, and socio-economic data. Thus, it provides a holistic view to understand the patients' needs, the non-clinical factors and places that are affecting the health of people and need special attention.

GIS has the ability to disseminate and manage the data globally via Internet platforms. The web-based GIS for the health system allows stakeholders in the health sector to share and manage data, and access information world-wide that enables them to find the specialized hospitals providing improved health services. Web-based GIS will certainly play a major role in moving communities and their nations forward to attain the optimal health that is needed in the whole world.

5 Use of Artificial Intelligence

Health intelligence refers to the specific application of AI and data science methods and tools to provide accurate, efficient, and productive insights into healthcare and medicine. Health intelligence applications include social media analytics for syndromic surveillance, predictive modeling to identify populations at high risk for disease, mobile health for healthcare delivery, and medical imaging interpretation. The AI-based Machine Learning has been increasingly used in healthcare, particularly with the rise of high-performance and cloud computing capabilities [3]. Machine learning, deep learning and data mining are modern methods for the analysis of big and temporal continuous data [15]. Machine learning includes AI methods and algorithms to obtain knowledge by iteratively extracting and learning from patterns present in the raw data. Deep learning is a sub-set of machine learning that allows algorithms to simulate the brain function to understand complex concepts in the real-world much more effectively. Data mining techniques are important part of machine learning to explore new patterns from large datasets in order to find out the solution [2].

Big Data and predictive analytics assist healthcare specialists with clinical decision-making. Prognostic modeling is widely used in healthcare, where some models can be used to predict future outcomes of diseases and/or treatments, or forecast the spread of diseases among the population [16] Others focus on identifying the patients who may be at risk for the development of a particular condition. For example, predictive modeling has been successfully applied in many countries to forecast the spread of the COVID-19 pandemic.

6 Geospatial Health Care Areas

Geographic data of population and healthcare provides the foundation for analysis and planning of various health services. Since health services and infrastructure are not spread evenly across the regions, it affects the need of population for healthcare, travel distance to obtain healthcare, and the quality of health services available to them. The benefits of GIS and its significant potential and advantages in the healthcare industry are now being realized [11]. Both public and private sectors in healthcare are utilizing the spatial data integration and visualization capabilities of a GIS. It plays a critical role to improve the quality of healthcare and accessibility of services, and keep the confidentiality of patients while making the data accessible.

Healthcare could benefit most through utilization of cutting-edge technologies. As hyper-aging has confronted all the society world-wide with a lot of challenges, the industry in Society 5.0 plans to build a new healthcare ecosystem while giving considerations to privacy and security of data [17]. The biggest challenge is to solve these issues while maintaining to provide high-quality healthcare services. With the trend toward a human-centered society, the Society 5.0 plans to improve the healthy life expectancy and vitality of individual citizen, improve human health world-wide, contribute toward the achievement of sustainable development goals, and resolve global challenges. Advances in ICT enable the digitalization of information on human biometrics and physiological functions, and allow detailed temporal and spatial observations of biological forms and functions. The ICT helps analysis of life forms as complex, and integrated systems. These massive data resources will generate a range of new values that would help from standardized care to personalized care, as shown in Fig. 4. It is expected that across the globe over 20 percent of the population will be over 60 years by 2050 [18]

There are several areas that are benefitted from the use of geospatial data and geospatial technologies, as summarized below.

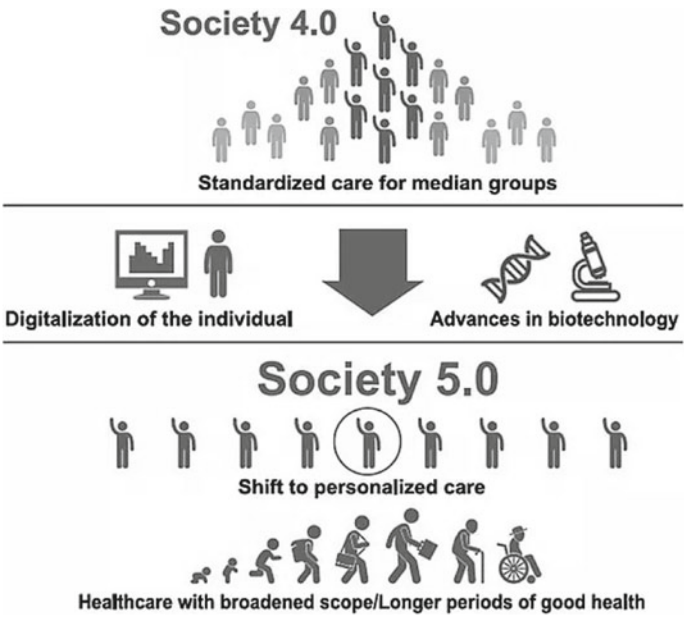

Fig. 4 Healthcare in society 5.0 [19]

6.1 The COVID-19 Pandemic

The COVID-19 has disrupted the lives and livelihoods of the people around the world. Due to COVID-19, the public health and associated economic activities have greater impacts on well-being of humans [20]. With several months of lockdown and other restrictions, the impact of human interactions with the Earth system is going to last long, widespread and varying across space and time, as shown in Fig. 5. Two pathways highlight the potential for responses: energy, emissions, climate and air quality; and poverty, globalization, food and biodiversity. Interactions will be visible differently in different regions and at different time scales. Some immediate effects of COVID-19 during reduced traffic congestion are already observed world-wide, such as clear sky, cleaner water-bodies, pollution free environment, changes in biodiversity and appearance of wildlife into human settlements [4]. These impacts are generally considered favorable to the environment, but there are negative effects as well which include increase in poverty, food insecurity, loss of mental health, and deaths due to disasters.

A wide range of long-term data from satellite remote sensing platforms, atmospheric, oceanic and surface measurement networks could be collected and analyzed to understand the Earth system changes during the COVID-19 pandemic. The changes in atmospheric pollutants, such as NO_2 during COVID-19 lockdown period have been observed world-wide from satellite data. For example, Space-borne NO_2 column observations from two high-resolution instruments, TROPOMI onboard Sentinel-5

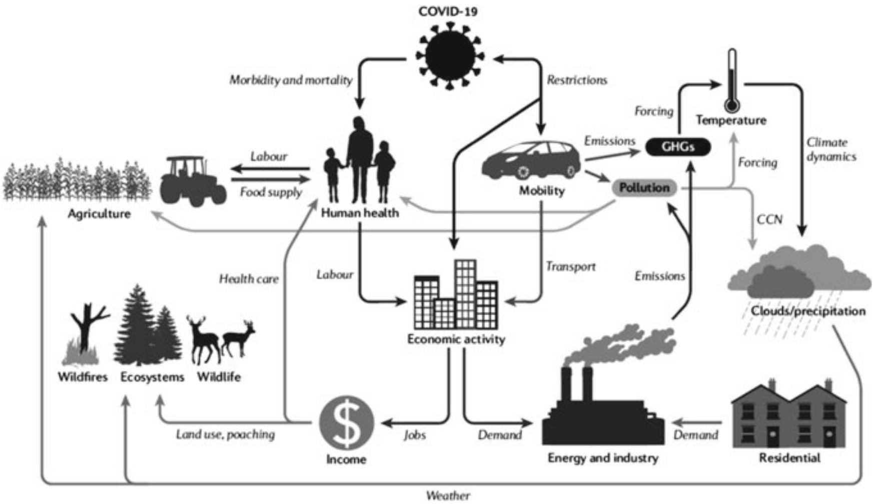

Fig. 5 Earth System interactions linked to the COVID-19 socio-economic disruption (CCN- cloud condensation nuclei; GHGs-Greenhouse gases) [20]

Precursor and OMI on Aura, found significant decrease in NO_2 over China, South Korea, Western Europe and the US, due to COVID-19 disease outbreaks in January–April 2020 [21]. Satellite-based NO_2 data showed substantial decreases by 40% on average over Chinese cities due to lockdown measures against the COVID-19 outbreak, while Western Europe and U.S. displayed robust NO_2 decrease in 2020, 20–38% relative to the same period in 2019.

6.2 Understanding Pattern of Demographic Data

The application of GIS in disease studies has improved the understanding between population, place and time of infectious disease outbreaks, and associated social and cultural factors. Although, these parameters are often non-uniformly distributed but the extent and intensity of a particular disease may be influenced by its spatial distribution [22]. Doctors at clinics and hospitals are required to understand their surrounding communities because, it is where their patients are located. While the geospatial technologies had been in use since long, but its use in proactive health service planning was relatively recent.

Disease prevention and control measures require the socio-economic, cultural, and educational data [23]. The GIS tools can be applied to establish a range of relationships between social, demographic, environmental, economic, and political parameters with the health outcomes. By understanding the distribution of social determinants of health, hotspots can easily be identified and pin-pointed strategies developed to address them. Applying the fundamental geographic concepts of proximity, travel time, correlation, and normalization by population and area to public health, datasets can identify the source of disease, and discover transmission patterns of specific health problems. These techniques in a GIS enable the integration of demographic, socio-economic, geographic, and environmental data that influence the disease risk and transmission and population health. Mapping socio-economic and cultural determinants has been successfully used to predict the occurrence of parasite co-infections. Generally, a strong correlation is observed between the economic growth and healthcare; whenever economic growth increases, government will provide adequate healthcare that would meet the needs of all individuals in the society.

Understanding the relationships between health and related factors e.g., socio-demographic, economic, political, and environmental variables can be a complex problem. The use of GIS is rapidly expanding as an emerging technology to effectively correlate and analyze the range of data necessary to address the complex question in health promotion, public health, community medicine, epidemiology, etc., [24]. The advancement in understanding of the distribution of social factors of health will continue to improve ongoing targeted monitoring and the development of strategies to prevent and control the infectious diseases.

6.3 Spatial Statistics and Analysis

Spatial statistics in GIS is used to examine the topological, geometric, or geographic properties of features. In public health research, spatial statistics can help to explore and quantify the statistical significance of observed trends in locations and spatial distribution [25]. Spatial statistics can be used to study the spatial patterns or trends in data, investigate the distribution of values, and identify potential outliers and errors in the geographic data. It provides an approach for statistical modeling, hypothesis testing, and inference. Spatial analysis in GIS can identify the areas where structural and environmental interventions might be most effective for the prevention of disease. Mapping coupled with spatial analysis techniques can provide patterns of disease spread and predict the future spread of disease to facilitate intervention [22].

Statistical techniques can be used to analyze the data and examine hypotheses to confirm the orientation and strength of a spatial pattern in the data, and the extent to which the data can be grouped in close proximity, i.e., clusters [2]. These techniques are used to draw conclusions from geographic data, and provide the best fit of spatial surfaces, as well as to integrate spatial and non-spatial data or attributes (i.e., directly accessed from a layer's feature attribute table, e.g., mean, standard deviation). The application of GIS for statistical analysis in medical research can be used to examine the statistical significance of clustering and spatial patterns through visualization (patterns), exploration (clustering), and modeling (predictive modeling, spatial diffusion), as shown in Fig. 6.

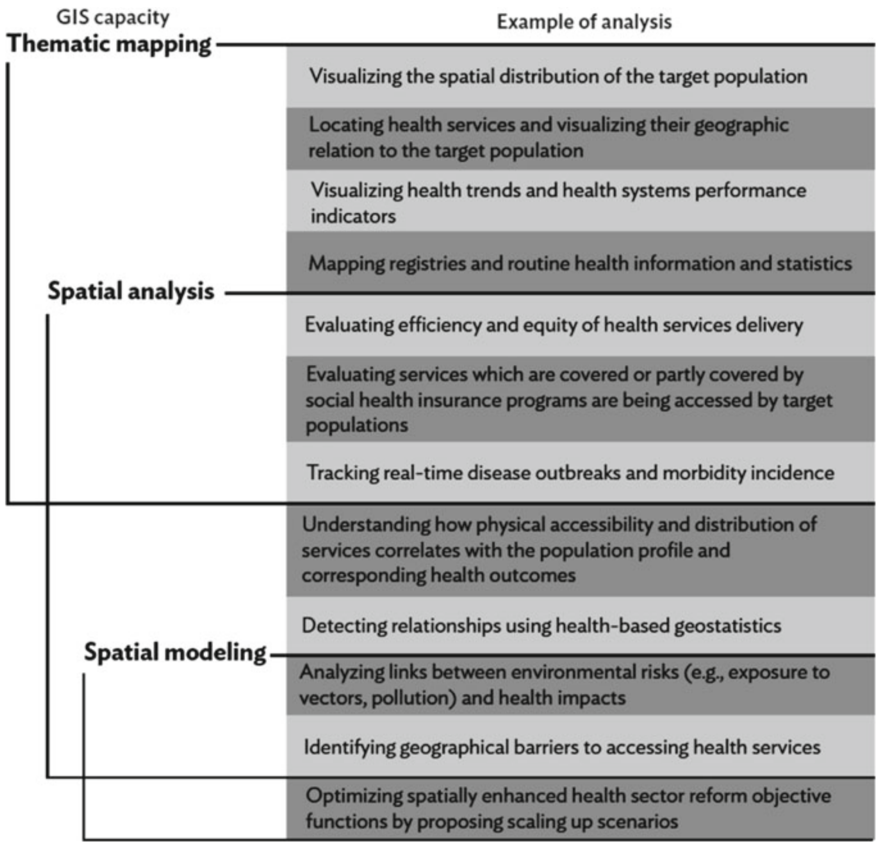

Fig. 6 Spatial mapping, analysis and modeling with GIS

A common task in public health is the identification of clusters of cases to examine the risk factors, transmission, and inform targeted interventions. For examining clustering, several statistical analysis functions and statistical modeling techniques are available through the Spatial statistics, Spatial analyst, and Geostatistical analyst extensions in the ArcGIS software. GIS combines sophisticated algorithms, spatial analysis, geostatistics and modeling, and thus making it a powerful tool for the prediction of disease patterns and associations [26]. Quantitative and statistical analysis methods within a GIS facilitate exploration of a broad range of determinants, including demographic, socio-economic, geographic, and environmental factors that influence disease transmission. Other statistical methods that may be optimally utilized in combination with other geographic analytic software programs are, such as GeoDa or SaTScan, or statistical software packages, such as R or S-Plus.

6.4 Epidemiology

The socio-economic characteristics of the population is considered as one of the most important factors for epidemiology studies [1]. GIS can be used to capture, store, handle, and integrate large amounts of epidemiological surveillance data, census, environment and other parameters. Public health resources, specific diseases, and other health events can be mapped in a GIS in relation to their surrounding environment and existing health and social infrastructures. The study of spatial epidemiology requires several information, such as; where do these epidemics occur? What are the environmental factors that lead to outbreaks of epidemics? What is the evolution of the spatial patterns of these epidemics? GIS can effectively provide the answers of these queries. For example, GIS can determine the locations of epidemics, and uses demographic, economic, and environmental data to study and analyze the spatial relationships within the affected area. The spatial planners can use the modeling approach for control of epidemic diseases. The spatial distribution of epidemic diseases can be implemented by modeling the prediction of disease risk using the kernel estimation method [16].

GIS plays an important role in strengthening the whole process of epidemiological surveillance, and information management and analysis. It provides excellent means for visualizing and analyzing the epidemiological data, revealing the trends, dependencies, and inter-relationships that would be difficult to discover from the tabular data. Such information in the form of spatial maps is extremely useful for monitoring and management of diseases and developing public health programs. The factors, including adverse environmental, behavioral and socio-economic conditions, are likely to increase the incidence of diseases, and therefore need to be monitored regularly. By tracking the sources of diseases and the movement of contagions, health agencies can respond more effectively to the outbreaks of epidemics by identifying the population at risk [12].

Monitoring of diseases requires continuous and systematic collection and analysis of data. Software packages, such as BodyViewer by GeoHealth, help medical personnel visualize clinical data. Such geoclinical information system is a useful tool when evaluating environmental risks and exposures. GIS serves as a common platform for convergence of multi-disease surveillance activities. The data in GIS has to be georeferenced accurately. The GPS can be used to obtain locations (coordinates) of features precisely that can be used for georeferencing purpose. GIS can be used to process aerial or satellite imageries to generate latest and accurate maps for epidemiological surveillance, and establish spatial correlations between potential risk factors and the occurrence of diseases [22].

6.5 Disease Mapping

Disease mapping is an effective tool used for understanding the behavior of diseases for their prevention. Disease mapping applications may include; vector-borne illnesses to communicable diseases to cancer, in both rural and urban areas as well as track the historical trends of disease. Many of these applications involve surveillance of disease incidence and prevalence for controlling the diseases. The minimization of diseases can be achieved by time-series mapping, evaluating health outcomes, and assessing population risks. These maps can be used for developing simulations, planning interventions, and identifying disease indicators. For example, spatial variation in urban densities and amenities can greatly influence the health and wealth of the people [24], and understanding such patterns would help targeting public health interventions.

Disease mapping can also be used to study the geographical distribution of disease in the future [27]. Integration of GIS technology into routine monitoring of health events helps identification of abnormal disease patterns. Interactive maps with geographical and environmental features help developing hypotheses and identifying the relationships of spatial patterns of diseases. GIS-based disease maps are also useful to support administration in decision making. These maps can also be used effectively by healthcare providers, public health managers, government, and policy makers [28].

6.6 Disease Surveillance

Public health surveillance is defined as "*the continuous, systematic collection, analysis and interpretation of health-related data needed for the planning, implementation, and evaluation of public health practice*" [29]. Public health surveillance is mainly based on a number of important elements, such as: (1) tracking epidemics, (2) evaluating potential infection; and (3) designing health interventions. Effective surveillance systems require early warning systems for public health emergency, able to assess the impact of interventions, and monitor trends in the development of health threats. Public health surveillance helps in; (i) monitoring the progress in achieving public health goals; (ii) detecting the impact of interventions aimed at improving public health; (iii) monitoring epidemic diseases and identifying associated problems; (iv) identifying public health priorities, policies, and strategies; and (v) predicting sudden emergency cases.

GIS tools are being used globally as part of disease surveillance and monitoring the health programs. It is one of the most common and popular uses of GIS in public health. The GIS techniques to disease surveillance applications have provided great opportunities in developing early warning systems for emerging and re-emerging diseases [30]. Disease incidence maps showing their geographical distribution can be used to improve the understanding of disease rates with time, and early detection of possible outbreaks or epidemics [31]. Disease surveillance with remote sensing and GIS techniques can effectively be carried out by creating risks maps showing areas affected by environmental parameters and contributing to the spread of diseases. It is an effective tool to monitor infectious diseases that basically spread by disease vectors and the environmental factors of disease vectors. The GIS also improves understanding of the spatio-temporal distribution of parasitic diseases to develop cost-effective disease control programs [24].

Disease mapping and disease modeling in GIS are two interrelated but important components of disease surveillance. GIS methods can support large amount of data for disease surveillance and health reporting, identify new cases and population at-risk, identify risk factors, and quantify risk and transmission patterns [12]. These provide a systematic way to spatially correlate the features of the environment with known epidemiologic diseases systems. GIS can be used effectively to explore the relationships between health and places that may not be otherwise feasible using traditional techniques [32]. Such correlation can be used to develop extrapolation-based models that predict the risk of disease over large geographic areas even if the data are either sparse or not available. For example, vector distribution in inaccessible areas can be mapped and assessed using remote sensing and GIS. Although the GIS for disease surveillance is the most established and well-developed application for public health, but there is still ample opportunity for growth and innovation in this area.

Since 2000, considerable progress has been made in combating the global burden of malaria [15] due to effective use of modern tools and approaches. Malaria is influenced by changes in land use, stagnant water, and settlement patterns, as well as movements of human population. Malaria transmission cycles are sensitive to climatic variability. Geospatial data, including satellite-based observations, are used for monitoring the environment affecting human populations in order to devise the action plans for malaria eradication. Satellite-based measurements include estimation of land surface temperature (LST), identifying polluted water, deriving the Normalized Difference Vegetation Index (NDVI) that are sensitive to vegetation and moisture. These measurements can provide accurate, reliable, and timely information to predict geographic patterns and changes in climate factors, LST, water storage, mosquito habitats, and land use and land cover (LULC) that may influence malaria spread and transmission, as shown in Fig. 7. The NDVI values are direct indicators of vegetation density and moisture-stressed vegetation, and are related to relative humidity, rainfall, vegetation growth, and to some extent as measures of surface climatic conditions. These climatic conditions significantly affect the transmission rates of diseases they carry. The NDVI is also used in models of vector suitability, abundance, and disease transmission and early warning.

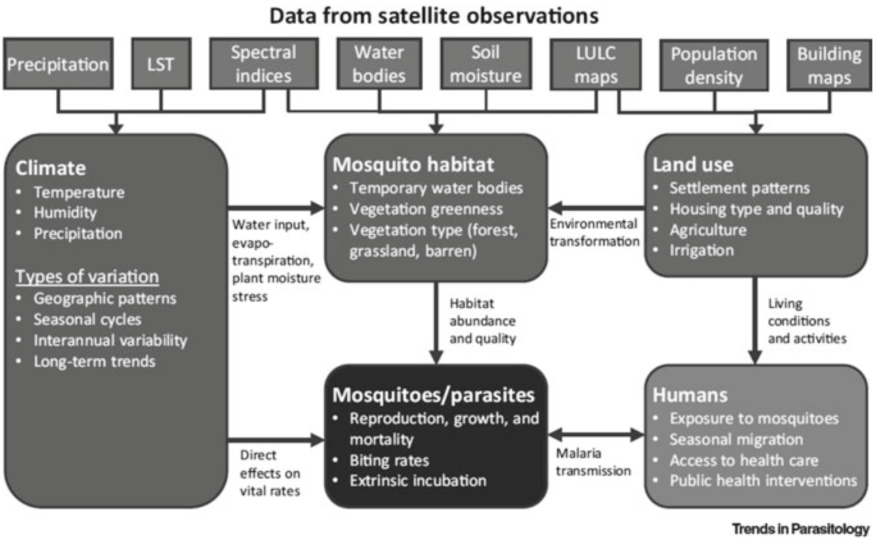

Fig. 7 Pathways through which satellite data provide information about Malaria [15]

6.7 Analyzing High-Risk Locations

Risk analysis is often information intensive, as it requires extensive data from the field (primary), secondary (reports), remote sensing images, etc. GIS for risk analysis includes risk mapping, assessment, evaluation, vulnerability analysis, or emergency planning, risk management, communication, or monitoring that could be used to explore various potential impacts of environment, landscape, or climate change on human health [24]. To facilitate risk modeling and prediction, data from multiple sources is required to be integrated. In general, the risk analysis is combined with the disease modeling to estimate and evaluate the environmental disease hazards for a given population. Typical risk analysis may determine the exposure to hazardous waste or pollution, proximity to polluting industrial sites or traffic, or stagnant polluted water. GIS-based risk analysis can be used to relate different sources of environmental exposure to the residential locations of people in a simple, and objective manner [33], in order to increase the effectiveness of control efforts, and prevent outbreaks and epidemics.

Integration of GIS with environmental and epidemiological research leads to the creation of maps that make interpretation of complex relationships easy. The use of GIS in risk analysis has lot of potential to help policy and decision makers understand the spatial relationships between pollution and health. The risk analysis includes some aspects of risk assessment, management, communication, or monitoring with respect to impact on health. Typical risk analysis examines the exposure to hazardous waste or pollution, proximity to industrial sites or traffic, or residence in a locality with characteristics that may influence diseases. The goal of these analyses is to identify urgent need, increase the effectiveness of control efforts, and prevent outbreaks and epidemics. In many cases, epidemiological knowledge of disease outbreaks is combined with GIS to help prevent its further spread [34]. The GIS applications can effectively demonstrate how humans interact with the environment to minimize the health risks. Risk analysis applications also have a great potential for situational analysis and policy development.

6.8 Community Health Assessment

Community health assessment and profiling is the compilation and mapping of information regarding the health of people in a community [35]. Community health profiling is required to (i) develop hypotheses and act as a catalyst for obtaining more information about individuals, families, groups, or neighborhoods, (ii) establish general relationships between the environment and health outcomes, (iii) track changes in the health of a community with time, (iv) make suggestions for follow-up analysis and research, (v) facilitate access to data by local health administrators and planners, and (vi) allow local governments and stakeholders to improve community health.

Health profiles can include data on health outcomes and direct and indirect factors that influence the health, such as socio-demographic characteristics, disease morbidity and mortality, health behaviors, and health policies. These data can be linked in a GIS with the geographical locations of community infrastructure, such as public utilities, schools, religious buildings, food courts, guest houses, hotels, malls, roads, etc., in order to establish the feasible relationships between health and surrounding infrastructures [11]. The above information on community infrastructure can easily be derived from high/very high resolution satellite images, such as IKONOS, QuickBird, WorldView, etc. The GIS could be used by the public health officials to identify and examine the potential exposures of diseases in a community, plan preventive activities, pinpoint the resources required, and implement screening tests and other precautions, including medical diagnosis and treatment [35]. This information may be very useful for taking community development initiatives, and valuable to decision makers for creation of suitable public health policies.

6.9 Disease Modeling

The development of models helps health planners to target immunization and take immediate initiatives as well as to take decisions to provide resources and staff. Disease modeling is often one important component of risk analysis of vector-borne or sexually transmitted diseases. Disease modeling helps extending the disease mapping applications to (i) predict the trend and future spread of disease, (ii) identify the factors that are responsible for disease transmission, (iii) locate high risk regions for disease prevention or intervention, (iv) target control efforts, (v) identify the gaps, and (vi) increase stimulus for data collection in these areas [27].

6.10 Health Access and Planning

The main aim of the health services is to improve health of people. Access is a multi-dimensional concept that describes people's ability to use health services as and when these are needed. It mainly refers to the relationship between components of services needed and the characteristics of service delivery systems [7]. On the other hand, accessibility focuses on the geographical location of services in relation to population in need. The distribution of health services is uneven over space in most of the cases. The WHO and the World Bank emphasized that nearly half the world's population faces difficulty in accessing the healthcare facilities. The accessibility and utilization of healthcare also depend on a number of important factors, such as socio-economic parameters, need, equity, and supply and demand [12].

The geographic accessibility can be focused on individuals' access to health services in time and space, and may offer valuable insights into health decision making. The accessibility of health services and the distance between them is also important, in order to know the travel time required. It is essential that easy and equitable access to healthcare services are made available to all, including those without their own transportation. Early healthcare applications worked with relatively simple logics, such as minimizing average distance or maximizing population coverage, and these considerations still remain important, especially in developing countries where use of health services varies strongly with the distance. GIS is an effective tool for dealing with healthcare services, especially related to locations [16]. Network analysis in GIS can be used to develop the network of health services in an area or to identify the population not having proper access to services within a defined area. Network analysis and segmentation can be used in GIS for planning proper health services and delivery [36].

GIS provides methods and tools for viewing geographical variation in accessibility. This can be achieved by (i) identifying the optimal location for healthcare services, (ii) understanding the relationship between the current locations of services and actual healthcare needs, and (iii) evaluating the spatial accessibility to healthcare services. GIS-based health maps and data are significant resources for health planning and services delivery, particularly at the local level. The visualization of spatial distribution of health status indicators can be used for mobilizing the community action to improve the health of people. Visualization of health data can help developing healthcare policies and resource allocation as well as planning targeted interventions [24].

One of the important applications of healthcare planning is modeling the optimal locations of healthcare services [11]. The spatial decision for allocating a healthcare service location may include adding a new service into the existing services, and removing the existing services. There are several GIS models that help determine the best location for healthcare services; the most popular being the location-allocation model that can be used to evaluate the accessibility to healthcare service after identifying the areas with poor accessibility to service locations. Location–allocation models are generally used to select the optimal locations; for example, a new location for a healthcare center may be identified by taking into account the existing locations for available healthcare centrrs, as well as basic demand for services to cater the need of the population. Such modeling in GIS is based on several layers, such as (i) existing healthcare service locations and their spatial distribution (supply), (ii) population distribution and their demographic data (demand/need), and (iii) transportation network linking potential patients and healthcare services. These layers can be merged and overlapped in GIS to determine the accessibility for planning of new healthcare services or improving poor accessibility to healthcare service locations. These models contribute not only to solving the optimization problems associated with public health scenarios but also evaluating the service delivery in an area.

6.11 Proximity Analysis

Proximity refers to the location of features through measurement of distance between points in a given area. It is an integral component of geographic analysis in public health research, as the location and proximity are equally important in linking the risk factors and disease outcomes to further understand the disease behavior and pattern [25]. The GIS techniques are best suited as transmission of infectious diseases are closely related to geographic proximity. The use of spatial analysis in public health helps understanding the location of vectors and transmission dynamics, and mapping public health surveillance. Geographic analysis has also been applied to link proximity to exposures and incidence of diseases, such as air pollution and risks of cancers and cardiovascular disease. Proximity is also important in assessing the access to healthcare services and healthcare utilization, monitoring and evaluation of disease control programs, examining the potential sources of diseases (vectors), health metric outcomes, and program planning and resource allocation [8].

Machine Learning has been used for air pollution exposure modeling. For example, neural network was used by [37] to model daily particulate matter < 2.5 microns in diameter (PM2.5) levels in the US using multiple predictors, including satellite-based aerosol optical depth (AOD) from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite. Variables, like NDVI, surface reflectance, absorbing aerosol index, and meteoroidal fields are also informative about PM2.5 concentrations. A trained neural network was used to make daily predictions of PM2.5 at 1×1 km grid cells, which allowed the epidemiologists to access PM2.5 exposure in both the short-term and long-term.

The GIS techniques are best suited for public health surveillance and disease control, as transmission of infectious diseases is closely related to geographic proximity. It includes case location, identification of clustering, mapping of epidemic dynamics, and mapping disease burden and response. Geographical methods have been applied to the fields of chronic disease epidemiology and environmental health to link proximity to exposures to incidence of non-communicable diseases. These methods can also compute the area, for example, area likely to be served by a hospital.

Population and healthcare facilities are considered as the demand and supply sides of a healthcare system. Generally, it is observed that uneven distributions of geographic population and healthcare providers can lead to disparity in accessibility of health facilities for the patients which determine the inequality in utilization of health resources by the people and subsequently their health outcomes. It also leads to assessment of work load in these health facilities that determine the stress level of healthcare professionals and quality of care they can provide. The GIS can be used to carry out specific computations, for example, the habitation falling within a given radius of a health center, that would likely to serve the population within the zone. [38] presented the results of a case study using all hospitalization data in Florida in 2011. It was observed that hospitals with higher values of crowdedness are generally in areas with relatively lower accessibility, as shown in Fig. 8. In areas where residents have

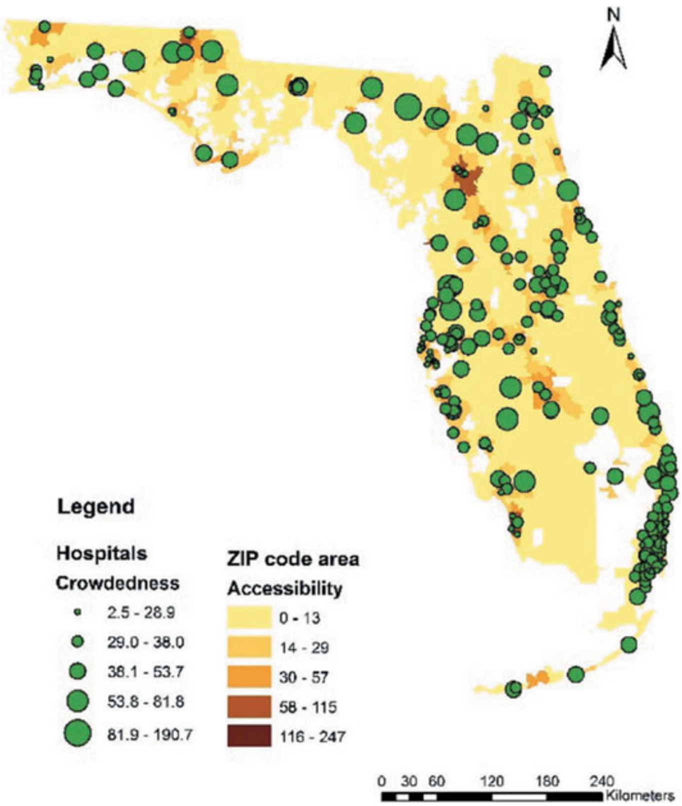

Fig. 8 Hospital potential crowdedness with respect to zip code area accessibility [38]

better accessibility for hospital care, those hospitals tend to have less crowdedness. Such an analysis based on residents' accessibility and facility crowdedness is very useful in examining the geographic variability of resource allocation.

6.12 Overlay and Buffer Analysis

The GIS can overlay a large number of information. It helps in multi-criteria modeling (for example, in understanding the association between prevalence of certain diseases and specific geographic features) and decision making for medical research [1]. GIS can create buffer zones around a selected feature. For example, a radius of 5 km around a hospital depicts its catchment area likely to be served. The users can specify the size of the buffer and then combines this information with the disease incidence data to determine the number of cases falling within the buffer. Buffer or proximity analysis can be used to map the impact zones of vector breeding sites, where control activity needs to be strengthened [27].

6.13 Travel Time

Human movement plays a significant role in the transmission of pathogens, spread of infectious diseases and drug resistance, and emergence of novel pathogens [25]. Human locations, dispersal patterns, and affected areas can be modelled with a GIS to track the movement of people, including travel time that can estimate the rate at which an infectious disease is likely to spread. The travel time can be used as a factor to identify the area likely to be affected and at risk populations. Travel time is a geographic concept within a GIS which is determined using the shortest distance between the two points along a network (such as roads). Attributes, such as length, speed, restrictions on travel routes, and obligatory points are to be taken into account to determine the realistic travel time [39].

The most frequent use of travel time in public health is to ascertain the accessibility to healthcare facilities. Measures of geographical access to healthcare facilities can be either area-based or distance-based. Area-based measures describe for areas, like towns, or states, while the distance-based measures focus on the distance or travel time. To assess travel along the transportation networks, GIS has been used to calculate the network distances and travel time based on road type and quality [16]. The network analysis in GIS provides information on maps to get there where health services are located. Health services delivered at home (e.g., polio vaccination) can also be scheduled in a more efficient manner by network modeling of transportation factors and street patterns, and by displaying the most efficient route. Ambulances can quickly reach to the patients in need through network analysis of roads.

6.14 Health Insurance

Insurance is a welcome necessary step for a fairer healthcare system. Its success is judged on how well new policies are developed with a cover beyond the hospitalization, how fairly and inclusively the cover is offered and how best the low premiums are established. Health insurance companies world-wide use GIS to make sure their customers are within reasonable distances of the medical services they need. Many large health insurance companies have developed large data warehouses containing demographic and socio-economic data, as well as geographic attributes of specific diseases, interventions, and treatments. Knowing the demographics of an area, health problems that exist and where these can be treated successfully, healthcare insurance companies decide how much money they will need to spend.

The GIS is also being used to find out the areas where rates of health insurance coverage is low or more likely to be at risk for not being covered, including governing factors (e.g., age, income, and health) that affect reasons for not having insurance coverage. The Electronic Health Records (EHR) are best utilized to locate the patients who are not insured. Increasing access to health insurance does not necessarily help lowering the risk of developing certain disease but can provide financial support. For example, a study on thyroid cancer using multivariate spatial regression analysis showed that socio-economic and environmental factors are more likely to drive that disease rather than access to insurance or healthcare facilities. With the recent opening up of the general insurance sector to foreign companies, new insurance products are expanding the business, mainly concentrating on urban middle and upper classes job holders. It would increase extensive hospital use and protection against huge hospitalization expenses.

6.15 Visualization

A GIS combines the cartography, maps, and multivariate statistical analysis to explore the spatial relationships (i.e., linking people to place or people to environment or disease to environment), and visualization of information in 2D or 3D [2]. GIS has been used for processing, analyzing, and visualizing data in the domains of environmental health, disease ecology, and public health [40]. The GIS offers powerful tool to present spatial information at individual level, and performs predictive modeling [1]. It determines the geographical distribution and variation of diseases, and their prevalence and incidence. GIS can be used in generating colored thematic maps to represent the intensity of a disease or a vector. In comparison with tables and charts, GIS-based maps in 2D or 3D are an effective means for communicating the information clearly even to those who are not familiar with the GIS technology.

The GIS can keep a track of the geographical locations of service providers, customers, resources, and health plans and programs. It allows policy and decision makers to easily understand and visualize the problems in relation to the available resources, and effectively targets the resources to those areas where these are needed most. GIS can create dynamic link between the databases and maps so that data updates are automatically reflected on the maps [8]. Using GIS tools, analysts can better represent the geographical context in identifying the optimal healthcare locations, and visualize and explore the model results.

6.16 Spatial Decision Support Systems (SDSS)

The GIS can provide access to view information about a particular feature, such as a hospital, while more advanced users can employ spatial analysis techniques to answer questions related to their health-sector concerns accessing relevant data from a Data Base Management System (DBMS) or Relational DBMS [2]. GIS can be used to develop interactive queries for extracting the desired information contained within the spatial and non-spatial data. It can answer the queries of location, condition, trends, spatial patterns, and modeling.

The Spatial Decision Support Systems (SDSS) integrates the GIS with an array of analytic methods to support healthcare planning and assessment [36]. The SDSS combines the geographic database, system for database management and querying, user interface, and analytical tools, like location-allocation and spatial interaction models. It includes a suite of sophisticated spatial analytic models and tools that are tailored for a specific type of health service to explore geographic questions of interest. The SDSS aims at incorporating the expert knowledge and more complex and appropriate analytical tools. It also emphasizes on data dissemination, community concerns, and participatory decision-making. Most SDSS for healthcare planning have been customized for particular types of health services. With the growth of internet-based SDSS for healthcare planning and analysis, these systems provide spatial data and simple tools to support decision making.

6.17 Web GIS

The GIS technology is useful to develop web-based GIS [2]. Health data may be stored in a central server which can be accessed from various terminals connected to the server through Internet or Intranet. A large number of health departments has recognized the capabilities of GIS software for public health preparedness. With the availability of robust internet connectivity and mobile GIS software (e.g., ESRI's ArcPad) as well as Google Earth images, many health departments have started publishing internal and public web-based data query systems (i.e., interactive health atlases) and web-based services locators. Statistical and epidemiological methods are required to be developed to protect individual confidentiality while putting up the data on open platform [1].

Dynamic maps published on the web allow patients to locate the most convenient services to their home or work easily. With mapping and spatial analysis capabilities of GIS, health departments have adopted electronic disease surveillance systems, and immunization registries. However, it is envisaged that web-based situational awareness systems available to general public as a standard practice might take another decade.

7 Challenges of Using Geospatial Technologies

The scale at which mapping and geostatistical analyses are carried out is very important when GIS is used as a tool to control the spread of diseases. Lack of updated GIS infrastructure has always been a barrier to the utilization of GIS technology. This is partly due to the need for sophisticated and expensive licensed GIS software, which may be a significant hurdle for the countries with limited resources [41]. Significant costs are also associated with the development of SDSS, which often requires specialized equipment. Open source GIS software is becoming increasingly user-friendly by incorporating graphic user interfaces (GUI), in addition to traditional command line operations, and a variety of algorithms and structured query language (SQL) packages analogous to those of the commercial software [42]. The use of low-cost internet and free GIS software can be effectively applied to mapping and preliminary geospatial analysis without the need for any centralized database or internet access [43].

The application of GIS technology requires from basic to more advanced skills. However, many organizations do not have even the basic technical expertise to operate GIS-related activities [5]. Many international agencies are routinely utilizing GIS as part of their work in developing countries but they also have lack of local technical expertise to build capacity for GIS-related activities [44]. It may increase the cost of using the technology to the local organizations, and therefore it is necessary that knowledge transfer, up-skilling and building of local technical capacity is also done [45].

The GIS experts in health applications must possess skills in mathematics, statistics, programming, analysis, image processing, modeling, and visualization as well as have skills to deal with big datasets. In addition, they must have basic knowledge of medical terms and in-depth understanding of the healthcare industry. The domain knowledge will help them to identify essential and important data for implementation of GIS-based functions and develop analytical models to derive the results. The availability of such qualified and experienced data scientists is one of the main challenges for its management in health sector. Lack of people with skills is the major obstacle for fast adoption of GIS and its use in predictive analytics. Table 1 shows the basic skills required by a healthcare scientist to use the capabilities of GIS.

While the use of GIS in various activities of healthcare is increasing, but literature indicates that health and population datasets are not routinely collected and stored or available for analysis [46]. This creates hindrances in the spatial analysis of statistical

Table 1 Healthcare data scientist skill set

Skills	Components	Examples
General skills	Dimensionality reduction	Data pre-processing
		Classification of patients
	Supervised machine learning	Forecasting of numeric values (e.g., length of treatment, number of staff needed for a shift)
		Hospital management
	Time-series analysis	Forecasting the growth in a certain healthcare sector
		Disease prediction
		Forecast of disease complications
	Natural language processing	Defining specific patient groups for research
		Improving quality and integrity of medical records
		Claims processing, feedback analysis
Healthcare specific skills	Medical coding classification systems	Analysis of patient records
		Billing operations and reimbursement
		Mortality and morbidity statistics
		Public health forecasting
	Hospital database	Hospital management
		Drug research and development

uncertainties occurred as an outcome of uneven distribution or low quantity and quality of data. Also, it affects the effectiveness of intervention due to the fact that most data-poor areas (e.g., low and middle-income countries, or less wealthy area) generally require the most intensive health monitoring systems. Thus, a foremost requirement for the use of GIS is availability of good quality data in sufficient quantity to ensure that public health policies and practices are derived by the best available examples [5].

Limited emphasis has been placed on the conduct of operational research that can determine the effectiveness of geospatial health data and methods in real-world settings. Such studies are essentially needed to demonstrate the effectiveness of geospatial data science for improving decision-making and resource allocation programs. With the availability of more advanced GIS technology, some of the problems of uneven data capture are resolved by regular updating of data, interpolation of the data, or adding environmental and geographical parameters to historical datasets that previously were missing [47]. Limited availability of spatial data, privacy and confidentiality issues, restrictions to the access and use of individual health incident and outcome data, are some of the challenges faced, particularly while working in

GIS with human diseases. Other challenges may be related to data ownership, ability to link publicly available data due to inconsistencies in collection parameters and systems for health, and limited knowledge of the application and interpretation of GIS data in decision-making processes [36]. The health data ownership is particularly problematic when it is accessed and used by others, as the laws may differ widely in different countries.

Many countries have made significant progress in developing infectious disease surveillance systems through GIS, particularly after COVID-19. These systems could somehow be used successfully to control the disease outbreaks. However, these countries face a number of challenges that affect the operation of these systems effectively and efficiently. The most important of these challenges are; (i) weak infrastructure and coordination between relevant health organizations, (ii) weak technical systems of health organizations and facilities, (iii) weak financial resources for systems development, and (iv) untrained human resources to use such systems. These challenges will negatively contribute to the decision-making process and interventions aimed at eliminating and controlling the infectious diseases.

Several developing countries now have access to GIS technology due to their participation in programs, such as the Global Fund for Tuberculosis, Malaria and AIDS program [48]. This is a collaborative program between the governments, civil society, private sector and people affected by these diseases to eradicate the Tuberculosis, Malaria, and AIDS, as epidemics (http://www.theglobalfund.org/en/). The availability of free or inexpensive tools (such as WHO's HealthMapper or CDC's EpiMap) for mapping disease distribution and community treatment information provides greater opportunities to public health workers to be more effective and reach wider population.

Some international organizations and countries have already declared open access policies to make data publicly available globally. However, the big challenge is to ensure that the global public health data is protected. Geospatial data are prone to global threats. The international public health community therefore has to ensure that adequate regulations are in force for sharing of public health geospatial data. This could easily be achieved through international collaborative approaches.

8 Conclusion

The GIS is a valuable tool to assist in health research, health education, planning, monitoring, and evaluation of health programs and health systems. It aids in faster and better health mapping and analysis than the conventional methods. It gives health professionals quick and easy access to large volumes of data. It provides a variety of dynamic analysis tools and display techniques for monitoring and management of epidemics. The application of GIS in public health, epidemiology and disease surveillance systems, etc., is expanding, due to increasing availability of the technology. The application of GIS technology to the study of parasitic diseases has contributed significantly to understanding of parasite ecology and their associations with disease distribution, leading to the development of effective control and prevention interventions, mainly in developing countries. While lack of infrastructure, training on GIS, long-term upgradation and maintenance of database, uniform and complete data collection, sharing of databases, have affected their low utilization in health sector, there are several opportunities in future to improve free or low-cost access to GIS data and software, enhance human capacity, and improve data storage and analysis capacity with low-cost cloud-based systems [15].

The GIS and spatial analysis can be used as an effective approach in a variety of programs, policy, and planning issues in health promotion, health facilities and public health. They provide capabilities for describing, analyzing, modeling, and visualizing health issues relevant for policy making. The GIS is an innovative technology that can be used to provide the interface between data and science by using spatial aspect to link health outcomes to individual's behavior and environmental factors. It can be effectively used not only to monitor and assess the program and policy implementation but also tracking changes in the health of a community.

Understanding healthcare needs and access also require different types of geographical information. Indicators of healthcare needs based on morbidity, mortality, and utilization have well-known limitations, similar to many standard indicators of healthcare access. The literature suggests that health planners may not have sufficient exposure to utilize the spatial concepts of GIS, and therefore restrict themselves with complex spatial analytic techniques. Through internet and mass media, people can acquire information about the quality of healthcare at different locations and about the types of health problems that exist in different communities. In Society 5.0, humanity and machines will solve the greatest issues society faces in the twenty-first century. The healthcare in Society 5.0 would provide improved longevity with longer periods of good health, and life-long care for patients with cancer, heart disease, psychiatric disorders, or other conditions that demand long-term monitoring.

The GIS has a vital role to play in the future [2]. Use of GIS in healthcare research has increased dramatically in the past decade. GIS has provided new ways to investigate healthcare needs for geographical areas, better measures of geographical access to health services, and new approaches to analyzing and planning services locations. Research areas that can benefit from GIS, such as geographic variations in healthcare utilization, have not made full use of GIS capabilities. Health services research requires spatial data on health resources, population, utilization, treatments, and outcomes, and such data are often not available at different temporal and spatial scales. Privacy and confidentiality restrictions limit the access to data about health status and health outcomes, especially for individuals. Data on healthcare utilization and treatments are often proprietary, controlled by health insurers and health organizations. Even for public data, there may be problems with compatibility and sharing of information among the agencies.

With increasing cost of healthcare combined with an increased number of patients, and with financial and human resource limitations, it is necessary that the available modern technology for existing healthcare systems is adopted. The possibilities are limitless, ranging from health sector management to resource implementation. Although, the advances in remotely sensed data and technology have enhanced the research in Earth sciences, environmental and global climate in the past, yet the potential for applying remotely sensed data to a range of human welfare and human health issues is largely underexplored. Health administrators, professionals, and researchers need training and user support in GIS technology, data and epidemiological methods in order to use GIS properly and effectively. The advances in wireless and mobile technologies can support the pervasive healthcare by improving and expanding the coverage of existing services. The hand-held devices combined with increasingly available wireless networks by healthcare professionals will be able to expand pervasive healthcare services. In addition, it can lead to considerable cost savings in the total cost of healthcare services.

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Chapter 3
Relevance of Spatio-temporal Data Visualization Techniques in Healthcare System

Satya Prakash Maurya, Anurag Ohri, and Shishir Gaur

1 Introduction

Over the past few decades, the changes in environmental patterns and food practices of human beings have affected the health of the people adversely. Changes in our environment are a big concern before whole community. Apart from this, food materials available naturally may not always be free from components or contaminants that are not safe for ingestion. The physical and chemical treatments involved in processing food may also generate or introduce substances that are not good for human health. Such contaminants of food with undesirable substances-natural or artificial may be called food hazards. By taking such food, we often invite, knowingly or unknowingly, many types of ailments [14]. This puts immense pressure on the medical practitioners. With the advancement of information technology, the growing volume of healthcare data is not available for the medical practitioners. This enables them to extend better treatment to their patients. These data, however, must be organized and interpretable to facilitate an effective healthcare system [10]. Healthcare data include, in its turn, the patient's medical history, previous diagnoses, consultant's records, pathological test reports, radiology images, medications recommended, diagnostic reports, treatment plans and medications, and duration of treatment as well as expenses along with other administrative information related to hospitals and health centers.

Apart from this, a geographical location may also be included to record the location, if the disease is peculiar or contagious in nature. The collection and interpretation of healthcare data is crucial to optimize patient care and treatment. Various sources, like U.S. Census Bureau, World Health Organization (WHO), National Center for Health Statistics, Human Mortality Database, National Cancer Institute provide data sets in the healthcare sector. Healthcare data may improve the decisions to be taken

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_3

by the healthcare facilitator to refer a specialist for the particular health condition of a patient.

This data can play a vital role in accurate decision-making when displayed properly. For this purpose, several visualization methods have been introduced including bars and charts. A few modern techniques and tools have also been proposed to visualize the growing electronic health data in integrated and well-managed forms. The development of computerized software solutions for essential services such as consultation appointments scheduling, medication slip, pathological reports, billing (expenses), and treatment duration has widened the horizon of the healthcare sector. However, there is unavailability of similar advanced support systems in routine tasks of healthcare and declaring interrelation among the various data such as reviewed laboratory reports and physiologic data, clinical trials data to identify or predict the forthcoming health condition of a patient or symptoms to new occurring health complications.

Undoubtedly, it is clear that there is an urgent need for computer-supported applications for optimized and standardized visualization of data in healthcare. In this chapter, different data visualization techniques are discussed, and have been compared vis-à-vis. The role and relevance of spatio-temporal data are discussed in detail which highlights the goals and usability of healthcare data visualization with best practices of techniques through selected implemented examples. Thus spatio-temporal data pose as a great diagnostic and therapeutic tool in the treatment of patients.

2 Data Visualization Techniques in Healthcare

2.1 Background

The increasing health issues with expanding urbanization and population have compelled for data visualization techniques as well as necessitated evaluation frameworks in healthcare [19]. There may be an improvement in the quality of healthcare services and its costs if visualization is well-organized and decisive. Information technology and modern computer usage initiated a new trend of data analyses which resulted in itself as a technology not only for corporates but also governments, public organizations, and other citizen's services.

Fortunately, an advent of software in healthcare services has the potential to contribute innovative and mutually reinforcing solutions to reach the desired goals. Thus, digitized data and visualization techniques have witnessed positive changes in healthcare services across the globe.

Moreover, the adoption of learning techniques in the healthcare domain can be promising due to an increase in the number of reported studies [15]. However, dynamic, multidisciplinary and cognitively complex healthcare data makes the visualization process a challenging task that can be handled with computational tools and techniques [11]. Furthermore, interdisciplinary initiatives create an opportunity to develop more efficient data visualization techniques and incorporate modern analyses tools for interpreting the challenging decisions among healthcare data of large volume, variety, quality, and conformance [6].

Although, computer-based visualization of healthcare data using various approaches has come into the picture, yet on a daily basis only a few success healthcare data are viewed which might be influencing the services efficiently. There may be reasons like unavailability of the common shared graphical user interface to patient healthcare. Besides challenging digital healthcare record management under the environment of vendor-driven integration systems is also a constraint in this direction.

2.2 *Challenges in Visualization of Spatial Healthcare Data*

Localization of Spatial Data

Public healthcare is an essential service that produces ample data. These data are unintelligible spatial data which is important and sometimes complicated too. Its accurate interpretation may be conclusive and have a preventive effect to control different diseases, especially for epidemics. Current socio-economic changes compel emphasis on cost efficient services all over the world. The ample healthcare data is categorized at local, national, and global levels with different objectives viz. to observe population health, resource distribution through stored targeted data, for the assessment of international liability of disease respectively. Visual elements like charts, graphs, and maps, are useful to interpret data enabling the medical practitioners and policy-makers to make decisions. A data visualization tool facilitates easier ways to visualize and analyze the trends, reveal the outliers, and assess the patterns from the given data.

Managing Data Framework

Usually, spatial data for healthcare activities used regularly by most of the organization. The relevant data available on the internet are considered as a data framework. These data may be generated from various sources of different locations. These data add preserved in a text files narrating the geographical coordinates i.e., longitude and latitudes. High resolution satellite imaginary is an important source to provide the relevant data. They may consist of text files, geographic coordinates of x (longitude) and y (latitude) with street address and high resolution satellite imagery or a paper map. Most of the organizations store the data in a standard format like Geography Markup Language (GML) which is XML grammar defined by the Open Geospatial Consortium (OGC) to represent geo-features and finally deals it on the internet. Nevertheless, spatial dataset creation is an expensive procedure, even half the cost of a project consumes to database creation, editing, and updating.

Another challenging task is to handle data sharing applications which also cover publishing and updating a static map over web-GIS periodically. These procedures must work for sharing of healthcare data such as demographic and healthcare data surveys, the multi-indicator cluster survey, household network survey, and international network for the continuous demographic evaluation [3].

Data Sharing Limitations

There are certain limitations of data sharing, such as legal (copyright and protection of privacy), ethical constraints (technical reciprocity and lack of proportionality), technical (healthcare data collection, restrictive data format, lack of metadata and standards), political (lack of guidelines and trust, restrictive data policies), motivational (lack of incentives, opportunity cost, work criticism, data use disagreement), economic (lack of resources and financial losses). These limitations in the healthcare information system are real-time challenges of public health data for accessibility and its usability. Some methods must be adopted to overcome these challenges.

2.3 *Different Healthcare Data Visualization Techniques*

Usually, raw data are present in tabular or graphical visualization formats which allow users to interpret facts and discover insights. There are many different ways to visually present the data. Visualizing healthcare data is a major tool and strategy which is an effective way to share urgent health information. There are various techniques developed for different types of variables that help in data visualization for analysis.

2.3.1 Visualizing Univariate Healthcare Data

The univariate graph presents information of a single variable's distribution without including excessive details contained in individual data points. Hence, univariate graphs help to visualize overviews of trends within the dataset.

Bar Charts

A bar chart is a common method to represent a set of categorical data. The bar chart displays data using many bars, each representing a particular category. It typically displays a quantitative data measure at one axis, and a categorical data measure at the other axis. An aggregation specific value is proportional to the height of each bar. The categories may belong to a particular disease or patient's information associated with a geographical location. To split a single bar into another categorical column in the data is a very powerful representation; it helps to visualize the contribution from different categories to each bar in a bar chart. Generally, the height of the bars correlates to the magnitude of data for both medical personnel and patients, so it is relatively easy to understand and draw certain conclusions.

An example of a bar chart has been presented in Fig. 1 which shows the broad cause of death worldwide for the year 2019. In this visualization death percentage and its cause of communicable, non-communicable, injuries and ill-defined have been plotted against the age groups. Another example (Fig. 2) shows continent wise spreading cases of Malaria, Tuberculosis (TB), and new HIV infection for the year 2019.

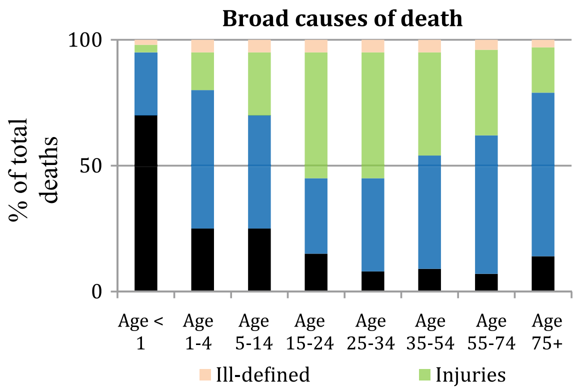

Fig. 1 Broad cause of deaths in Brazil for the year 2017 (WHO 2020)

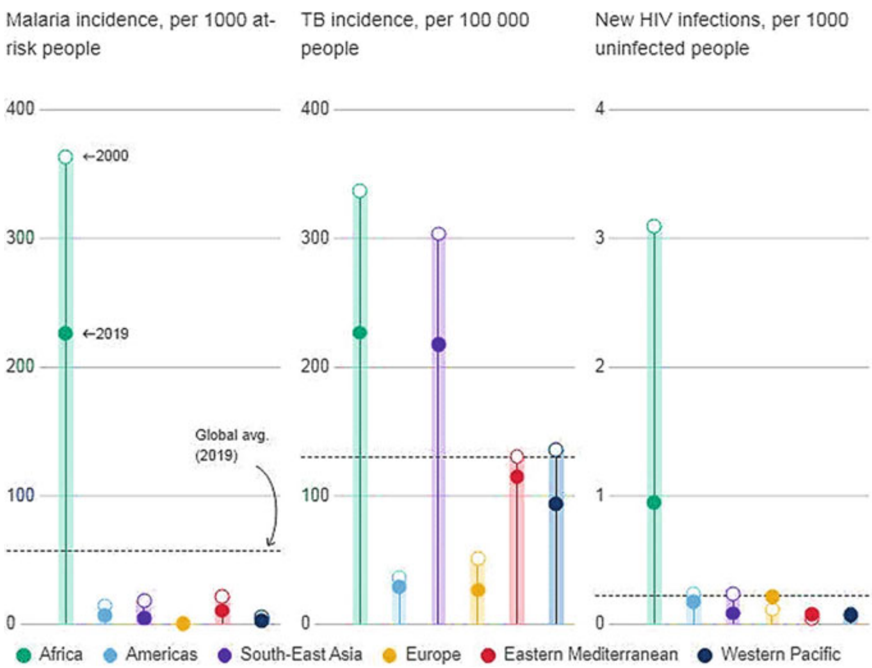

Fig. 2 Continent wise Malaria, TB, and new HIV infections (WHO 2020)

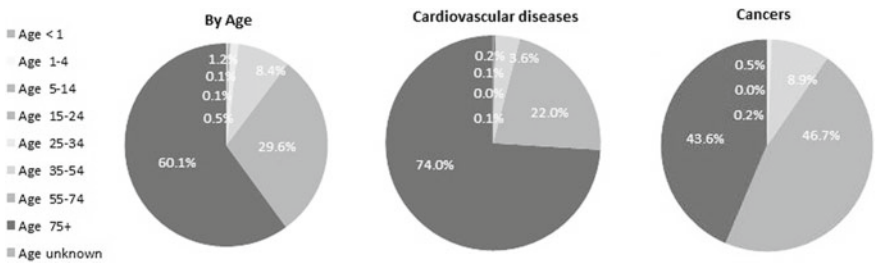

Fig. 3 A comparison of total deaths by age, cardiovascular disease, and cancer (WHO 2020)

Pie Charts

Pie chart is a popular method for visualizing univariate data in quantitative form. Pie charts are used to represent percentages out of a total. Unlike bar graphs and line graphs, pie charts are static over time. Structurally, they are circular shaped and divided into individual slices to visualize relative data that contribute to the overall total of different quantitative data categories. Several psychophysical studies have proved that it is much more efficient for visualizing proportions in comparison to other visualization techniques as it is intuitively easy to understand the visual. For categorized visualization, a color coding may be opted to each slice ease. Additional information can be labeled with respective names and percentages with each slice for a better interpretation to users. The visualization presents a comparison of total death with cardiovascular disease and cancer by age groups. This shows the majority of deaths of the age group 75+ is due to cardiovascular disease whereas age group 55–74 due to cancer (Fig. 3).

2.3.2 Visualizing Bivariate Healthcare Data

Bivariate healthcare data deals with two paired datasets that have a correlative relationship with each other. Bivariate statistics are used to analyze two variables simultaneously to analyze how the value of an outcome variable may change based on the modifications of an explanatory variable.

Scatter Plots

To visualize bivariate healthcare data scatter plots are the most frequently used techniques which represent individual pieces of data using dots. If two variables are related to each other it makes easier visualization. The resulting pattern indicates the type (linear or non-linear) and strength of the relationship between two variables. Structurally, these are square or rectangular plots made in a Cartesian coordinate system using measured data results against a parameter. They allow users to simultaneously identify a possible relationship between two variables and outliers in the data.

2.3.3 Visualizing Multivariate Healthcare Data

Radar Plots

The Radar plots technique deals with an arbitrary number of variables. Structurally, it is represented as a spider's web so also known as a spider graph. It has as many rays as variables projecting from an origin point, where lengths of the rays represent the values of the variable. This technique is useful to display clinical studies of multiple variables in a single individual or different groups which change over time. It may also be useful to display differences between disease status on multiple variables in multiple treatment groups or on multiple outcome measures [16].

Treemaps

Hierarchically structured large amounts of data can be easily visualized using treemaps. A quantitative sized and ordered variable is split up into rectangles in visualization space. Different levels of hierarchy can be visualized as looped rectangles in a treemap. At the same level, each set of rectangles in the hierarchy represents a column in a data table and each individual rectangle on a level in the hierarchy represents a category in a column [7]. In healthcare, treemaps are space constraints that are typically used to visualize genome data or statistics by a large window subdivided into multiple parts, where each rectangle is proportionate of a specified data dimension [8].

Estimates from the Global Burden of Disease (GBD) study, facilitating to analyze world's data of health levels and trends during 1990–2019, have been presented using tree map (Fig. 4). This analysis allows comparing causes, injuries, and risks within a country and compare countries with regions or continents of the world, and explore patterns and trends according to country, age, and gender.

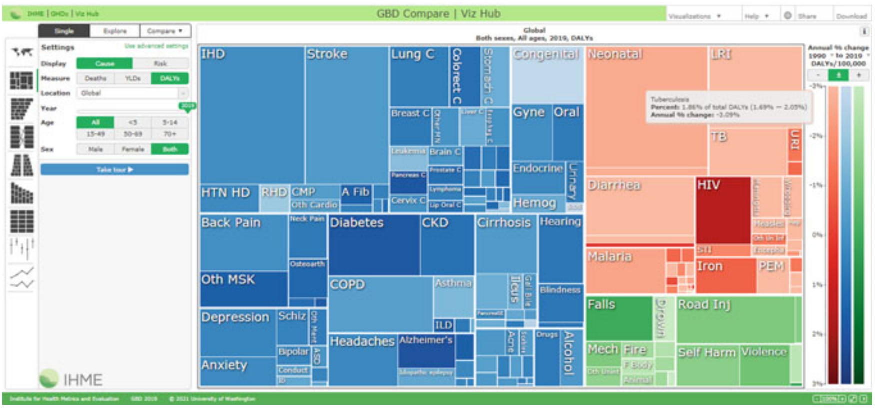

Fig. 4 A treemap showing Global Burden of Disease (GBD) trends from 1990 to 2019 *Source* https://vizhub.healthdata.org/gbd-compare/

Bubble Charts

Bubble charts like scatter plot where the data points are replaced with bubbles in two groups of numbers as a series of Cartesian coordinate system and the third set of numbers represents the size of the bubble. Sometimes a fourth variable is also visualized by using colors for different bubbles [1]. Bubble charts show the relatedness of three different sets of values. Different bubble sizes are useful to visually emphasize specific values. It allows the comparison of data in terms of their relative positions with respect to their sizes, axis, and color. The major issue with this technique is one may face trouble discerning and comparing the sizes of the circles. A bar chart with sorted data can perform a superior job of instantly distinguishing the difference between categories. Figure 5 shows a bubble chart shows a global scenario to live longer and live more with good health. The analysis during 2000–2019 reveals, global life expectancy (LE) at birth increased from 66.8 years in 2000 to 73.3 years in 2019, and healthy life expectancy (HALE) increased from 58.3 years to 63.7 years. Despite sharing similar increasing trends, LE and HALE among females were consistently higher than males.

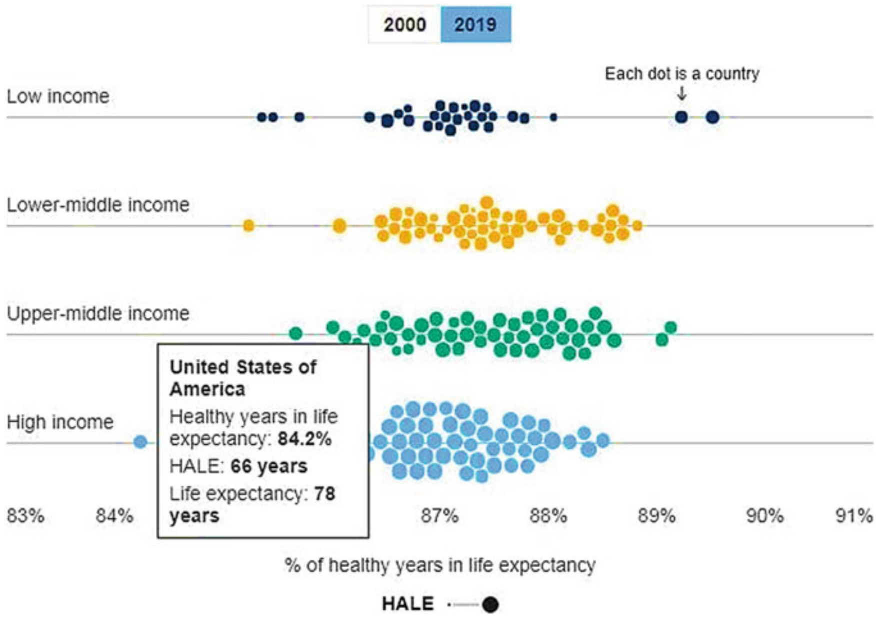

Fig. 5 Percentage of healthy years in life expectancy and leading causes of death by the country during the year 2019 (WHO 2020)

2.3.4 Visualizing Multivariate Healthcare Data Associated with Geospatial Regions

The representation of multivariate healthcare data on maps is a typical problem in the domain of data display and visualization. However, presenting multivariate healthcare data on a geo-space map may be more useful and interactive to users for conveying meaningful data at different levels of detail. In such data representation and analysis, maps are the most convenient one for visualization and conveying information to both a new user and a professional data analyst. A few multivariate data visualization techniques have been discussed hitherto.

Spiral Theme Plots

Usually, healthcare data are tightly associated with geographical regions and need geospatial map visualization. Displaying this type of data requires integration of time-variant information and multidimensional geo-visualization [17]. For this purpose, spiral theme plots have been developed as a visualization tool. This visualization technique combines other information visualization methods including the theme plot, scatter plot, and spiral plot. Spiral theme plots allow visualizing temporal data for abnormal patterns of seasonal diseases of patients such as Malaria, Influenza, and CAD. Spiral theme plots have a spiral pattern composed of stacked categories, or themes, along a spiral curve that represents the time axis. Each data point is plotted within the regions of the themes.

Ring Maps

Apart from spiral theme plots, ring maps are also useful to plot healthcare information to visualize geospatial health data. It is a recent development in cartographic display to visualize multivariate spatial health as separate data information rings using individual datasets. A segmented dataset may be circular or elliptical that surrounds a base map of a given geographic region of interest [13]. This setup facilitates visualization of geo-referenced multiple layers of data presented in an array of regional attributes.

Cartograms

Cartograms are another technique to visualize geospatial health data of a large population. These are the maps that distort the shape of geographic regions so that the area encodes a data variable. This feature makes them valuable for their abilities to offer spatial representations of a variable of interest while also retaining the semblance of a world map.

Heat Maps

Heat maps are a very common data visualization technique nowadays. It is a graphical representation with a system of color-coding of data to represent different values. They are applicable in various analytics tasks where user behavior on specific obvious visual cues varies over space. Heat maps use a gradient of colored matrix cells to visualize the intensity of individual data in a single view which interprets relationships

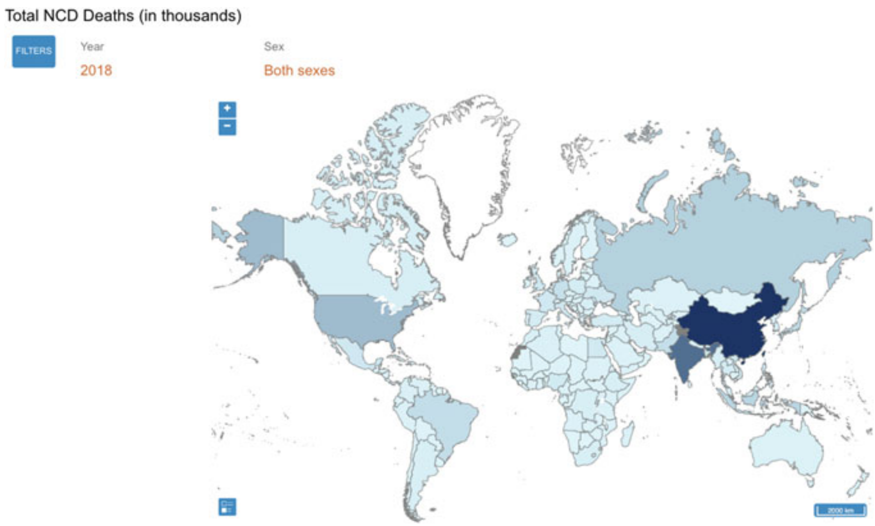

Fig. 6 Region wise comparison of deaths due to non-communicable disease (WHO 2021)

among the dataset. The combination of cell location and color gradients facilitates analysts to retrieve conclusions of the dataset.

Heat maps are very useful due to its better understanding through visuals where urgent attention is required. A comparative analysis of deaths due to non-communicable disease (NCD) in WHO regions for the year 2020 has been shown in Fig. 6. It is evident from this figure that the Republic of India and the Republic of China have observed the highest deaths. These two countries need further diagnosis of diseases. This may help to understand the present situation over non-communicable disease and attention of international communities for further analysis.

2.4 Comparative Analysis Strength and Limitations of Different Data Visualization Techniques

A comparative analysis has been worked out to facilitate a clearer view of data visualization techniques in Table 1.

3 Interventions of Spatio-temporal Data in Modern Visualization Techniques for Healthcare Data

The digitalization of data in healthcare systems is being completely integrated with the frameworks which are centralizing data at national or even international scale.

Table 1 Strength and limitation comparison of different data visualization techniques

Data visualization technique	Strength	Limitations
Bar chart	• Easy to interpret data trends • Straightforward to understand • Displays categories proportions and relative numbers	• Scalability • Less suitable for interpreting • Statistical data • Limited to relatively small datasets
Pie chart	• Straightforward data representation as a fraction of whole • Additional information can be added to slices for better visualization	• Similar size slices may be difficult to visualize • Slice location may affect data interpretation in the whole
Scatter plot	• Represents a range (max to min) of data • Straightforward observation	• Represents only qualitative relationship • Limited to bivariate data
Radar plot	• Effective visualization of a wide variety of data in a single view • Additional information may be added without overwhelming • Efficiently presents the larger view	• Statistical analysis makes it complex due to multidimensionality • Complicated due to the use of mathematical techniques • Data perception may be impacted due to variable arrangements
Tree maps	• Potential to display large datasets in a single view • Facilitates a hierarchal clear overview • Color and size encoding can be done	• Size distortion may occur • Tree map layout may affect the interpretation • Layout design can affect decision-making
Bubble chart	• Represents 3–4 variables without using 3D graphs • Relative comparisons are easy due to visual size	• Ability to ascertain actual values are dependent on the circle size • Difficult to display large dataset • Bubbles overlapping may cause visualization error
Spiral theme plot	• The longer time axis can be displayed • Ability to visualize time-variant geospatial data • Suitable for visualizing large health datasets	• Exhibits high information density • Needs guidance or descriptions to understand details in lower prevalence regions may be overlooked
Ring map	• Useful to visualize a variety of datasets at multiple geographic scales • Spatial data can be summarized at various geographic levels • Different time series data can be displayed	• Inaccurate representation of the spatial topology • Due to space cost, limited rings and spokes can be displayed • Unable to convey statistical data (e.g., correlation between geography and illness diagnostic rates)
Cartograms	• Global geographical data distribution can be displayed conveniently • Color encoding can be used to represent the quantity	• Variability of scale • Size distortion in geographic map may occur

(continued)

Table 1 (continued)

Data visualization technique	Strength	Limitations
Heat maps	• Common for spatial representation • Color gradients can ease data interpretation	• Legibility dependent on colors • Data interpretation may influence by a checker shadow illusion

The quantitative, as well as qualitative analysis in the healthcare domain has become equally important. Consequently, the large and complex healthcare data must be effectively visualized in desirable formats/patterns for making an efficient decision which is a challenging task. Another challenge in healthcare data visualization is how to display integrated multiple attributes with time-series data which is also associated with geospatial information. In modern public healthcare monitoring services, location base analysis over temporal changes of a particular disease can be easily done using spatio-temporal data. This is the most common method for displaying two or more maps in the layered form frequently superimposed over each other. Such spatio-temporal visualizations can be classified in three major categories i.e., (i). existence or non-existence of features also known as existential variation, (ii). change in location shape or size also known as alteration of properties, (iii). appearance of qualitative and quantitative characteristics which is known as thematic mapping [2]. The practical implication of this technique is to develop web-GIS-based application which can display the actual data items collectively and can perform a select or deselect operation over the attributes and also shows numeric values of selected attributes. A spatio-temporal visualization for under-5 mortality rate (U5MR) per 1000 livebirths in India from 2000 to 2017 has been plotted for monitoring and decision actions (Fig. 7).

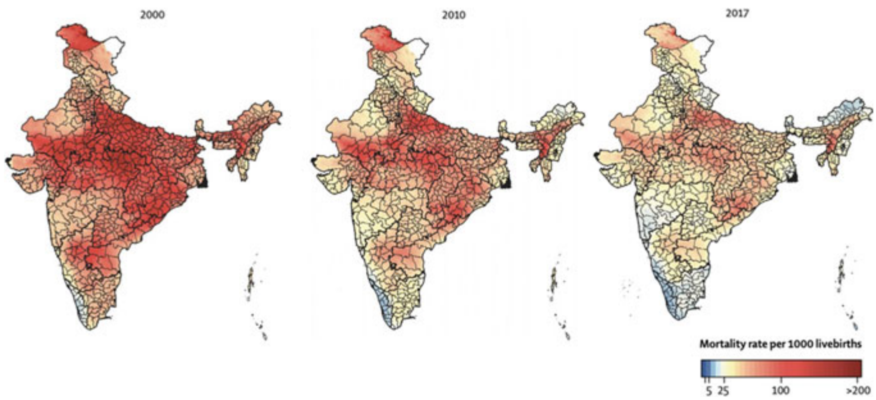

Fig. 7 Spatio-temporal mapping of under-5 mortality rate (U5MR) per 1000 livebirths in India from 2000 to 2017. *Source* Dandona et al. [4]

Apart from plotting data onto map, the map can also be visualized according to the available location information and highlighted using texture colors. Jiang et al. [9] made an attempt in this direction by mapping texture images onto the geospatial surfaces. In this approach, effective visual texture representations have been applied for the interpretation of multiple attributes and time-series information in a texture. For geospatial areas, visualizing individual patient's records and their improvements over the time may be aggregated and associated with global trends and patterns in a geospatial context.

A texture map visualization for over the Indiana state map for Influenza, Typhoid Fever, and Hepatitis B using County-based time-series data is presented in Fig. 8a, b and Zip-code-based time-series for multi-disease data in Fig. 8c, d during year 2004–2012. These attributes are typically defined over a geographic area which provides

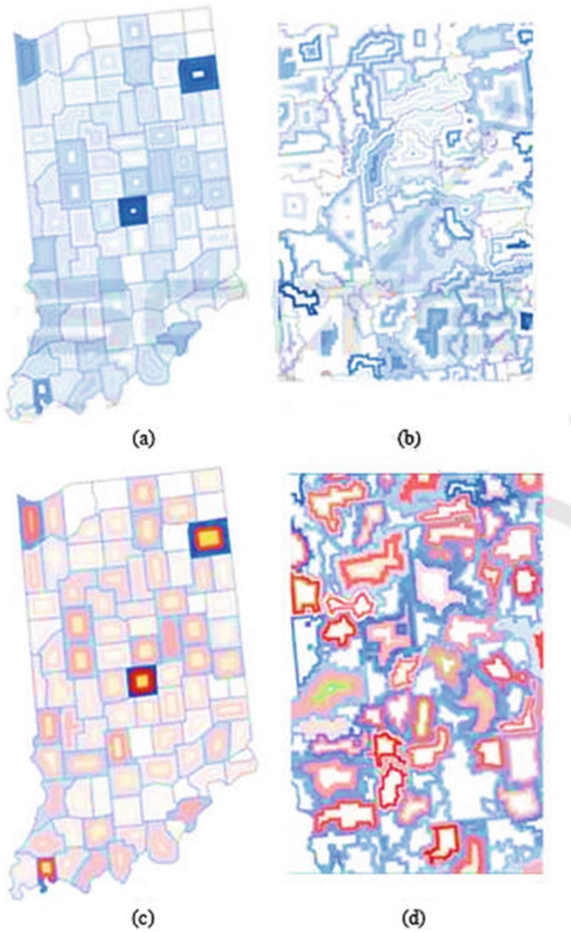

Fig. 8 Visualization of texture map with offset contours over the Indiana state map **a, b** shows the time-series views of Influenza, from the year 2004–2012 **c, d** shows three diseases, Influenza, Typhoid Fever, and Hepatitis B. *Source* Jiang et al. [9]

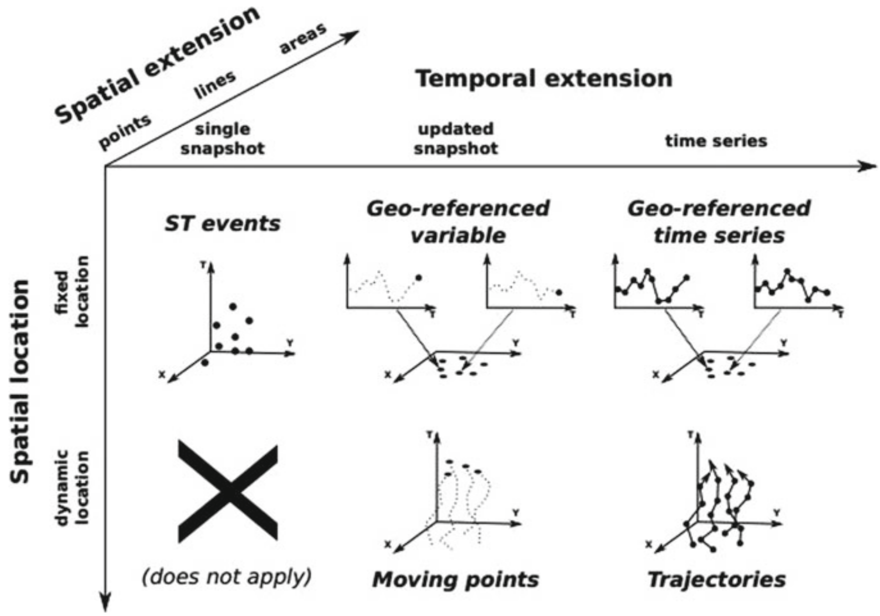

Fig. 9 Methods of spatio-temporal data visualization in cluster map [12]

a convenient platform for texture-based visual encoding. The texture map has been plotted with contours offset with color encoding.

Another method for spatio-temporal data visualization is clustering which is complex operation to perform due to synchronizing with time series data. A spatio-temporal mapping may have three dimensions i.e., temporal, spatial, and a spatial extension of objects, like points, polylines, and polygons. The simplest case, which is also the most popular in real-world case studies, considers point-wise objects, while more complex cases can take into consideration objects with an extension, such as lines and areas. Figure 9 shows the methods for spatio-temporal data visualization in cluster maps which has spatio-temporal events, Geo-referenced variables, and Geo-referenced time series for fixed location visualization and Moving points and Trajectories for dynamic location services.

The spatio-temporal events (e.g., records of epidemic) are information about the location and the corresponding timestamp data (both are static in nature) was recorded. Geo-referenced variable is to observe the evolution in time of some incident on a fixed location. Geo-referenced time series is about to store complete history record of an evolving object which provides a geo-referenced time series for the measured variables. In case of moving objects, spatial location of the data object is time-changing which may be helpful in healthcare service providing. Trajectories are applicable if the whole history of a moving object is needed for analysis and object visits the sequence of spatial locations together with the time-stamps of such visits.

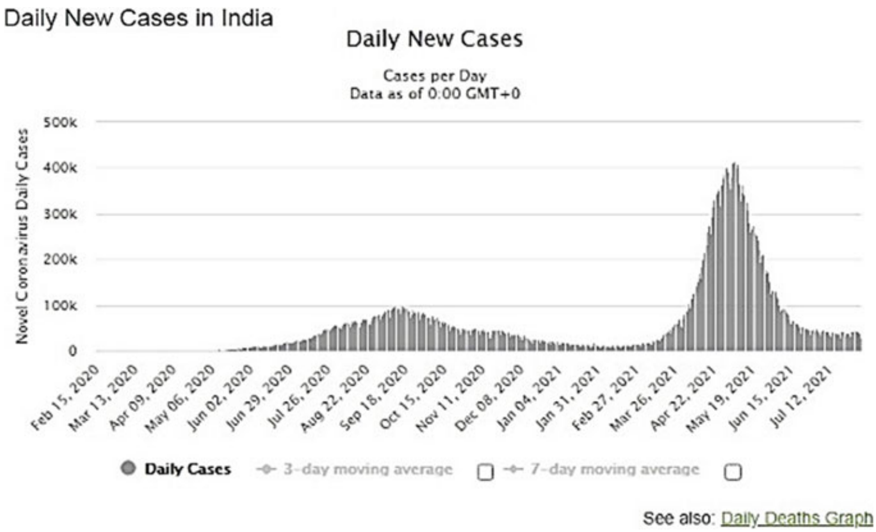

Fig. 10 Comparison of confirmed Covid-19 cases in India Feb 15, 2020–July 12, 2021. *Source* https://www.worldometers.info/coronavirus/country/india/

The collaborative efforts of interdisciplinary technologies lead to observe from granular to concrete information which may help in decision-making; more precisely a short-term or long-term policy-making. A comparative analysis of the Covid-19 outbreak in India during Feb 15, 2020–July 12, 2021 has been displayed using a bar chart (Fig. 10). This analysis shows clearly that how Covid-19 spreading cases affected Indian regions.

Therefore, spatio-temporal data is contributing a significant role in healthcare decision-making including facilitating medications as well as surveillance over large spatial regions.

4 Some Important Implemented Examples of Data Visualization: Web-GIS Approach

In the changing socio-environmental world, patients suffering from the multiple-organ diseases have emerged, hence different types of healthcare data including cardiac, pulmonary, microbiological, chemistry, medication, and infectious disease data pertaining to be displayed simultaneously to analyses for extending a better service in the particular cases. For this purpose, the patient's medical history data as well as a general pattern of treatment in the particular case must be available within a scheduled time. In the recent past, public healthcare across the globe has grown significantly over the internet in which geospatial data play a vital role for analysis. A geo-referenced information visualization is an essential tool to protect people especially in case of the burst of infectious disease. Web-GIS-based visualizations could be useful for predicting, warning, monitoring, and emergent events through visible spatial information. Moreover, among these most of the databases are available under static or dynamic mapping schemes. With the development of advanced ICT technologies, the web-GIS has become a popular tool and technology for building the public health information system to visualize healthcare information and to handle public health crises. To cite, hypertension cases visualization of Isfahan City (Iran) over the maps facilitates one or more detailed static web-GIS displays of geographic area and disease outcomes. These maps compare individual zip codes with expected cancer cases where static display data from a source geospatial database could be prepared [18].

A web-GIS-based application has been developed to visualize healthcare services and status (https://healthheatmapindia.org/). This application has been developed by the Metastring Foundation (https://www.metastringfoundation.org/), a non-profit entity and part of the biodiversity initiatives. This application facilitates data visualization of defined indicators (Fig. 11) over the geographic area. Another feature available is IBP layers, a well-defined vector layers; which can be superimposed over the present view geographic area for a better analysis and interpretation too.

An analysis of women anemic patients of age group of 15–49 has been displayed in percentage over all districts of India which shows Rajasthan, Uttar Pradesh, Bihar and Madhya Pradesh and Andhra Pradesh are dominating and need proper attention (Fig. 12). Black rendered regions represent that data are not available for those districts.

Other analysis of household's data of states in India that do not use government hospital facilities has been in percentage which shows Uttar Pradesh, Bihar and Jharkhand is the most critical. This analysis ensures that healthcare administration is

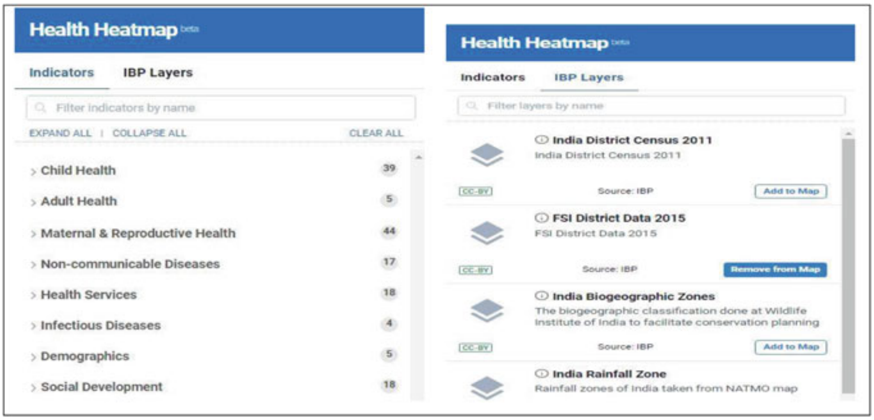

Fig. 11 Indicators and IBP layers listed in different categories wise. *Source* https://healthheatmapindia.org/

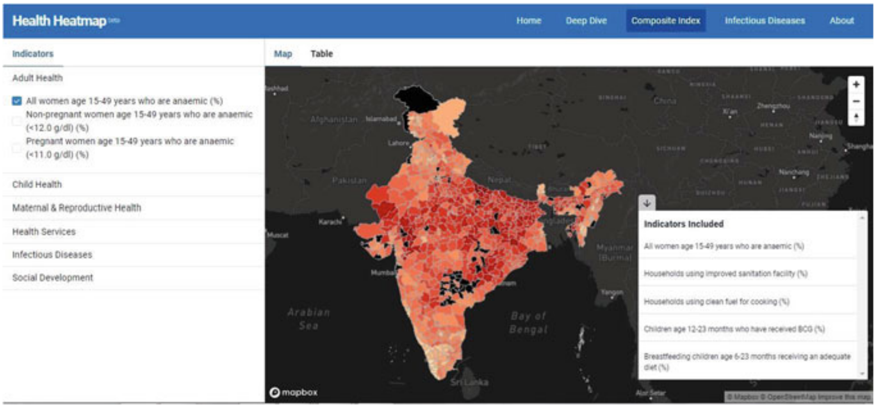

Fig. 12 Visualization of Anaemia cases in women aged 15–49 from different districts of India with state boundaries

not sufficient as per the need of the population. People are less aware of government facilities too. Several other important visualizations of healthcare data like diabetic cases, heart disease, asthma, dengue, child diarrhea, infant mortality, chickenpox, and non-communication diseases are also shown in the website.

Another web-GIS based healthcare information system has been developed by an Indian portal https://www.Covid19india.org/. This administers detailed Covid-19 outbreak spatio-temporal data for India which facilitates visualization of Covid-19 cases growth district wise (granular scale) and diseased in the last 7 days (July 10–July 16, 2021) (Fig. 13). At different spatial scales viz. district level, state level, and national level monitoring of spread, testing, tracking, and medicinal facilities can be made available for the better management of healthcare services. Another aspect of the Covid-19 management can be observed using data of active cases and vaccine dodges administered at state scale. In both the visualization, color encoding has been done with spatio-temporal information over a static map which is either based on district boundary or a state boundary map.

In future trends, it can be easily observed the effect of present vaccination drives in non-spreading regions to analyze the efficiency of the vaccines and the management applied to avoid spreading of Covid-19. In this sense, geospatial analysis can be game changer in the critical healthcare situations.

A web-GIS-based healthcare monitoring platform is developed by Institute of Health Metrics and Evaluation (IHME) (http://www.healthdata.org/results/data-visualizations). In data visualization section, data have been arranged according to geography, health conditions & injuries, and risk factors etc. for more than fifty categories like cancer and child health. Some important visualization like lower respiratory infection prevalence, mortality rate of Tuberculosis (TB), oral rehydration to reduce child mortality, Diarrhea, Hepatitis, Viral Hemorrhagic Fevers are well-managed. This would prove useful for future projections as Global Burden Diseases (GDB)

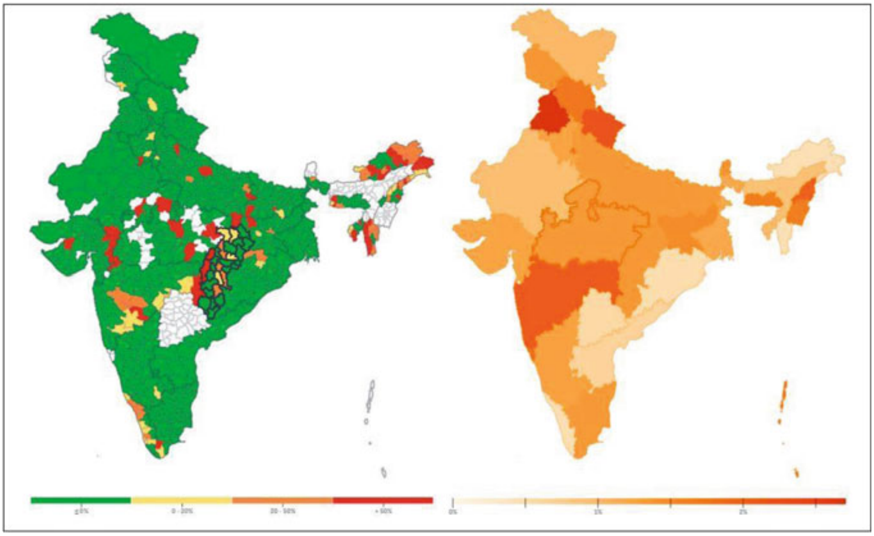

Fig. 13 Visualization of Covid-19 cases growth (left) and number of diseased patients (right) in different states of India

etc. This facilitates the visualization of different diseases with their related statistics over the different geographic regions. A visualization of HIV mortality rate per 100,000 population over Latin America static map has been prepared (Fig. 14). The analysis of different disease analysis in a spatio-temporal domain leads to foresight projections.

Spatio-temporal data in the healthcare sector is essentially observable and helps to predict future scenario at a global level. With the above examples, it has been

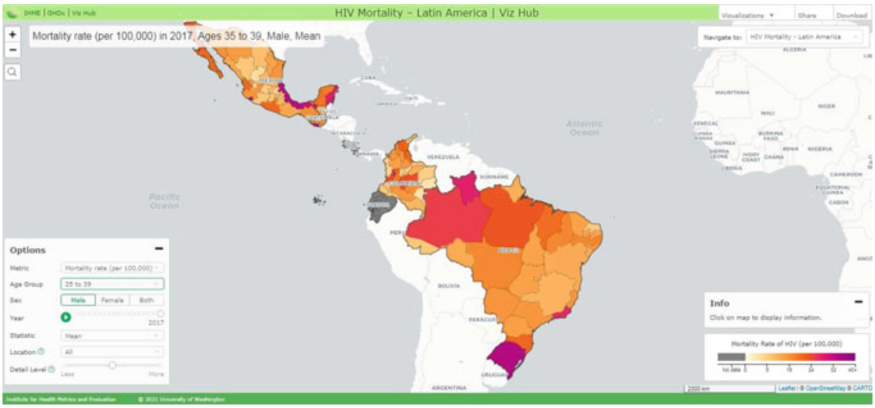

Fig. 14 Visualization of HIV mortality rate (per 100,000) over Latin America for the year 2017. *Source* https://vizhub.healthdata.org/lbd/hiv-mort-la

advocated that the forthcoming era in healthcare science would be largely benefited with the spatial-based analysis which is going to be efficient tool and would play game changing technology with a volume of big data analytics.

5 Concluding Remarks

In the present challenging and complex healthcare services domain, the technology is much dependent on data visualization have, transfer and utilize important data in a real-time environment. Significantly, interactive visualization of healthcare data observes many interesting opportunities and challenges. With growing attention and requirement in healthcare visualization, these challenges give a platform for the concerned researchers to advance this field through collaborative research and advance studies with healthcare practitioners to improve the state-of-the-art. This may create a venture for an enhanced treatment scheme with cost reduction in terms of time and money.

In this chapter, we have discussed the use of data visualization techniques under univariate, bivariate, and multivariate datasets of healthcare. The strengths and limitations of these techniques are also explained for a clear understanding of their uses. However, the distribution and adoption of spatial healthcare data visualization are limited for complex analysis. To perceive the ability and effectiveness of data visualization techniques with spatio-temporal data we have demonstrated various healthcare data reported by World Health Organizations (WHO).

With the continuous growth in the volume of healthcare data, it is challenging to display and review the temporal data. Combining the spatial technology with those of visualization techniques together, the accurate information in a certain time could significantly improve the medication schemes of healthcare practitioners. In such a scenario, Web-GIS-based visible and interactive public health information visualization environment will be helpful. It may facilitate the tools to visualize various diseases trend analyses, the availability of relevant infrastructure in the hospitals, the history of medication for particular disease analysis and the recourses equipment management. Certainly, this innovative technique will play a vital role in the visual public health information system leading to protect life and enhance the quality of lives. On the other hand, a poorly designed visualization tool may lead to more confusion than effective information retrieval. The selection of inappropriate color, font, clutter, or misleading display pattern may significantly distract the goal of visualization. Other issues like quality and type of data collected, and the inadequacy of data may lead to less interpretable visualizations.

In future, healthcare data domain will be predominantly governed by spatio-temporal analysis. As healthcare service issues are becoming popular over the world and the digitalization of data is mounting day by day, the web-GIS-based application will attain an important place in this domain.

Important Websites

https://healthheatmapindia.org/

https://www.who.int/data/gho/data/indicators
https://guides.library.duke.edu/datavis
https://vizhub.healthdata.org

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Chapter 4
GIS and Remote Sensing for Public Health

Martin Kappas

1 Introduction

With the "spatial turn", geographical health research is facing a great opportunity, but also a double challenge: on the one hand, it is about recognizing, communicating, and using the new methodological possibilities (e.g. new spatial databases for public health, spatial clustering of health events, analysing environmental hazards or analysing risk and spread of diseases, [1] in a meaningful way.

In addition, GIS can be used to map care in the health sector, to document health care facilities and their performance. People thus have easier access to the locations of the health centres and their equipment, as they can specifically locate these health centres and access their options. An oversupply or undersupply of health services can thus be spatially recorded for each region using GIS. So-called health care shortage areas can be identified in order to ensure better spatial coverage with health facilities in the future.

2 GIS for Public Health

2.1 Meaning of Public Health

There are many definitions of public health. For this chapter of the book, the definition of [2] should be used. He defined Public Health as.

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_4

" ... the science and art of preventing disease, prolonging life and promoting health and efficiency through organized community effort for the sanitation of the environment, the control of communicable infections, the education of the individual in personal hygiene, the organization of medical and nursing services for the early diagnosis and preventive treatment of disease, and for the development of the social machinery to insure everyone a standard of living adequate for the maintenance of health, so organizing these benefits as to enable every citizen to realize his birthright of health and longevity".

The Winslow definition emphasizes two essential differences to clinical medicine. Public health focuses on prevention and Public Health uses a community or population-based approach [3].

3 Meaning of GIS

GIS, the abbreviation for geographic information systems, are computer-based systems (e.g. ArcGIS, Terrset 2020, GRASS GIS or QGIS) used to store, visualize, analyse, and interpret geographic data. Geographic data, a synonym for spatial, geospatial data, or simply geo-data identifies the geographic location of features on earth. The geographic data of a certain location include anything that can be associated with this location, or anything that can be mapped for this location. For example, land cover, land use, settlements, roads, country boundaries, or post address are all types of spatial data. All of these data can be georeferenced to a geographic or geodetic reference system. That is why it is easy to compare or relate all the attributes of a place or location in the GIS. Within GIS there are a large number of tools for this purpose, for example the intersection of data or the overlaying of data levels. In Public Health, we can use GIS to help answer questions about how location influences disease and disability [4–7].

Taking into account the data type, we differentiate between GIS systems that are more vector data or raster data oriented. Vector data store spatial features as points, lines, or polygons and provide descriptive information (data attributes). Raster data are stored as electronic images, mostly coming from pictures taken as aerial photographs or satellite images. The smallest item of the raster data is a picture element, called "Pixel". Therefore, we can distinguish two GIS types—a more vector or more raster data oriented type. The Terrset (known earlier as IDRISI GIS) and the GRASS GIS started as Raster-GIS. The ArcGIS and QGIS are more known as Vector-GIS, but today modern GIS Systems have a hybrid style and are able to work with both data types. Concerning the data type there are many different analysis techniques. The most commonly used GIS software are ArcGIS, QGIS (open source), Terrset, and GRASS GIS (open source). Another GIS type is uDig, which is an open source (EPL and BSD) desktop application framework, built with Eclipse Rich Client (RCP) technology. GeoDa, also a free and open source GIS is usable for exploratory spatial data analysis (ESDA), such as spatial autocorrelation, data aggregation, and basic spatial regression analysis for point and polygon data. GeoDa is released under a GPL license (General Public License). It builds on several open source libraries and source-code files. Another helpful tool is FreeMap Tools, which is an online resource that enables visitors in WEB to easily and quickly use maps in order to measure, search, and overlay mark-up elements on maps for a wide range of useful applications. The MapWindow GIS project is a further initiative that provides a free and open source desktop geographic information system (GIS) with an extensible plugin architecture, a GIS ActiveX control, and GIS programmer library called DotSpatial. DotSpatial is a geographic information system library written for NET 4. It allows developers to incorporate spatial data, analysis, and mapping functionality into their applications or to contribute GIS extensions to the community. OpenJUMP is another open source GIS written in the Java programming language. It is developed and maintained by a group of people from around the globe. SaTScan is a free software that analyses spatial and temporal data. It is designed for any of the following interrelated purposes: Perform geographical surveillance of disease, to detect spatial or space–time disease clusters, and to see if they are statistically significant. With SaTScan one can test whether a disease is randomly distributed over space, over time, or over space and time. Further one can do time-periodic disease surveillance for early detection of disease outbreaks.

The WhiteboxTools interfaces with major GIS applications, including QGIS and ArcGIS, and it can be used in Python, R, and Nim scripting environments.

Well-known GIS systems
Terrset; Link: https://clarklabs.org/terrset-2020-landing-page/
ArcGIS Pro; Link: https://www.esri.com/de-de/arcgis/products/arcgis-pro/overview
QGIS; Link: https://www.qgis.org/de/site/
GRASS GIS; Link. https://grass.osgeo.org/
GeoDa; Link: GeoDa on Github (geodacenter.github.io)
FreeMap Tools; Link: https://www.freemaptools.com/
MapWindow; Link: https://mapwindow.org/
Open Jump; Link: http://www.openjump.org/
SaTScan; Link: https://www.satscan.org/
WhiteboxTools; Link: https://whiteboxgeo.com

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These types of programs can be used in conjunction with other types of software such as databases, statistical packages, or programming languages (Java, Python, R) to increase functionality. In addition to the GIS systems, there are numerous GIS forums and platforms on the Internet for the exchange of knowledge. One well-known GIS environment is Wiki. GIS, where a variety of different GIS resources is available (http://wiki.gis.com/wiki/index.php/List_of_GIS-related_Blogs). Another well-known forum or Blog is the GIS Lounge (https://www.gislounge.com/geogra phic-information-system-blogs-geoblogs/). Further information on the use of GIS, data sources, and many GIS-related issues can also be found on the website of World-Wide Human Geography Data Working Group (https://www.wwhgd.org/). Another very active group is the Geography and Geospatial Science Working Group (GeoSWG), which is an organization of geographers, epidemiologists, statisticians, and other disciplines who work with spatially referenced data at the Center for Disease Control and Prevention (CDC, https://www.cdc.gov/gis/geo-spatial-data.html) and the Agency for Toxic Substances and Disease Registry (ATSDR, https://www.atsdr.cdr.gov) of the United States of America. Ten years ago, the GeoSWG Committee formed specific guidelines and best practices to produce high-quality, consistent map products for the public health community. The guidelines issued by the GeoSWG are very well known and advance the application of geospatial concepts and methods within public health practice and research (for more information visit: *Cartographic Guidelines for Public Health (cdc.gov)*). In the next section we focus on geospatial data resources for Public Health applications.

4 Geospatial Data Resources

A variety of data sources for use in the public health sector have emerged in recent years. These data can be divided into different categories. First of all, we have data and projects that are directly related to public health issues. These resources include links to publicly available health-related data sets. In Germany, for example, this data is stored in the federal health reporting information system. The online database of health reporting (GBE Germany) of the federal government brings together health data and health information from over 100 different sources in a central location, including many surveys by the statistical offices of the federal government and the federal states, but also surveys by numerous other institutions in the health sector. Clear graphics, understandable texts, and precise definitions complete the range of health data. Documentation on the data sources, their survey characteristics, methodologies, and contact persons contain additional information inside the GBE. The health data and health information offered are continuously enriched in terms of content and updated regularly (see Fig. 1).

In addition to the German health data, there are data from the OECD or WHO and the associated statistics. Furthermore, more than 80 indicators are listed, which describe the health situation in the country or in the whole of Europe. These "European Core Health Indicators" (ECHI) contain ***Demographic and socio-economic factors*** (e.g. Indicator 1: Population by sex and age, Indicator 2: Birth rate, crude, Indicator 4: Total fertility rate, Indicator 5: Population projections) data about ***health status*** (e.g. Indicator 10: Life expectancy; Indicator 11: Infant mortality; Indicator 12: Perinatal mortality; Indicator 13: Disease-specific mortality; Indicator 14: Drug-related deaths; Indicator 18: Selected communicable diseases; Indicator 19: HIV/AIDS; Indicator 21a: Self-reported diabetes; Indicator 23a: Self-reported

Fig. 1 Screenshot of the "Information System of the Federal Health Monitoring" in Germany (access on July 2021 https://www.gbe-bund.de/gbe/pkg_isgbe5.prc_isgbe?p_uid=gast&p_aid=0&p_sprache=E)

depression; Indicator 24: Acute myocardial infarction; Indicator 25: Stroke; Indicator 26a: Self-reported asthma; Indicator 27a: Self-reported COPD; Indicator 28: Low birth weight; Indicator 30b: Injuries: road traffic: register-based incidence; Indicator 31: Injuries: workplace; Indicator 33: Self-perceived health; Indicator 34: Self-reported chronic morbidity; Indicator 35: Long-term activity limitations) and ***health determinants*** (e.g. Indikator 42: Body mass index; Indicator 43: Blood pressure; Indicator 44: Regular smokers; Indicator 46: Total alcohol consumption; Indicator 49: Consumption of fruits; Indicator 50: Consumption of vegetables). Other ECHI indicators are the Health interventions and health services indicators (e.g. Indikator 57: Vaccination rate in elderly; Indicator 62: Hospital beds; Indicator 63: Practising physicians; Indicator 64: Practising nurses; Indicator 66: medical technologies (CT/MRI); Indicator 67: Hospital in-patient discharges, selected diagnoses; Indicator 68: Hospital day-cases, selected diagnoses; Indicator 69: Hospital day-cases as percentage of total patient population (in-patients and day-cases), selected diagnosis; Indicator 70: Average length of stay, selected diagnoses; Indicator 76: Insurance coverage; Indicator 77: Health expenditure in percent of GDP; Indicator 79: 30-day in-hospital case-fatality of AMI and stroke; Indicator 80: Equity of access to health care services), as shown in Fig. 2.

The Information System of the Federal Health Monitoring of Germany is a good example of global data storage in the public health sector. The Geospatial Data Resources are mostly organized into four topic areas (see Fig. 3): ***Public Health Resources***, ***GIS Data***, ***Social Determinants of Health***, and ***Environmental Health Data***. The OECD and WHO follow the same data structure or data organization into these four topics. The Public Health Resources normally include data on various diseases and conditions and on health behaviours, health resources, rural health, health indicators, mortality, and morbidity [8].

Fig. 2 Most important ECHI Indicators with Indicator sets (accessed July 2021 at https://www.gbe-bund.de/gbe/abrechnung.prc_abr_test_logon?p_uid=gast&p_aid=3814870&p_sprache=E&p_knoten=TR80000)

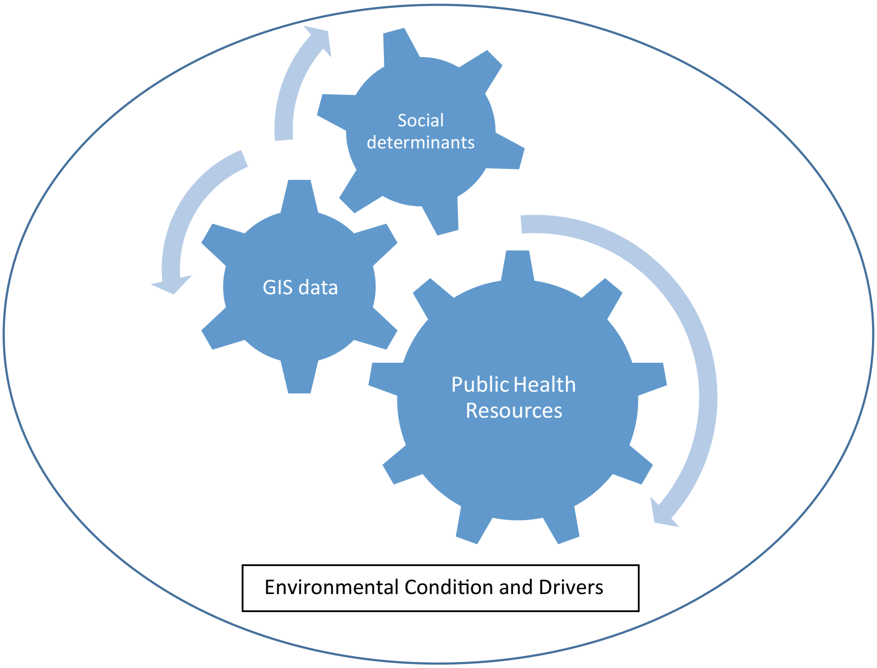

Fig. 3 Public health, GIS data and social determinants are embedded in an environment under change (e.g. climate change, pressure on landscapes—drought or flooding—overpopulation)

GIS data include various sources of GIS boundary files and population data. Social Determinants of Health Resources point to data, maps, statistics, and information related to the social determinants of health such as poverty and lack of education. Environmental Health Data Resources point to data related to environmental issues (e.g. temperature and extreme heat waves or flooding risks). Examples of environmental information include data on climate, vegetation sites, access to parks, air quality, water quality, and much more. The Environmental Protection Agency (EPA, US) provides data on the following environmentally relevant topics: EPA Air Data; EPA Toxics Data; EPA Ambient Water Data; EPA Drinking Water Data or data about Flood Hazard Mapping from the US Federal Emergency Management Agency (FEMA). These examples from Germany, Europe, and the USA show the different data sources that are available when using GIS tools.

Figure 3 shows how geospatial science, GIS, and public health are connected. A major intersection exists between location or place and health. The main topic of research is the examination of the convergence of geospatial health determinants that vary by place. Inside geospatial epidemiology the relationship between place and health is explored. In the last years, the relationship between geographic variations of disease and environmental, demographic, behavioural, socioeconomic, genetic, and infectious risk factors get more and more important. Many countries have set up research groups for this field of work. In the United States, the main one is the GRASP group. The Geospatial Research, Analysis, and Services Program (GRASP) is a group of public health, geospatial science, technology, and analysis experts. They analyse the geospatial trends and patterns associated with environmental conditions, infectious and chronic disease, injury, and emergency preparedness and response (e.g. flooding or droughts) within an interdisciplinary perspective. GRASP has also proposed a framework, the ***Geospatial Determinants of Health (GDOH)***, that articulates the various geospatial drivers that influence disease prevalence and promote health.

GRASP works at the intersection of place and health to promote health and prevent disease. Program scientists examine the convergence of geospatial health determinants that vary by place. As part of its work, GRASP has proposed and is shaping a framework, the Geospatial Determinants of Health (GDOH), that articulates the various geospatial drivers that influence disease prevalence and promote health.

The purpose of the Geospatial determinants is to define the geospatial drivers of health with an emphasis on factors that vary by place (e.g. water quality; [9]). Further, with the help of GDOH we can define, promote, and advance the use of place (knowledge about locations) in research and practice across the public health community. Today we can, for example, localize the risk of contracting water-based diseases much better. With the help of water analyses in the field and feeding the water quality data into a GIS, risk maps of the water quality can be provided. People who live near contaminated waters can be warned of the danger in short time. On the other hand, the pollution can be deliberately investigated. The culprit can be identified using a GIS-supported monitoring system (e.g. [10, 11]).

Another example is the investigation of the increase in temperature and its influence on the spread of infectious diseases. Today we know that the temperature increases due to anthropogenic climate change coupled with changes in land cover and land use (e.g. changes in wetlands, cultivation of wet rice in dry areas, etc.) lead to the considerable spread of vector-based diseases (malaria, dengue, schistosomiasis, etc. [12, 13]).

As digitization progresses, more and more databases are being built on environmental data that can be used to link with health data. In Germany, the individual federal states have set up geoportals that contain both geographic base data and environmental data (e.g. Geoportal.de). Increasing the environmental data, regions can be examined specific to their exposure to diseases. Especially in cities with large area expansion and many inhabitants, extreme heat waves affect people's health. Most megacities already suffer from a pronounced heat island effect today. Satellite data make it possible to derive arable information about the surface temperature. (e.g. Land Surface Temperature, LST derived from Modis satellite data; e.g. Noi [14]). Today, heat waves and cold waves belong to the most important direct influences on human health. Therefore, today information about the land and ocean surface temperature are provided. Temperature measurements are not only important for the assessment of direct health effects, but are also increasingly becoming the assessment of the risk of vector-transmitted diseases. In addition to the temperature, water is an essential environmental variable that has an impact on health. This influence is two-sided. Either there is too little water in a region available (drought) or there is too much water in a region (flooding). Due to droughts, people have to drink too little. Water is not available for the preparation of food or for easy body hygiene.

Flooding, on the other hand, can lead to contamination of the drinking water sources and trigger diarrhoea conditions up to cholera. Cholera outbreaks are observed worldwide in many countries (e.g. Africa, Southeast Asia, and Caribbean) and usually affect the local population, which lives with inadequate hygienic conditions with insufficient sanitary facilities. Cholera is present primarily in countries with very poor sanitary facilities and lack of clean drinking water as well as in war and disaster areas in which the infrastructure has collapsed. GIS data can be used to map the distribution of drinking water sources and their water quality.

One of the earliest examples of cholera mapping is the nineteenth-century cholera outbreak map in London (UK). Dr. John Snow mapped cholera deaths in proximity to the water pumps in London's Soho district (see Fig. 4) and his investigation identified the likely source of the cholera outbreak as the Broad Street Pump.

Upon closing the pump, cholera cases went down substantially. Today, we can say that John Snow is the starter of epidemiology. In historical retrospect, the first considerations of geography and disease can be seen in Hippocrates (400 BC). Hippocrates was one of the first scientists to recognize the connection between disease and the environment. He told us that people's health depends on the air they breathe, the water they drink, and the environmental condition in which they live. Today we can assign this work to the area of "medical geography". This field of work has its roots in antiquity and can be found in other works later in the eighteenth century, for example at Finke in the year [15]. Finke's "Medical Geography" is a groundbreaking example of the use of geographical knowledge in medicine [16].

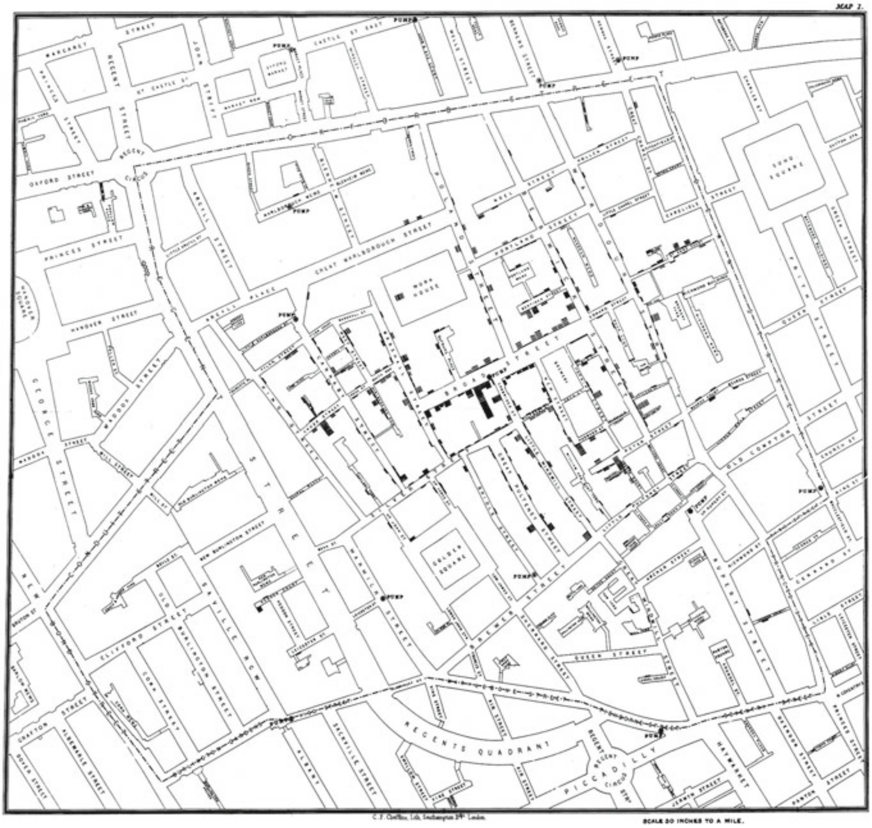

Fig. 4 Map of Dr. John Snow with the accumulations of deaths at the cholera epidemic 1854 in London. His card drawing with the epidemic cases goes beyond epidemiology as one of the first proven spatial analyses. Cholera cases are highlighted in black (*Source* "On the Mode of Communication of Cholera" by John Snow, originally published in 1854 by C.F. Cheffins, Lith, Southhampton Buildings, London, England. The uploaded image is a digitally enhanced version found on the UCLA Department of Epidemiology website)

In Tom Koch's book (2005) "Cartographies of disease: maps, mapping, and medicine" (ESRI Press), different examples of cartographic mapping and diseases are presented. Koch [17] emphasizes the historical development of medical geography and the mentioned examples show that geography is becoming more and more important for health assessments. Starting in the seventeenth century with the map of pest in Bari (Italy, map of pest 1694), we find follow ups of maps related to specific diseases such as pest, cholera, yellow fever, and many others. A comprehensive presentation of the historical development of geographic applications and GIS in the health sector can be found at [15].

Now-a-days, many countries have maps and statistics showing the least diseases such as cancer, malaria, or other health threats. Today these are mostly not paper maps,

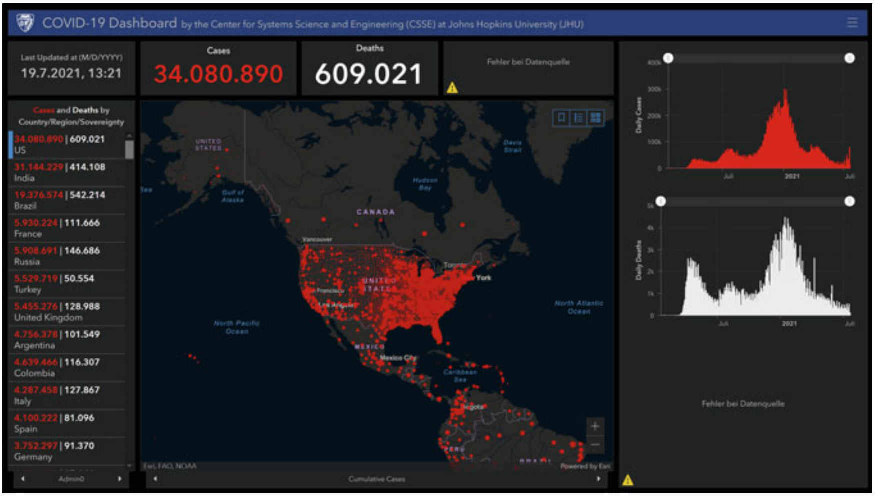

Fig. 5 COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), situation in USA at July 19th 2021. *Source* https://gisanddata.maps.arcgis.com/apps/dashboards/bda7594740fd40299423467b48e9ecf6

but are in the form of dashboards and other digital representations. The digital maps can now be updated in real time and represent an important decision-making tool for politicians in the health sector. A popular example is the current dashboard of the John Hopkins University on the current corona pandemic worldwide or the national dashboard of the Robert-Koch Institute in Germany about the specific Corona pandemic situation in Germany (see Figs. 5 and 6). The information on the corona pandemic situation in Germany has a resolution at the district level. With this resolution, hot spots of the infection process can be regionalized. This allows targeted measures to be taken to contain the pandemic.

Another prominent example of the last few decades is the AIDS outbreak maps in the individual countries of the world (e.g. AIDS outbreak maps in US). Many of the earliest disease maps were initially created manually. But with the development of GIS technologies, many epidemiological studies have become possible in the last few decades.

Another important milestone in the use of GIS data was the provision of demographic data by conducting population surveys [18], [19],[20]. By including population data on a small scale, such as at the postcode level or later on the household or house number level, the population data were used for the first time on a local scale. One of the first uses of GIS in hospitals and medical administrations occurred shortly after the release of the 1970 Census of Population in the United States. The former US Census Bureau developed two software products that would forever change the use of GIS in health mapping. These programs were called **Admatch** and **DIME**. Admatch was a street address management program that would link a street address to a specific geographical location. The process of attaching geographic coordinates

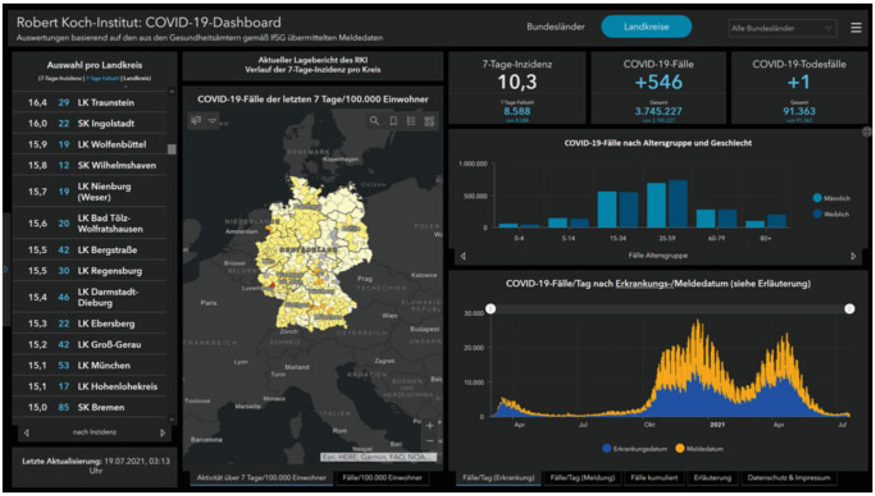

Fig. 6 Robert Koch-Institute: COVID-19-Dashboard for July 19th for Germany based on districts (*Source* https://experience.arcgis.com/experience/478220a4c454480e823b17327b2bf1d4)

or codes (e.g. ZIP codes) to data records is called “geocoding” and is the “key” of modern GIS applications today. DIME (Dual Independent Map Encoding) was a reference file for presenting map features numerically. The combination of Admatch and DIME was a revolution for the geocoding technology and enables new location-based analysis of data sets. From those early beginnings, many epidemiologists worked on large data sets to assess the spread of disease. Biostatistics developed for this purpose. Biostatisticians are working on large datasets (e.g. cancer or HIV registry) and also pushed the capabilities of GIS for data management, analytical functions, and visual display / reporting such as modern dashboards. The majority of countries and their governments around the world have built up geographic information systems to assess and protect the health of the populations they serve. As shown in this chapter, GIS is widely used in the health sector. In the past decades, essential areas have developed pragmatically. In the following, individual important areas in the health sector in which GIS has established itself are presented.

A very topical area at the time of the expiring corona pandemic in 2020/21 is the **status of immunization** in the individual countries of the world. GIS can provide very strong support to the individual countries in their immunization campaigns. With the support of GIS, epidemiologists can answer questions such as “What are the current vaccination rates in the region?” “Where there are enough vaccine doses available, there are regional disadvantages?” “Is the vaccination delivery network of the country sufficient?” Location-based information is important to assess vaccination needs and intervention planning. The GIS-based visualizing and monitoring results are important to communicate the information to the public and to gain understanding and acceptance for the immunization process. Following the recent Corona pandemic in 2020/21, there has been an increased recognition of the utility of GIS for mass immunizations and better management of vaccine logistics. Health authorities have used GIS applications to track inventory levels (including vaccines) in real time. Further, areas of under-immunization and spatial-temporal clusters of adverse reactions to vaccinations can be detected and spatial visualized. GIS can help local health authorities to track communities and to show who was treated by geocoding patient data. By calculating the vaccination rates inside GIS, health departments can determine who needs to be treated and inform those people who need to be treated (e.g. in areas with low vaccination rates).

With accurate location information by geocoding all GIS and health data in a common reference system, GIS can provide a spatial detection of complex interrelationships between cases, contacts between people and animals, and objects in the area in time and space. The spatial detection of these tricky relationships enables to identify sources of diseases and to implement the optimum of countermeasures and response strategies. We can summarize the role of GIS in this area as a monitoring task (**Disease Surveillance**, **Syndrome Surveillance**, and **Outbreak Surveillance,** see an overview of syndromic surveillance by Henning [21]. In this work direction of disease observation and surveillance, the database can be significantly improved through the use of GPS-based and mobile GIS through recordings in the field (e.g. rapid screening [22]). Another important area of work is public **health emergency**. Natural disasters such as storms, heavy rain and floods, wildfires and earthquakes are ideal working areas for the application of GIS. Preparedness and response on emergency use location-based data about the location of incidents, the number of people in danger and which emergency services and health facilities are inside the region available. Emergency preparedness is helped by GIS through various analysis content such as evacuation planning (route planning, intact infrastructure overview, emergency notifications etc.), destinations for distribution points for aids and health assets. For the so-called **e**mergency **o**perations **c**enters (EOC), the information stored in the GIS can provide a quick overview of the situation before and after the disaster (including supporting materials such as a maps and aerial photos of the event region or available equipment and supplies, see WHO [23]. In addition to the standalone GIS applications, there are also Internet-based solutions, like WebEOS. One example is a WebEOS from Juvare Exchange that facilitates communication and collaboration across public, private, and healthcare sectors, as well as geographical and jurisdictional borders, in a single real-time dashboard (https://www.juvare.com/juvare-exchange/). With WebEOC app's, you can capture data, conduct assessments, and complete reports in the field to automatically update WebEOC boards. When setting up a WebEOC, the question arises as to which data layers must be available for efficient disaster management. Some basic data layers are important regardless of the respective scenario, other data layers are event-specific. Examples of data layers that are more specific to the type of event are the locations of first responders (e.g. real-time feeds from ambulances or helicopter locations), the diversion status of hospitals, flood plains/flood boundaries, the extent of the smoke plume (wildfires), electricity suppliers Information and others.

Basic or essential data layers inside an emergency-oriented GIS are layers about "event locations", "distribution of hospitals and their health facilities", "refuge areas", "distribution of schools", "road network and road quality", "public transportation system", "demographic data" or "municipalities". In addition to these basic layers, we need dynamic layers in which the information on injured parties per event, current weather situation (e.g. probability of rain, amount of precipitation, wind speed, etc.), medical stockpile or ambulance locations is regularly updated.

Many health officials have reiterated the importance of being able to obtain neighbourhood-level population estimates in the event of an emergency. It's worth noting that many of the key layers of data do not need to be captured from scratch. A lot of data layers are already available at the health department or other government agencies (or regional geoportals). Some are likely already geocoded. The greatest challenge is merging the existing data in order to quickly initiate suitable countermeasures in the event of an emergency. In July 2021, Germany was hit by a major flood disaster. Information about the amount of precipitation was provided in high temporal and spatial resolution. Nevertheless, the people in these flood regions were not prepared for this flood event and many people lost their lives. This raises the question of whether the existing warning systems are sufficient or should be expanded to take account of ongoing climate change. What is certain is that GIS will be an integral part of any disaster and risk management now and in the future.

Another area of work for the use of GIS is assessment and planning of **community health**. A community health assessment supports communities with comprehensive information about the current health status, problems, and solutions. This assessment can help a community to develop a health improvement plan by using GIS for resource allocation and justifying which resources meet best the community health needs [24].

Another field of work in which GIS can be used is the analysis of environmental influences on human and animal health. The area of environment and health or **environmental health** records all influences on our environment (temperature, soil, vegetation, landscape, water availability, air hygiene, and air quality, etc.). Inside GIS all the physical, chemical, and biological factors external to a human person or animal, and all the related factors impacting their behaviours can be analysed. Environmental health enables the assessment and control of environmental factors that can potentially affect health (e.g. water borne diseases or soil and air contamination) [25], [3]. GIS helps also to develop landscapes and physical environments that create or preserve health-supportive surroundings (see: WHO, Environmental health [26, 27]). Environmental Health assessment is one of the best-established working areas of GIS use inside the Public Health sector. The Environmental Public Health Performance Standards (EnvPHPS) developed by Colon and Elligers [26] and CDC (Centers for Disease Control and Prevention, US, https://www.cdc.gov/) are an important standard to measure the capacity of local environmental public health systems or programs. After CDC standard [28], environmental public health tracking requires the ongoing collection, integration, analysis, and interpretation of data about possible environmental hazards, the potential exposure to these environmental hazards and corresponding health effects potentially related to exposure to these environmental hazards. In recent years, environmental research has also focused on the human-built environment. Increasing urbanization leads to artificial environments with a high proportion of surface sealing and a human-made climate of its own (urban climate). Nowadays, more than 50% of the world's population live in urban agglomerations to huge megacities, which have a significant impact on the environment. The man-made, artificial environments can prevent chronic diseases such as asthma. In many megacities around the world, the air hygiene conditions are very poor. Cities like Mexico City, Beijing or Ulan Bator suffer from heavy air pollution. GIS can be coupled with air pollution control stations to control the contamination and to show hotspots of air contamination. The results of the GIS-supported air quality monitoring can be connected with efficient GIS-supported traffic control systems. Finally, we can resume that GIS is a strong tool for chronic disease prevention and control in many different environments. In the field of disease prevention and control GIS helps also to monitor other chronic diseases or tracking control activities. In most countries of the world GIS is used to set up cancer registries or helping to support heart disease programs or stroke and diabetes registries (e.g. obesity is a major problem for the so-called industrial countries). In the last decades, there has been extensive research into the various impact of the built environment, our food systems, and on all possible risk factors that accompany our lives. A new emerging field of research integrating GIS is the study of exposomics [28]. The exposome can be defined as the measure of all the exposures of an individual in a lifetime and how those exposures relate to health (Fig. 7).

Inside this new field of research, GIS can support linking environmental exposures and pollution-related diseases, environmental health tracking, and body burdens in populations. These environmental exposures are combined with biomonitoring projects. GIS helps environmental public health tracking (EPHT) with an ongoing collection, integration, analysis, interpretation, and dissemination of data on environmental hazards, exposures to those hazards, and health effects that may be related to the exposures. (see: The National Institute for Occupational Safety and Health (NIOSH), https://www.cdc.gov/niosh/topics/exposome/default.html). Further information on Exposome research and the role of GIS can be found on the website of the research project "*the human exposome project*" (https://humanexposomeproject.com/) or inside the new book from [29].

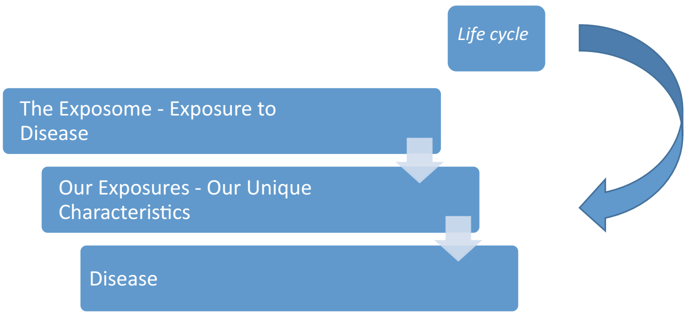

Fig. 7 Exposomics: understanding how exposures from our environment, diet, lifestyle, and other factors interact with our own unique characteristics such as genetics, physiology, and epigenetics impact our health is how the exposome will be articulated

In the following section we look at the integration of remote sensing data and GIS.

5 Introduction Remote Sensing for Public Health and Earth Observation for Climate Change and Vector-Borne Diseases

The launch of ERTS-1 (Earth Resources Technology Satellite, later called Landsat) in 1972 gave us the first opportunity to acquire global remote sensing data on a regular basis [30]. Since the 1970s there have been numerous studies on the integration of satellite data in epidemiology. The first International Conference on Applications of Remote Sensing to Epidemiology and Parasitology was hosted in 1990 by Louisiana State University (LSU). A focus in the application of remote sensing data in the field of epidemiology is the observation of vector-based diseases such as for example Leishmaniasis, Zika, Chikungunya, Dengue, Malaria, Schistosomiasis [31], and many others.

There exist many attempts to use remote sensing and GIS for the study of vectors, biodiversity, vector presence, vector abundance and the accompanying vector-borne diseases (see Palaniyandi [32]). The main focus is on the use of remote sensing and GIS applications on spatial prediction of vector-borne diseases transmission. The presence and abundance of vectors (e.g. Mosquitoes) and vector-borne diseases, the infection and transmission are related to geographical, environmental, and climatic factors, which are special for a region. Therefore, the complex conditions for the occurrence of vector-based diseases can be determined on the basis of certain factor complexes. The occurrence of vectors and the diseases they transmit therefore depend on certain environmental characteristics. The presence of vectors is associated with the geographical, climatic, and environmental factors including man-made factors (e.g. certain land use types such as irrigated rice fields). Satellite data provide information about vegetation type and cover or soil types and their moisture, texture and depth. Inside GIS, we can gather all this information to derive specific environmental variables for the potential living space of vectors. Ecological modelling inside GIS provides relevant information to understand the spatial variation of the vector biodiversity, vector presence, vector abundance, and the vector-borne diseases in association with climatic and location specific variables.

Vector-Borne Diseases are a global problem that affects societies at different environments and raises significant concern, especially the Malaria burden [33–35]. Due to the ongoing climate change, more and more people on earth will be endangered by vector-based diseases. Nowadays, more than 80% of the global population lives in areas at risk of at least one major vector-borne disease. Europe is experiencing an increasing number of human cases of vector-borne disease in the last two decades, such as West Nile Virus, Malaria, Chikungunya, Dengue, and Zika. In

Europe, the EuroGEO Action Group “Earth Observation for Epidemics of Vector-borne Diseases” delivers satellite and in-situ earth observations, state-of-the-art AI generic and scientific knowledge in the field of epidemics. Most of the work is based on the data from the Copernicus satellites (Sentinel satellites). This initiative is part of EO4GEO, which is an Erasmus + Sector Skills Alliance gathering 25 partners from 13 EU countries, most of which are part of the Copernicus Academy Network (a webinar of this group can be found under: http://www.eo4geo.eu/training-actions/early-warning-for-disease-epidemics-at-regional-level/). This webinar offers basic knowledge about the development and application of an early warning system to help prevent outbreaks for mosquito borne diseases. The EO4GEO is also linked to Earth Observations for Health (EO4HEALTH), which includes vector borne infectious diseases, Copernicus Atmospheric Monitoring Service (CAMS), and Copernicus Climate Change Service (C3S). The EuroGEO Action Group for Epidemics proves the importance of big earth observation data through the development of EYWA (an **EarlY Wa**rning) System for Mosquito-Borne Diseases. The system is based on plenty of satellite and in-situ earth observation data and state-of-the-art technological tools such as new artificial intelligence-based analysis tools. Early Warning Systems like EYWA could play an important part in supporting climate change adaptation and sustainability processes. The EYWA (see Fig. 8) system combines interdisciplinary scientific fields (entomology, epidemiology, ecology, earth observation, big data, AI/ML, Data Fusion, and Citizen sciences) towards building new applications for public health, such as outbreak forecasting and decision support modelling for vector control applications and other mitigation actions (see: http://beyond-eocenter.eu/index.php/web-services/eywa).

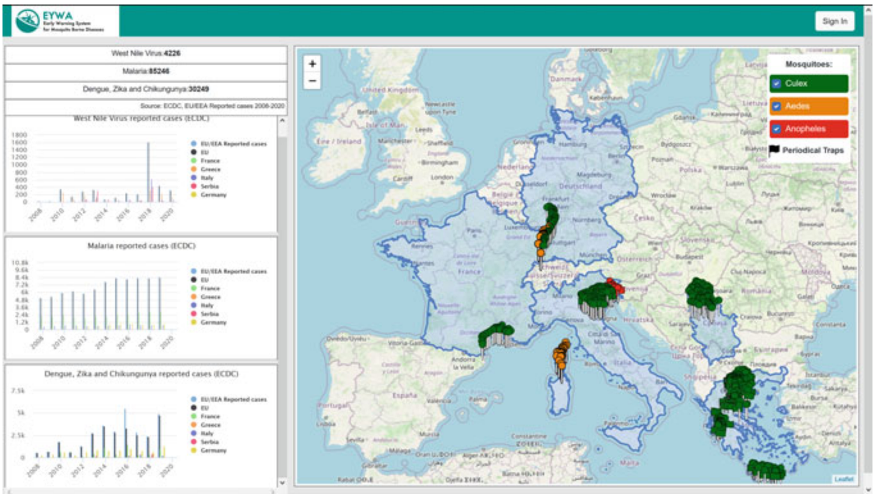

Fig. 8 EYWA—early warning system for mosquito borne diseases http://epidemics.space.noa.gr:8081/

Another recent development is MAMOTH: An Earth Observational Data-Driven Model for Mosquitoes Abundance Prediction (see Tsantalidou et al. [36]). MAMOTH, a generic and accurate Machine Learning model that predicts mosquito abundances for the upcoming period with high accuracy. The designed model relies on satellite Earth Observation and other in-situ geospatial data to solve the problem. Both examples of Model development integrate remote sensing data and help also to reach the aim of the Agenda 2030 and the Sustainable Development Goals (SDGs).

Starting 2021, OGC (Open GIS Consortium) has launched a request for Information concerning the capture and use of spatial data during health emergencies (request funded by AmeriGEO). The results of this request will be soon published in the "Health Spatial Data Infrastructure Concept Development Study Report" by OGC Public Engineering Report. The report will bring together the health and geospatial communities. Core of the initiative is the prototype of a geospatially enabled Health Data Model and corresponding Health Spatial Data Infrastructure (SDI). The model and SDI will support planning, preparedness, response, and recovery for future health emergencies including epidemics/pandemics of infectious as well as environmental-related diseases.

In the future, remote sensing data will be processed in such a way that it can be used in the public health sector even without expert knowledge. These data need to be readily available to public health workers in a format that they can use. Inside the Group of Earth Observation (GEO) we have a working group that is focusing on Earth Observation for Public Health Surveillance (https://earthobservations.org/area.php?a=phs). The freely available data are gathered and distributed through the Global Earth Observation System of Systems (GEOSS). The Earth observation data help to improving our knowledge of how the environment affects human health and life-cycle. Key data sets include airborne, marine, and water pollutants; stratospheric ozone depletion; land-use change; persistent organic pollutants; food security and nutrition; noise levels; weather-related stresses and disease vectors; and many others (see GEOSS portal, https://www.geoportal.org/?m:activeLayerTileId=osm&f:dataSource=dab).

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Chapter 5
Infectious Disease and Their Tracking in GIS

M. Ramalingam and J. Jayachandran

Abbreviations

AI	Artificial intelligence
ANN	Artificial neural networks
AVHRR	Advanced very high-resolution radiometer
BC	Before Christ
CDC	Centers for disease control and prevention
CDC	Centers for disease control
CHAART	Center for health applications of aerospace related technologies
CIDT	Culture-independent diagnostic tests
CoViD-19	Coronavirus disease-2019
EMPRES	Emergency prevention system
GIS	Geographical information system
GLEaM	The global epidemic and mobility model
GLONASS	Global navigation satellite system
GPS	Global positioning system
H5N1	Hemagglutinin 55 and neuraminidase 1
HIV/AIDS	Human immunodeficiency virus/acquired immunodeficiency syndrome
IOT	Internet of things
LDA	Latent dirichlet allocation
LIDAR	Light detection and ranging

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_5

MERS	Middle east respiratory syndrome
MIDAS	Models of infectious disease agent study
MODIS	Moderate resolution imaging spectroradiometer
NASA	National aeronautics and space administration
NB	Naive Bayes
NOAA	National oceanic and atmospheric administration
PCA	Principal component analysis
PCR	Polymerase chain reaction
PRoMED	Program for monitoring emerging diseases
RS	Remote sensing
SARS-CoV-2	Severe acute respiratory syndrome coronavirus 2
SEIRD	Susceptible infectious exposed recovered dead
SEIRS	Susceptible-exposed infectious recovered
SIQR	Susceptible infectious quarantine recovered
SIR	Susceptible-infectious-recovered
SRTM	Shuttle radar topography mission
TADS	Transboundary animal diseases
TRANSIMS	Transportation analysis and simulation system
TRMM	Tropical rainfall measuring mission
USGS	United States geological survey
WHO	World Health Organization

1 Introduction

Infectious diseases can be caused by bacteria, viruses, fungi, and other microbes. Many microorganisms choose our bodies as home. They're usually not harmful, and in some cases, they can be beneficial. However, certain organisms can cause sickness if they are exposed to particular conditions. Certain infectious diseases can be transmitted between people via the air [1], water, or food. Some diseases are spread through the bite of an insect or another animal. And consuming tainted food or water, or being exposed to organisms in the environment, can lead to the acquisition of further diseases.

Fever and exhaustion are common signs and symptoms, albeit they depend on the pathogen that caused the infection in the first place. While minor infections may be treated at home with rest and over-the-counter medications, more serious illnesses may necessitate a trip to the hospital. Vaccines help in the prevention of a variety of infectious diseases, including measles and chickenpox. Handwashing, particularly with soap and water, aids in the prevention of the spread of a wide variety of infectious diseases.

1.1 Ancient History of Infectious Disease

Since the dawn of civilization, communicable diseases have affected mankind. As society began to move to the countryside around ten thousand years ago, the threat of these diseases increased. Because of the growth in population and increased interconnection, infectious diseases had greater time to proliferate and propagate epidemically. Diseases like smallpox and leprosy have been on the rise since this change has occurred.

Pandemics have become more likely as human civilization has progressed and as communities have gotten more interconnected. In the paragraphs that follow, we explore the evolution of infectious diseases and how they will proceed to have an impact on our daily lives in the future.

A pandemic was first documented in Greece during the Peloponnesian War around 430 B.C. During the siege, the sickness was spread from one side of Athens to the other. According to historians, the disease killed almost two-thirds of the people.

After that, in 163 A.D., the Antonine Plague appeared, which is today thought to be an early occurrence of smallpox. When the Huns brought the disease to Germany, they infected the Germans, who subsequently spread it throughout the Roman Empire. The Antonine Plague had the potential to spread over the Roman Empire once it was in the hands of the Romans.

Some historians believe that about 250 A.D., the Cyprian epidemic began in Ethiopia and travelled through Northern Africa to Rome, where it resumed its northward journey. It took three centuries for the Cyprian plague to resurface again. Saxons helped the British in their war against the Picts and Scots after a plague epidemic forced them to seek help from the Saxons. Infectious diseases have more opportunity to spread as civilizations and empires expand over the globe. An epidemic known as the Justinian plague swept through Egypt and the Byzantine Empire in 541 A.D., eventually reaching the Mediterranean. Emperor Justinian's aspirations to consolidate the Roman empire were drastically altered as a result of this disease. Approximately 26% of the world's population died as a result of the Justinian plague, which is now thought to represent a significant outbreak of the bubonic plague.

1.2 Recent History of Infectious Diseases

More recently, in the eleventh century, leprosy plagued Europe, followed by the dreaded Black Death in the fourteenth century. A staggering 30–60% of Europe's population perished during the second and most devastating epidemic of the bubonic plague. The bubonic plague returned to London in 1665, killing 20% of the city's inhabitants in what is now called The Great Plague of London.

Since the first pandemic in 1817, there have been seven major cholera pandemics. Despite the development of a vaccine in the mid-to-late nineteenth century, cholera outbreaks have continued. More than 15 million people died during the bubonic plague's third epidemic in the 1800s. In 1875, a measles epidemic struck Fiji, killing 40,000 people, or about a third of the country's population.

As the twentieth century proceeded, influenza pandemics became more frequent. The Russian Flu killed 360,000 people in two years, in 1889 and 1890. There was just a fraction of the 50 million individuals who perished during the 1918 Spanish Flu epidemic. After the Spanish Flu pandemic of 1918, there were two waves of the Asian Flu pandemic in the 1950s. The AIDS outbreak, which first appeared in 1981, was the last major pandemic of the twentieth century. HIV/AIDS was the final major pandemic of the century. HIV/AIDS is still considered a pandemic because it has claimed the lives of more than 32 million people in the last forty years.

1.3 Transmission and Control of Infectious Diseases

The first step in solving a mystery and stopping the spread of a disease is to determine who is infected with a certain virus when tracking infectious diseases and outbreaks. Culture testing has long been the principal method of determining the pathogen's identity. This technique takes two or three days to complete since cultures must be evaluated in a laboratory setting. Diagnostic assays that are not culture-dependent are often used to detect foodborne diseases (CIDTs), a new approach of identifying infections. CIDTs identify germs by looking for certain genetic sequences or antigens in the body fluids of the infected person.

Emerging viruses have the potential to have devastating effects on human populations in terms of death, morbidity, and economic costs. In order to monitor the transmission of infectious illnesses and aid in their control, previous methods have depended on case data analysis. To better understand infectious disease epidemiology, we describe how recent advances in virus sequencing and phylogenetic have made it possible to answer many previously unanswered questions, from early detection and characterization of outbreak viruses to transmission chain tracking and outbreak mapping. We demonstrate the usefulness of this technique by imagining an outbreak of "Disease X," a pathogen unknown to science that the World Health Organization believes could cause a large epidemic in the future.

2 Epidemiological Studies

Epidemiologists now employ study designs, or the methods used to collect data in order to test a hypothesis, in the same way that researchers study other phenomena that occur in populations. Studies that use observational methods do not manipulate their subjects in any way, while experiments do (in which subjects are manipulated).

These studies, taken together, allow modern epidemiologists a wide range of instruments with which to investigate the relationships between infectious diseases and the populations they may affect.

Observational study
Measurements (such as physiological indicators like white blood cell count) or answers to interview questions collect data from research participants in an observational study (such as recent travel or exercise frequency). Random selection from a population of affected or unaffected people is common in observational studies. An observational study, on the other hand, does not include researchers manipulating the subjects in any way. Even though experimental research is more difficult to carry out, observational studies are sometimes the only option due to ethical considerations.

A causal relationship cannot be proven solely by observational studies, which can only evaluate relationships between disease development and possible causative agents. Let's say, for example, a study reveals that people who drink a lot of coffee had a lower risk of skin cancer. There's a chance that coffee can protect against skin cancer due to its antioxidant properties, but it's also possible that other factors like how much sun exposure individuals get have an effect. The decreased prevalence of skin cancer may not be attributed to coffee drinking if it turns out that coffee consumers spend less time outside in the sun because they spend more time in offices. According to the findings, there was no discernible difference between the two options.

Observational studies can be approached in a variety of ways. In epidemiology, there are two main subfields: descriptive epidemiology and analytic epidemiology (both descriptive and analytical).

2.1 Descriptive Epidemiology

In an exploratory stage of the study, descriptive epidemiology collects data on a disease epidemic, the people who are affected, and how the disease has spread through time. Interviews with patients, their connections, and family members will be a part of this study, as will the evaluation of samples and medical records, as well as histories of beverages consumption. There is a chance that such a study will take place while the outbreak is still ongoing. Descriptive studies may serve as a springboard for more rigorous observational and experimental investigations that test a hypothesis of causality.

2.2 Analytical Epidemiology

For the purpose of evaluating hypotheses concerning the likely origins of a disease outbreak, analytic epidemiology works with small, carefully chosen groups of people.

Because the instances are chosen at random, the results are not skewed by the individuals' shared traits. Retrospective studies obtain data by travelling back in time, while forward-looking studies collect information as events unfold in the present (prospective studies).

Retrospective Studies
Retrospective studies use data from the past to inform their findings on current situations. It's possible that the data collected will include information about the patient's medical history, age, gender, or place of employment history. This sort of research looks for links between a researcher's selection of risk factors and the occurrence of disease.

Prospective Studies
Prospective studies keep track of research participants and keep tabs on their health conditions as the study progresses. In order to compare study volunteers who, get sick to those who don't, data on the characteristics of the people and their settings are collected at the beginning and during the study. When looking for links between illness states and study factors, researchers can use this information to their advantage.

Analytical Studies
The design of analytical investigations incorporates groups to help elucidate illness correlations. The design of analytical investigations integrates groups to better clarify sickness linkages. Cohort studies, case-control studies, and cross-sectional studies are all viable research options. Cohorts may include persons born in the same year and place, or they may include people who engage in or avoid a particular behavior, such as smokers or nonsmokers.

Examples of cohorts include these. In a cohort study, participants can be tracked either in the present or in the past. When a single cohort is examined, the afflicted people are compared to the unaffected peers. Patients' health outcomes are tracked and evaluated to see whether there are any links between their personal qualities and their risk of contracting certain diseases. Cohort studies are a good technique to find out what causes a problem without exposing people to a risk factor, which is against ethical guidelines. These groups of people are referred to as cohorts since they have already been exposed to a variety of risk factors through their own decisions or circumstances.

Case-Control Studies
A case-control study compares a group of people with an illness to a different group of people who don't have it. In comparison to cohort studies, case-control studies are significantly more effective since researchers may choose participants who have already been affected by the disease rather of waiting to see which subjects from a random sample will develop the disease.

Cross-Sectional Study

In comparison to cohort studies, case-control studies are significantly more effective since researchers may choose participants who have already been affected by the disease rather of waiting to see which subjects from a random sample will develop the disease. To see if there are any links between certain quantitative characteristics and a sickness or condition, researchers compare individuals. To find out how common an illness is, researchers turn to cross-sectional studies.

2.3 Experimental Epidemiology

An investigator manipulates the research subjects in a laboratory or clinical study in order to look for links between diseases and their possible causes or to evaluate remedies in experimental epidemiology. Treatments can include things like the administration of medication, dietary changes, physical activity, or a specific surgical procedure. Test subjects can be either animals or people. It's harder and even impossible to conduct experimental investigations because they require manipulating subjects.

According to Koch's theories, finding the disease's root cause necessitates conducting experiments. Research that manipulates a subject provides more evidence for a cause than observational studies that only look at one variable at a time. There are two groups studied: one receives the treatment, and the other does not. The results for each group are compared. For example, one group may be given a pill-based pharmacological regimen, while the untreated group is given a control medication instead (a pill that looks the same but has no active ingredient). Except for the administration of the medication, all groups are handled as equally as possible. The researcher can be confident that any change in the treated group is a direct outcome of the manipulation because other factors are kept constant in both groups.

However, experimental investigations provide the most conclusive evidence about illness causation because of their rigor in avoiding bias. Double-blind studies are the norm when it comes to research involving humans, which means neither the subjects nor the researchers are privy to who is receiving therapy and who is not. This design eliminates the placebo effect, a well-known source of bias in research that occurs when either the participant or the researcher is aware of the therapy.

2.4 Pioneers of Epidemiology

To better understand how to avoid disease, epidemiologists first looked for trends in the occurrence of cases. Understanding some of the patterns began with the hypothesis that disease may be passed from person to person.

Girolamo Fracastoro first proposed the germ hypothesis of disease in 1546 in his essay De Contagione et Contagiosis Morbis, although this idea remained in conflict with other hypotheses like the miasma hypothesis for a long time after that. The fact that we didn't know exactly what caused the sickness wasn't a complete roadblock to learning from patterns of disease.

By accepting germ theory, scientists gained a mechanistic foundation for studying disease patterns in the late nineteenth century. Researchers in the nineteenth century, such John Snow, Florence Nightingale, Ignaz Semmelweis, Joseph Lister, Robert Koch, and Louis Pasteur, planted the seeds for contemporary epidemiology.

The 1854 London cholera pandemic was traced back to John Snow, a British physician who became known as the "Father of Epidemiology" after identifying the outbreak's cause. Based on findings obtained during a previous cholera outbreak (1848–1849), Snow asserted that cholera was spread via the fecal-oral route and that the infectious agent was a bacterium. He investigated the 1854 cholera pandemic in two ways [2]. Snow began by tracking the disease's transmission back to a single source: contaminated water. Residents who drank water from the Thames River upstream of London had the greatest incidence of cholera. This water was contaminated by garbage and sewage from the cities upstream, including London. Additionally, he added that none of the brewery's employees contracted cholera, and an inquiry revealed that the owners had given the employees beer to drink, so it's safe to assume they didn't drink water [3]. Second, he methodically tracked the cholera outbreak and discovered that people who used a particular Broad Street water pump had a higher incidence of the disease.

Because of Snow's recommendation, the Broad Street cholera epidemic was successfully contained after the pump's handle was removed.

Florence Nightingale

Another early epidemiological research is that of Florence Nightingale. During the Crimean War in 1854, Nightingale was one of a group of nurses sent by the British military to care for the injured. When it came to disease and death in the war, Nightingale kept thorough records. Her meticulous record-keeping was crucial to the development of epidemiology as a field of study. It wasn't until 1858 that she published the results of her research and analysis of the data she gathered from her experiments. She used a wedge chart histogram to show monthly death frequency data. Because of the peculiar way it was presented at the time, this data showed that the great majority of wartime deaths were not caused by combat-related injuries, but rather by infectious infections that Nightingale believed could have been prevented. In many cases, these ailments were brought on by hygienic conditions and a scarcity of healthcare options. The medical system in the British military experienced several modifications as a result of Nightingale's work. Figure 1 shows the Causes or Mortality in the Army in the East.

Wuhan, in Hubei Province, is a Chinese city where the WHO has reported cases of pneumonia with an unclear cause as of December 31, 2019. A novel coronavirus (CoViD-19) was identified as the cause of the epidemic on January 7th, 2020 by Chinese officials. The International Committee on Taxonomy of Viruses ultimately designated the SARS Coronavirus as SARS-CoV-2 on February 11, 2020. Concerns about afflicted countries have spread around the globe, raising questions about public health. Although it has not been verified, the virus may have been created by animal

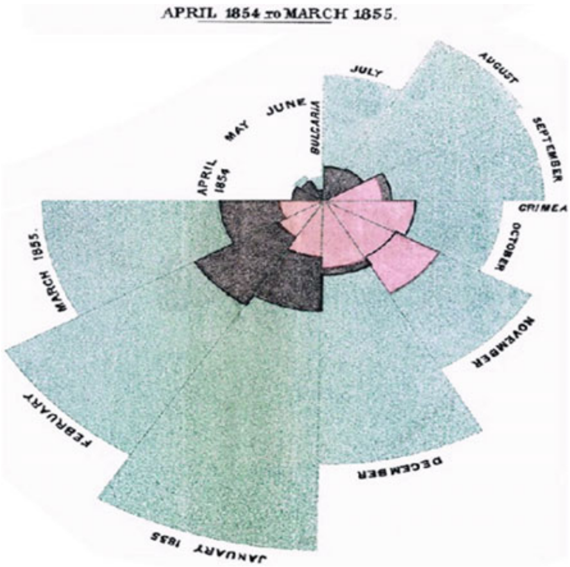

Fig. 1 Diagram of the causes or mortality in the army in the east. https://opentextbc.ca/microbiologyopenstax/chapter/tracking-infectious-diseases/

populations and transferred through the Huanan wholesale market, whereas clinical studies showed that international transmission was primarily caused by commercial air travel. The World Health Organization (WHO) declared SARS-CoV-2 a pandemic on March 11th, 2020. To stop the virus's spread and find treatments and vaccines, scientists were working around the clock. However, scientists were baffled by the dynamics of the outbreak.

Public health has been severely impacted by several past epidemics of infectious illnesses. Severe Acute Respiratory Syndrome, Swine Flu, and the Middle East Respiratory Syndrome Coronavirus are just a few examples, all of which occurred between 2003 and 2012. MERS is still alive and well, causing occasional spikes. An additional roughly 28,000 people were infected with the Ebola virus in West Africa between 2014 and 2016. Its fall occurred at the same time when the Zika virus broke out in Brazil. As a result, global interdisciplinary efforts are needed to decode important epidemiological traits and their transmission patterns in order to design feasible control plans in the event of a catastrophic pathogen outbreak like the one described above [4].

2.5 *Overview of Diagnostic Methods*

Tissues must include a virus, bacterium, fungus, or parasite, fluid, or excreta of the patient in order to provide a proper laboratory diagnosis of infection. Traditionally, pathogenic agent detection has relied heavily on microscopic examination, microbial growth, and staining. Phenotypic features, such as fermentation profiles of bacteria, tissue culture cytopathic effects for viral agents and microscopic parasite and fungus morphology, are used to identify infections. Though effective, these methods take time to master. A growing number of laboratories are turning to genotypic-based tests, such as those based on nucleic acids or quick real-time PCR. For PCR assays, a minimal amount of the specimen is all that is required for analysis, and the results are available immediately. Though effective, these methods take time to master.

A growing number of laboratories are turning to genotypic-based tests, such as those based on nucleic acids or quick real-time PCR. For PCR assays, a minimal amount of the specimen is all that is required for analysis, and the results are available immediately. Thus, quick and low-cost diagnostics can be provided without the use of high-end, high-cost laboratory equipment. The causative organism is identified using a battery of conventional diagnostic procedures. Thus, quick and low-cost diagnostics can be provided without the use of high-end, high-cost laboratory equipment. As a result, many staining processes are utilized to help narrow down the identification of an organism. These procedures include Gram staining, fluorochrome staining, and immunofluorescence. An organism must be identified microbiologically by cultivating and growing pathogens on proper media in order to fully characterize it. A suitable sample must be placed in the proper medium for growth or amplification in order to culture bacterial or viral pathogens. Another way to categorize microbes is by using biochemical approaches. Fourthly, a confirmatory test based on the ability of an antibody to bind with high specificity with one or a small range of pathogens is employed in immunological experiments.

A wide variety of pathology labs and hospitals have access to phenotypic approaches for detecting pathogens since they have been thoroughly tested, are economical, and are widely used. These approaches, however, have considerable drawbacks. When compared to indirect visualization or culture, direct visualization evolves more slowly and has poorer sensitivity and specificity. Using conventional approaches, only the most important organisms can be identified because of the high cost [5]. Traditional biochemical identification procedures sometimes necessitate keeping a patient for 24 h to complete the battery of tests. It takes time to screen for staphylococcal and streptococcal latex agglutination, oxidase, and catalase. It takes longer for staff to manually read plates and stops the flow of the subsequent biochemical tests, therefore the entire procedure is prolonged. Phenotypic diversity can also occur even during pathogen's life cycle, such as in the form of eggs, larvae, and adults of a species that vary wildly according to their developmental stage, the associated host or vector, and whether or not the organism is free-living. As a result, antibodies and is enzyme methods have detection limitations and are stage-dependent.

Even after an infection has been cleared, the host's immune system may be slow to respond or remain dormant. In order to distinguish between isolates, genera, and species, phenotypic methods can be utilized, although these approaches are less efficient when trying to identify changes within a species. Bioterrorism fears and the introduction of new infections have made it even more urgent to develop faster and more accurate technologies for detecting pathogens and predicting their future virulence [6]. When it comes to infectious illnesses, conventional techniques have serious limits in terms of speed, timeliness, and dissemination of data, but this model offers logistic, operational, and economic benefits for many non-life-threatening disorders and chronic diseases.

3 Infectious Disease Surveillance Using GIS and Remote Sensing

Geographic information systems (GIS) and related technology such as remote sensing are progressively being used to research disease geography, particularly the relationships between pathogenic variables (causative agents, vectors and hosts, and humans) and their physical environs. GIS applications have been utilized in the United States to characterize the origins and geographic distributions of disease agents, to identify time and space regions where individuals may be caused by environmental and biological agents, and to map and analyze spatial and temporal trends in health outcomes. While geographic information systems (GIS) have demonstrated great promise in research and treatment, their full potential will not be realized until environmental and disease surveillance systems are developed that distribute data on the geography of environmental factors, disease agents, and health outcomes over time based on user-defined queries for client-based geographical areas [7].

Infectious illness surveillance relies heavily on maps. They are commonly used to depict the geographic distribution of infectious disease occurrences and may also be used to generate ideas about the factors that influence disease case spatial distribution.

Spatial data on infectious disease cases can now be gathered and combined with other types of geographic information much faster and more precisely using geographic information system (GIS) technology, allowing researchers to track disease case distribution and decipher pathogen transmission dynamics. GIS is used to identify the areas where infectious diseases are most prevalent, how people are exposed to the pathogens that cause them, and when and where the next outbreak is most likely to happen, and how we can best avoid future occurrences.

From New York, where the virus was initially detected in 1999, to the United States' West Coast, where it had become widely established by 2004, GIS technology was utilized for mapping the virus' westward expansion. Consequently, the CDC and USGS were able to offer the public with up-to-date maps on time using GIS-based map services that contain information on West Nile virus human infection, domestic animals, wild birds, and vector mosquitoes. This came from the collaboration between the CDC and USGS. Environmental variables (such as temperature, precipitation, elevation, and land cover) were combined with epidemiological data for West Nile virus illness inside a GIS to identify environmental correlates of high disease risk regions and forecast where further cases were most likely to occur. As discussed in this chapter, GIS technology can help answer fundamental questions about infectious disease surveillance, such as where disease cases have occurred, how causative agents persist, and how limited surveillance, prevention-and-control resources can most effectively prevent future outbreaks. GIS in infectious disease monitoring has several challenges, which we cover in detail as well.

These GIS databases have been designed to store and show geographical information and combine data from many sources for a certain spatial extent on computers. They are relational databases with graphic user interfaces (GUIs). Collection of data or model output geographical extent is referred to as GUI, which is short for graphic user interface. When it comes to databases, a relational database connects various bits of information together (in this example, to a specific geographical place). Using a GIS, you may design and examine custom maps. Comprehensive geographical analysis capabilities are often included as standard in advanced GIS applications. For example, Google Earth provides access to photographs of the actual world but does not give any extra functions other than basic feature-making tools for map overlays. GIS technology, on the other hand, differs from newly developing, Internet-accessible mapping technologies. Data layers in a GIS include related properties for each data point that's included. For instance, illness case's locations can be mapped using GPS receiver data depending on the infection's source location or the affected person's home address. The longitude and latitude of the illness case's location, serve as a point of reference for the research using GPS data. In this way, the data from an individual patient's case file may be connected with, or layered over, additional geographically explicit data layers holding relevant information, as described above. To continue with the cholera example from above, GIS data layers can include information like the number of cholera cases found in a certain area. Attributes such as the age and gender of patients, as well as the fate of the infection, may be recorded in conjunction with this data layer. Afterwards, for each cholera case in the GIS, the locations of water pumps and sewers would be plotted alongside other data layers as well as the locations of streets and dwellings. Each of these extra data layers may additionally contain relevant attribute data, such as records of pump maintenance or socioeconomic information about neighborhoods or individual houses.

Through the use of geographical and temporal data layers and features included in a GIS, it is feasible to perform space-time studies of infectious disease patterns. Maps may be generated from any of the data layers included within a GIS, and spatially referenced data can be accessed and used in statistical analysis. While conducting infectious disease surveillance, it is not uncommon to use epidemiological data, administrative boundaries (such as a country or state), the location of medical facilities or healthcare facilities, as well as socioeconomic data (such as census statistics) (e.g., locations of water sources for waterborne diseases, land-cover type and climatic variables for vector-borne diseases). Satellite imaging and aerial photography are both examples of remote sensing technologies that may be used to collect data about the physical terrain (such as plant types, elevations, or the locations of waterbodies) [8]. Data layers are accessible from a variety of sources and can be obtained for free or at a significant cost. There are numerous methods for digitizing information that is not already available as a GIS data layer, such as through the use of paper maps or surveys, or through the use of Internet-accessible mapping technologies that provide images of the physical environment, such as various aspects of infrastructure in developed areas or political boundaries.

3.1 Remote Sensing Application in Disease Surveillance

The following are the most closely linked environmental variables to vector-borne endemics that may be seen from space platforms: Environmental variables include the temperature of the air and water, as well as the moisture content of the soil and the amount of plant cover. Other factors include things like urban features, ocean color, and topography. Some of the environmental change factors may be measured for the first time thanks to satellite sensors that have different temporal, spatial, and spectral features and resolutions. More than 90 missions, carrying more than 200 instruments, are now in orbit. It is possible to evaluate organisms whose features have changed over time in order to determine the level of environmental pollution and the implications of that contamination for human and animal health, as well as to offer early warning of such consequences. The emergence of new diseases (e.g., Ebola hemorrhagic fever, hantavirus, SARS, H5N1 avian influenza) and the reemergence of old diseases (e.g., plague, Rift Valley fever, West Nile virus, malaria) demonstrate not only the importance of microbial and viral factors on public health, but also the importance of the complex relations between these aspects and social and environmental determinants. Though our ability to cure, control, and prevent infectious illnesses has improved dramatically, the danger of their spread has also increased due to changes in society, technology, and the environment (natural and human-induced). Health groups have urged for the development and adoption of new disease surveillance technologies in light of these critical developments. As a result of the new technologies, climatic and environmental characteristics of vector habitats should be characterized, as should disease risks have associated with those circumstances. Several environmental change and disease pattern characteristics are now constantly detected remotely by equipment onboard aero planes and satellites, and spatially modelled with specialist computer software. They are now continually sensed.

The use of Remote Sensing and Geographic Information Systems (GIS) technology to characterize local and landscape-level characteristics that impact disease patterns and prevalence and then simulate the occurrence of the health event in space and time has thus been extensively employed. Environmental variables such as vegetation, temperature, landscape structure, humidity, and rainfall impact the majority of infectious and vector-borne illnesses (pathogens, vectors, and zoonotic reservoirs) and their interactions with people.

Remote Sensing and GIS have various uses in infectious surveillance systems because they enable users to respond quickly and effectively to epidemic threats. It focuses on abnormalities in automated news alert services (e.g., Bio Watch) and human clinical data (i.e., spikes in uses of International Classification of Disease diagnostic codes). The worldwide population is made aware of outbreaks via the World Health Organization's ProMED system, media tracking, and government illness reporting (WHO). Because of this, timely information on epidemic occurrences is critical in animal disease surveillance and forecasting. In order to transfer signals from one station to another throughout the world, the usage of communication satellites (Telecom) like "palapa B2-p" is extremely beneficial. These high-altitude satellites, dubbed "Live Telecommunication," operate at much higher altitudes.

Mapped characteristics and illnesses in natural or human populations frequently have statistical correlations. When disease patterns and distributions are clearly linked to mapped environmental factors, RS and GIS become extremely valuable tools. There may be diseases which are connected with specific types of plants or physical features (elevation, average precipitation), thus RS and GIS might indicate areas with a high risk. Malaria has been seen in southern Mexico and Asia in the past, according to research. Human and animal cases of African trypanosomiasis and schistosomiasis in the Southeast U.S. Warning and disease transmission have happened simultaneously in the same locales, as the proliferation of bluetongue and its vectors demonstrates. Climate change is accelerating the spread of vector-borne diseases into new locations.

The Rift Valley fever epidemic in Kenya in 2005, which killed more than 150 humans, and the cholera outbreak in Sudan in 2007, which killed over 200 people, show that this is not the only hazard to animals. More than 75% of new human illnesses developed in the previous two decades were caused by animal sources. As a result of being labelled zoonotic, a "one medication" strategy to address the world's pressing requirements should now be developed and implemented. The diagnostic purposes have proved useful in the detection and characterization of particular medico-veterinary pathogen nucleic acids and proteins. Increased speed and accuracy have been made possible by the integration of signal amplification and detecting systems incorporating online real-time devices. Increased speed and accuracy have been made possible by the integration of signal amplification and detecting systems incorporating on-line real-time devices. Commercially accessible real-time field equipment and robotic sample processing systems are already in existence. NASA Ames' Center for Health Applications of Aerospace Related Technologies developed this website (CHAART).

Since mid-1981, data from the Advanced Very High-resolution Radiometer (AVHRR) sensors on the NOAA series of polar orbiting meteorological satellites have been used to make the majority of evaluations of global or regional vegetation conditions. The thermal channels of the AVHRR sensors provide data on apparent surface temperature, which has been utilized in epidemiological research. Rare climatic events including Ebola hemorrhagic fever, rift valley fever, and bubonic plague outbreaks have been related in place and time to the onset and leading edge of infectious diseases observed by Remote Sensing. Several NASA and NOAA remote sensing platforms, including the Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat TM data, the Shuttle Radar Topography Mission (SRTM), and the Tropical Rainfall Measuring Mission (TRMM), are currently being evaluated, validated, and benchmarked in New Mexico, Arizona, and Colorado (four corners states).

It was during an epidemic in Nzara and Maridi, Sudan, in June 1976 when Ebola hemorrhagic fever, named for the Ebola River in Central Africa, first occurred. In Yambuku, Democratic Republic of Congo, a separate epidemic was discovered in September 1976. In June 1977, a fatal case was found in Tandala, DRC, and in

July 1979, another epidemic occurred in Nzara, Sudan. In October, primatologists discovered an epidemic in a chimpanzee group they were studying that included one human illness. Gulu District in Uganda saw a major Ebola hemorrhagic fever epidemic between August 2000 and January 2001. Ebola made a comeback in Gabon's Ogooue-Ivindo Province in December 2001, extending to the adjacent Mbomo District in the Democratic Republic of the Congo. This outbreak lasted until July 2002.

Hemorrhagic fevers like Ebola and Rift valley fever have been linked to climate change in studies with satellite data like cholera and the hantavirus. In addition, EMPRES-I (information, intelligence, intervention) focuses on animal disease surveillance as a partner. With the launch of the new EMPRES Global Animal Disease Information System, which is a web-based platform, it will be easier for veterinary epidemiologists throughout the world to share and collaborate on eradicating important TADs in their respective countries and regions. It may be possible to better comprehend animal and human migration and the consequent influence on the spread of animal illnesses by monitoring climatic factors suggestive of drought, floods, or other natural or human-induced calamities.

Remote sensing and GIS in COVID-19 have a lot to offer and a recent study from Boston Children's Hospital in the United States shows that they employ internet media sources for real-time surveillance of public health concerns, resulting in a product called Health Map. Using information from a variety of sources, including official alerts (such as those issued by the WHO) and expert opinions, they create a Health Map that shows the spread of a pandemic in near-real time with geolocated updates. Modelling disease transmission with spatial analytic methods can identify patterns and statistically relevant hotspots, this may then be used to anticipate the recurrence of such patterns in the future.

3.2 Understanding Ebola

During the Ebola epidemic from 2013 to 2016, health and government organizations used GIS to better comprehend the illness, pinpoint its causes and origins, and track its spread. Ebola is spread by bodily fluids such as blood, and it causes severe bleeding and organ failure, and it is typically deadly. The WHO provided live maps of confirmed cases in Sub-Saharan Africa to aid in the fight against the epidemic, which marked the first time the illness spread over several international borders.

Officials might, for example, the use of a constantly updated Ebola map depicts the deadly disease's progress across the area is shown in Fig. 2 to examine one afflicted individual and establish where they had travelled in order to determine where others might be exposed. Agencies also used mapping technology to locate emergency Ebola treatment clinics, manage bed capacity, and determine how a sick individual might obtain care effectively.

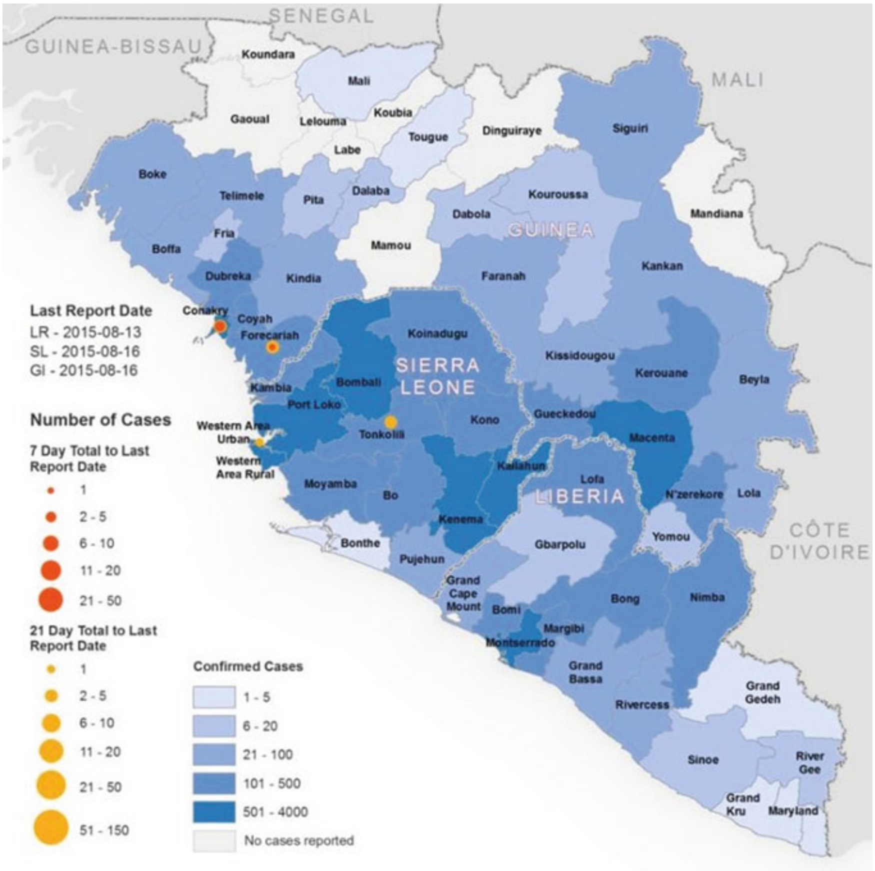

Fig. 2 The constantly updated Ebola map from August 19, 2015 depicts the deadly disease's progress across the area. https://www.esri.com/about/newsroom/wp-content/uploads/2020/03/WHO_Ebola_19-august-2015-map2-768x768.jpg

This deadly outbreak was labelled a worldwide public health emergency, prompting a better coordinated response that included increased field data gathering utilizing mobile phone applications.

During the 2002 and 2003 SARS outbreak in China, local GIS specialists assisted health agencies in tracking the disease. SARS, an infectious and potentially deadly respiratory infection caused by a coronavirus, spread quickly throughout the world. In response, the WHO updated illness maps on a SARS website on a daily basis. Even though the maps were not accessible, they were up to date, based on the most recent data supplied by local governments.

Because the area was originally the worst impacted, an SARS map team has taken it to another level in Hong Kong. To geocode case information against Hong Kong Street and buildings records, the SARS map team used health dept. updates every morning throughout the outbreak. Tables containing building names and statistics were transformed into data that could be viewed, studied, and understood by anybody using a local map.

The Distribution map of SARS affected area around the world is shown in Fig. 3. The map displayed information on SARS affected cases area wise that were confirmed and recovered. There is a website that allows residents and tourists to Hong Kong to quickly find out which buildings in their area have or may have inhabitants who are sick with the illness, as well as which buildings have been cleaned of the disease's presence. In the early days of the epidemic, people were fearful and worried because of a scarcity of information. This alleviated some of their anxiety and worry.

Some of the elements included in today's real-time illness reporting applications may be found in the 2003 static SARS dashboard. The SARS pandemic of 2003 and the current COVID-19 pandemic, both brought on by coronaviruses, are the most recent pandemics. Before quarantine measures effectively controlled the SARS outbreak, 774 individuals had died. In the eyes of global health organizations, the SARS epidemic served as a wake-up call because it showed how unprepared the world was to cope with and prevent the spread of infectious illnesses before they became pandemic.

Many people saw the SARS outbreak as a wake-up call from global health authorities who thought the outbreak showed how unprepared the world was to cope with and

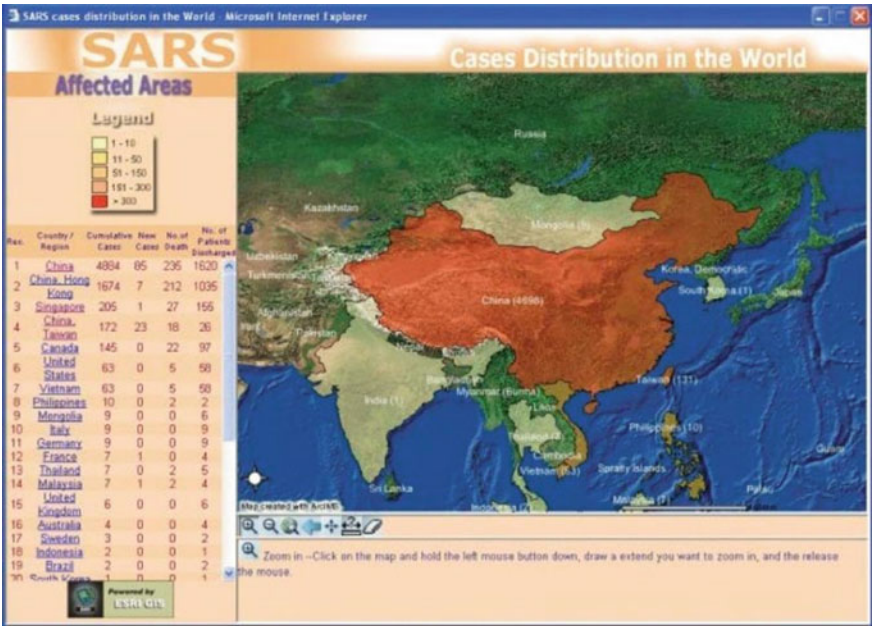

Fig. 3 SARS affected area—cases distribution in the world. https://www.esri.com/about/newsroom/blog/maps-that-mitigate-epidemics/

prevent the spread of dangerous illnesses. COVID-19 has been labelled a worldwide pandemic by WHO on March 11, 2020 despite this, the world is still unprepared.

Lessons Learned from COVID-19
More than 4.13 million deaths have been linked to COVID-19 as of July 22nd, 2021, with more than 192 million instances of the virus already confirmed. Beyond the number of people killed and cases, COVID-19 had a profound influence on the globe, as it halted economies and hindered social connection, both of which had negative consequences for global populations' mental well-being, food security, and much more.

The COVID-19 outbreak also taught the world how to respond to and prepare for future pandemics, which many experts predict will occur in the future. It is probable that the precautions used to contain the spread of COVID-19 will be maintained in the future to safeguard us from the transmission of infectious illnesses.

For diseases that may overcome these obstacles, the world now possesses the experience necessary to develop effective vaccinations in record time. While infectious illnesses cannot be entirely avoided, several steps may be done to mitigate their impact on human life.

4 Application of GIS for Infectious Disease Tracking

Geographic Information System (GIS) has found extensive use in detecting and fighting viral infections since 1964. Many infectious diseases, including cholera, fever, and the influenza pandemic (1981), were once combated, tracked, and understood using traditional GIS approaches. In the 1960s, the advent of computerized geographic information systems opened the door to new methods of disease analysis, visualization, and detection. In a 2014 study, its application was restricted to mapping infectious disorders [9]. The use of web-based GIS in the health industry has progressed with time. There is no doubt that web GIS will play a big role in this pandemic when it comes to studying data from sources, providing results in real-time analytics, and providing spatially specific information on the COVID-19. When it comes to decision-making, social mobilization, and community reactions, GIS for COVID-19 can be extremely helpful. GIS in health geography has a tremendous impact on political decision-making that must be held accountable to all sections of society by 2020. When geospatial technology is utilized, numerous positive effects can be achieved. By doing additional analysis, the COVID-19 pandemic may be displayed geographically and visualized in the determination of future results. It is hoped that the findings of this study would aid in the formulation of vaccination policies and programs, as well as speed up current vaccination campaigns.

While using web-enhanced GIS, the differences between databases, networks, hardware, and software are masked, but standard GIS does not. As a platform, it offers GIS resources to numerous organizations, allowing them to share and collaborate on

GIS materials through the Internet. As a result, Web GIS makes global geographic data, including information data, easily accessible, managed, and shareable.

One of the GNSS (Global Navigation Satellite System) utilized in current GIS systems is GPS (Global Positioning System). Other satellite navigation systems, such as the Russian GLONASS and the European Galileo, are available. As an example, Twitter uses latitude and longitude data for each tweet, making it easy to follow the spread of an infection. LiDAR (Light Detection and Ranging) uses lasers for mapping, while more advanced systems utilize lasers. Because of its ability to generate highly realistic 3-D earth surface models, this approach was used in 2012 to estimate the effects of Hurricane Sandy off the coasts of New York and New Jersey. Earthquakes are another example of how GIS may be used beyond just the location and depth of an event.

For example, in a study on communities and health, researchers looked at how residential environments can influence health and contribute to health disparities based on race and ethnicity, particularly obesity and its risk factors, and mental health. They discovered that the development of GIS and spatial analytic tools has enabled them to analyze space in far more detail and sophistication than was previously conceivable.

It's not new to use GIS to track disease outbreaks. In late summer of 1854, Dr. John Snow utilized a proto-GIS to map the causes of a cholera outbreak in London's Soho district and map the discovered cases. From August 31 to September 3, 127 people died of cholera. As a result, and within a week, 500 people died, and about one in seven people who developed cholera eventually died. All of this occurred 250 m from the intersection of Cambridge Street and Broad Street. Snow was able to pinpoint the outbreak's origins and the source of the contamination thanks to this prototype GIS.

Current epidemiological thought still adheres to Snow's main concepts in spite of advances in technology since the publication of his cholera map. Brewer provides an example of how to build a GIS project on the development of a system for tracking prostate cancer mortality in a timeline (how a collection of events occurs over time) and incorporating diverse demographics [10].

5 Geospatial Technology and Mathematical Modelling for Tracking Infectious Diseases

As Greg Bunce describes in his article "Digital Maps—How Chance, Timing, and Heritage Shaped Modern GIS," GIS made its health-related debut when it supported in the resolving the London cholera outbreak. John Snow, a British physician, conducted an analysis of the link between water pumps and cholera cases and concluded that water was responsible for the disease's transmission. He established a geographic link between the pumps and the illness, which was critical in limiting future spread. Even in this early case study, mapping was a technique used by officials involved with dealing disease invasion and medical staff tasked with treating those afflicted. Both then and now, mapping served and serves the science of its day.

Since then, GIS has impacted a variety of additional health situations:

- In 1890, Theobald A. Palm "delineated the geographical spread of rickets" using maps [11].
- H. F. Blum and H. O. Lancaster, respectively, utilized spatial analysis to investigate the link between sunshine and cancer in 1948 and 1956 [11].
- (GIS) and Cancer Research was released by the National Cancer Institute in 2006, describing numerous uses of GIS in connection to cancer cases. (In addition, the institution now has an entire website devoted to GIS materials linked to cancer.)
- In 2017, GIS was used in an Ebola virus investigation [12].

As seen by these instances, GIS has proven effective in fostering a more nuanced knowledge of public health concerns. With such a stellar track record, it's no surprise that people turn to GIS for coronavirus information. GIS has assisted in the past, and it may be able to do so again.

"In which locations are there an increase in COVID-19 cases?" One would need to examine statistics such as each nation's geographic limits, population, number of cases inside the country, and number of instances in prior weeks within the country. And then all of that data would have to be compared to data from another nation, and another country, in order to have a true picture of where instances are rising. If one were to write down this information vocally, it would likely take many paragraphs to discuss the patterns in various nations, especially depending on the number of countries being compared https://gis.utah.gov/ [13].

However, GIS can assist us in establishing links between each of these many levels and in comprehending the general patterns in COVID-19 data. To truly understand case counts, demography, causes, or any other element of the virus, one must first understand the geographical component. What are the case numbers for a certain jurisdiction? Who is impacted in a given area? How did the virus get started? And so forth. Without the geographical anchor point for coronavirus knowledge, the information isn't relevant or helpful.

To answer "Where are COVID-19 instances increasing?" The Johns Hopkins Coronavirus Resource Center offers an interactive map that color-codes the population for each nation each week [14].

The map can convey the same data in a few seconds that would take chapters to describe otherwise. A list of nations with COVID-19 case numbers could answer the question, "Where are COVID-19 cases increasing?" But by looking at the worldwide trends in COVID-19 case numbers through time, the map provides a more comprehensive explanation. And here is where GIS shines. The Covid-19 Dashboard by CSSE at Johns Hopkins University [15] is shown in Fig. 4.

GIS inherently includes intergroup communication, which is critical for coronavirus management. Collaboration among groups is a key aspect of the GIS discipline, which is why GIS might be so significant in connection to the coronavirus. Now that we know where COVID-19 instances are on the rise, let's apply that to the state of

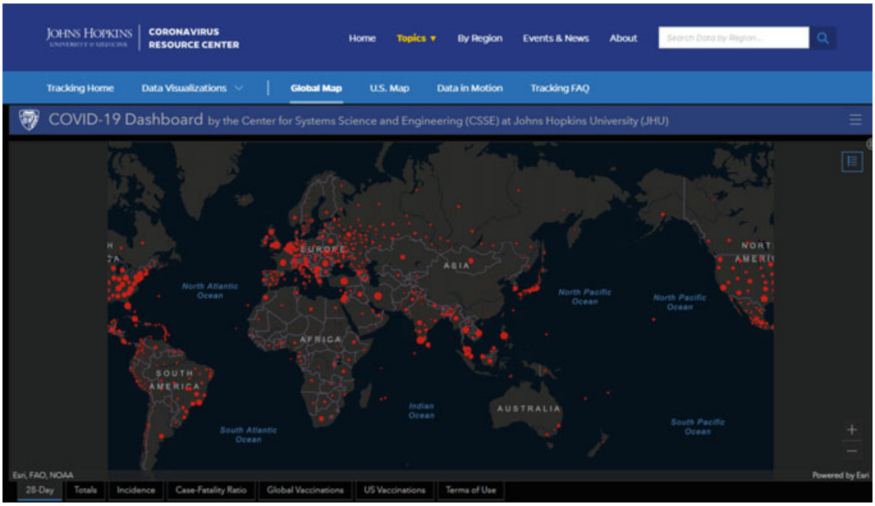

Fig. 4 Covid-19 dashboard by CSSE at Johns Hopkins University. https://coronavirus.jhu.edu/map.html

Utah. This question may be answered by looking at Utah counties first, then working with the state's county recorders will allow you to determine the exact borders of each county. The county health agency may have information on the number of coronavirus incidences in a county. So on and so on. Finally, UGRC in Utah would be the repository for all this information, so we'd have to coordinate with people from all of those organizations [13].

GIS data collection and interpretation include a wide variety of parties, as is shown. When it comes to geographic information systems (GIS), the only thing more essential than data quality is collaboration across the various groups that contributed to data collecting.

Geospatial information system (GIS) technology has the potential to allow this single operational picture for multi-agency collaboration using location as a common denominator, according to Esri India president Agendra Kumar. Additionally, he describes how Esri, a global leader in geographic information systems (GIS), is working with a variety of organizations to combat the coronavirus.

Esri is partnering with a number of governments and organizations, including the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDCP), to use GIS technology, to assist them plan and communicate various actions to slow the spread of a pandemic epidemic. In the next several years, to effectively respond to the coronavirus, multiple local and national entities must work together to communicate information, analyze that information, and take action based on that assessment. GIS, by its very nature, facilitates this kind of collaboration.

5.1 Climate Change Versus Covid-19

There are several similarities between the present COVID-19 epidemic and other ongoing global issues. Each requires a global-to-local reaction and long-term planning; each requires scientific guidance and the protection of the most endangered among us; and each requires the political will to undertake major changes when confronted with existential threats.

In this way, the coronavirus pandemic may help us get a better awareness of the links that bind us all on a global scale and may aid us in confronting the century's greatest public health issue, the climate catastrophe.

The World Health Organization (WHO), which is a member of the climate change team, is witnessing the devastation caused by unprepared health systems when confronted with these more frequent shocks. Several of these health consequences are clearly linked to climate change, such as the growing frequency and severity of extreme weather patterns or the expanding range and spreading of vector-borne illnesses such as malaria or dengue fever.

Climate change may be a factor in some diseases, as the COVID-19 pandemic.

5.2 Mathematical Model of Covid-19 Pandemic

Examining infectious illnesses mathematically may uncover underlying patterns and structures that drive outbreaks. Stakeholders uses available information about the current and prior outbreaks to anticipate infection rates, devise strategies for limiting disease transmission, and finally implement the most successful vaccination programs. Epidemiology is primarily a branch of biology that focuses on population health, and as such, mathematical theory may have a significant impact. It's impossible to decipher most population-level events merely by looking at the traits of a single individual. Epidemiological data statistical analyses aid in characterizing, quantifying, and summarizing disease transmission in host populations. Even if tests on real populations have ethical and practical limits, mathematical models emerge as effective tools to investigate and evaluate diverse epidemiological theories. Conceptual conclusions can be derived from models about things like the fundamental reproduction number, effects at thresholds, or herd immunity, among others. Epidemiological modelling also incorporates the use of statistical tools to connect with data. Virus and bacterial illnesses necessitate more complicated epidemiological models irrespective prevalence of simple ones. There are several models in the literature for single epidemics, endemic diseases, and spatiotemporal disease dynamics.

In order to anticipate the geographic spread of infectious illnesses, the novel early warning system optimizes the selection of monitoring locations and then applies a computer model to the data from these sites. For a long time, mathematical models have generated quantitative epidemiological information and provided valuable guidance for epidemic management and policy formulation. Population biology underpins epidemiology, which studies how diseases spread and how to prevent them. As a result, mathematical theory has a significant impact on epidemiology. For this reason, it's difficult to draw conclusions about occurrences at the population level from observations of a single individual.

One of the major objectives of epidemic modelling is to aid in the understanding of disease propagation in host populations through time and location. Systematic clarification of model assumptions, interpretation of variables, and estimation of parameters are all critical steps in figuring out what causes the patterns we see. Human and animal illness may be controlled with the use of mathematical modelling and simulation, which are powerful decision-making tools. The models, on the other hand, must be tailored to each individual instance in order to deal with real-world conditions, as each illness has unique biological features.

5.3 Susceptible-Infectious-Recovered (SIR) Model

Mathematic epidemiology is a branch of epidemiology that uses mathematical equations to describe the transmission of infectious illnesses. Epidemiology studies patterns and occurrences of disease in place and time in relation to other factors, such as environment demography. By classifying people into susceptible, infectious, and recovered compartments, the mathematical epidemiology model is used to better understand the transmission dynamics of communicable illnesses [16]. The SIR model is a collection of nonlinear ordinary differential equations that have the following mathematical definition:

$$\frac{\mathrm{d}s}{\mathrm{d}t} = \mu(N + S) - \beta SI \tag{1}$$

$$\frac{\mathrm{d}I}{\mathrm{d}t} = \beta SI - \lambda I - \mu I \tag{2}$$

$$\frac{\mathrm{d}R}{\mathrm{d}t} = \lambda I - \mu R \tag{3}$$

here

S denotes the class of susceptible individuals who have not yet contracted disease,

I denotes the class of infectious individuals who have contracted disease and have become infectious enough to infect others,

R denotes the class of recovered individuals who have recovered and are no longer classified as susceptible individuals,

N denotes the total population size. $N = S + I + R$, where t is the time in days or weeks,

β is the daily rate of contact between an infected person and a suspected person,
λ is the infectious period and average infectious period is $1/\lambda$,
μ is the per capita death rate which is adjusted by birth rate μN.

In other words, it's the mortality rate divided by the population's birth rate multiplied by l. In addition to the basic epidemic model (SIR), there are numerous different compartment models that incorporate additional compartments and transitional phases [17]. They are Susceptible-Exposed Infectious Recovered (SEIR), Susceptible Infectious Exposed Recovered Dead (SEIRD), Susceptible-Infectious Exposed Recovered Susceptible (SEIRS), Susceptible Infectious Quarantine Recovered (SIQR).

For the first 25 days of the pandemic, the SIR model is used to study the dynamics of COVID-19 transmission from one person to another. India provides data on genuine COVID-19 cases are shown in Fig. 5, which are then utilized in the SIR model in R software.

For the next 90 days, the likely SIR model is built using the given parameters to determine how much of the population may be affected. The Model Optimization as per actual cases for first 25 days & *SIR Model in 90 days* is shown in Fig. 6.

The SIR model is optimized using parameters $\beta = 0 : 00021$ and $\lambda = 1/14$, versus actual illness cases.

As a result of this, the SIR model may be extended by an additional day or two by lowering the population size and raising the survival time.

The SIR model can provide clarity on the virus' spread over time in a way that raw data alone is unable to achieve. Providing you have access to accurate data, you can use it to better communities. With the addition of fresh data, the model's

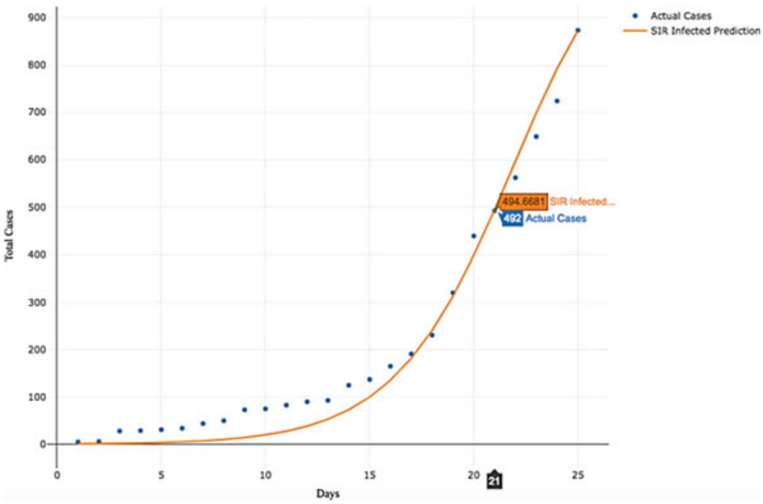

Fig. 5 Model optimization as per actual cases for first 25 days. *Source* https://doi.org/10.1007/s12524-020-01140-5

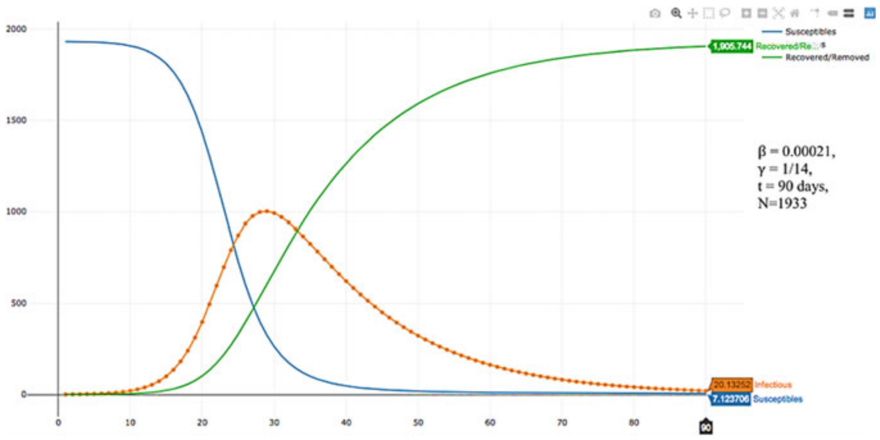

Fig. 6 SIR model in 90 days. *Source* https://doi.org/10.1007/s12524-020-01140-5

power increases since its parameters can be easily adjusted to give the best-fit curves between actual data and model predictions. It has the ability to forecast future death tolls as well as the time it will take for infection rates to fall in a community. With its ability to tolerate surges and be modified to recorded data, the SIR model is more suited to forecast epidemic trends caused by disease transmission. To further understand how the COVID-19 virus spreads among communities, researchers have used the SIR model.

5.4 *Agent-Based Simulations*

Agent-based modelling is the cutting-edge of mathematical epidemiology today for understanding and simulating complicated epidemic systems. These take into account characteristics such as the transportation networks, population migrations, and demographics of the simulated area, as well as epidemiological concerns such as disease development inside a host and transmission between hosts.

Epidemiologists, academics, and public health officials are increasingly relying on these complete models for ethical, financial, timeliness, and appropriateness considerations. In epidemic systems, investigating experimental conditions may endanger public safety, creating an ethical quandary. In other cases, evaluating an existing system in real time may take an unreasonable length of time. In the case of a catastrophe, for example, simulation may be used to rapidly analyze a huge number of previously unconsidered options. Due to the intricacy of the underlying real-world system in each of these cases, multi-agent simulations are used since they are judged to contain the required level of complexity https://www.epimodels.org/midas/pubglobamodel.do.

For example, the Models of Infectious Disease Agent Study (MIDAS) a network founded on May 1, 2004 and funded by the United States National Institutes of Health, has as its pilot project comprehensive modelling of the dynamics of a hypothetical flu pandemic.

Eubank described the use of EpiSims, a complete agent-based simulator that incorporates TRANSIMS population mobility data as well as epidemic models of host-pathogen and host-host interactions [18]. EpiSims was created at Los Alamos National Laboratory and uses the Transportation Analysis and Simulation System (TRANSIMS, http://code.google.com/p/transims/) to build a synthetic population. The scientists simulated the spread of an infectious disease over a network of 1.5 million people (nodes), 180,000 locations, and 1.6 million vertices in the Portland, Oregon, US area. Southeast Asia is now undergoing a pandemic due to the H5N1 influenza virus. 133 They simulated 85 million agents stationed in Thailand and a 100 km-wide zone that encompassed neighboring countries.

The analysis of demographic data included information on households, the locations of schools and workplaces, and population mobility. They used sophisticated agent-based simulations to evaluate containment strategies in terms of their capacity to avoid a pandemic and the distribution of drugs necessary to stop the spread. Burke created a model of smallpox spread using agent-based simulations. The program examined hypothetical communities with populations ranging from 6000 to 50,000. 134 A distribution of residences, workplaces, schools, and hospital units was constructed using US population data. The authors assessed the efficiency of several contagion control measures, including vaccination of families and school-aged children, isolation of sick persons, and immunization of hospital staff. Balcan explored how the spatiotemporal pattern of a pandemic can be influenced by short- and long-scale interactions caused by air travel. The scientists used the GLEaM agent-based computational platform (http://www.gleamviz.org/), which supports three types of data: demographic/population, mobility-related, and epidemic modelling. To build a spatial metapopulation pandemic model, real-world data from 29 countries was merged with flight data from 3362 IATA-indexed airports.

5.5 *Empirical/Machine Learning-Based Models*

Data acquired from internet-based communication platforms and search engines has been used to uncover early indicators of social trends using machine learning techniques in the past several years. Online search engines, microblogging services, and social networking sites have all changed how private and public information is shared. Personal data mining agents stand to benefit greatly from this innovative new technique. Stock market fluctuations and movie box office earnings have been anticipated using such services. Flu symptoms were searched for 50 million times on Google between 2003 and 2008. Based on data made available by the CDC's US Influenza Sentinel Provider Surveillance Network (http://www.cdc.gov/flu/), an equation was developed that used log chances of a physician visit in one area and the log odds of a relevant search query from the same location as input to the equation. This technique has led to the development of a web-based tool for tracking flu patterns (http://www.google.org/flutrends/). Researchers Hulth et al. analyzed the web searches made between 2005 and 2007 on a Swedish influenza website (2009). Two models were created and fitted together to match the volume of web inquiries to the total number of laboratory-verified influenza and persons in Sweden who were treated by physicians for influenza—like symptoms. In real time, the models were used to estimate disease outbreaks and anticipate the progression of influenza. According to Chan between 2003 and 2010, a linear model was used to look at the correlation between Google search queries on dengue in Bolivia and Brazil as well as India and Singapore based on publicly known dengue cases.

6 Recent Technologies for Infectious Disease Tracking

Some of the most cutting-edge approaches to detecting infectious illnesses in recent years include the ones listed below.

6.1 Blockchain Technology

The "**Blockchain Technology**" has established itself as a resource that may be used in a variety of ways. Numerous Blockchain systems were suggested or deployed in the aftermath of the COVID-19 epidemic. The COVID-19 epidemic will certainly need the use of Blockchain technology. Numerous Blockchain applications have been discovered in recent years, however the most of them are not matured enough to demonstrate their anticipated influence in the battle against COVID-19.

Governments, health authorities, and politicians must examine all Blockchain uses when addressing COVID-19-related issues. There is an urgent need to do empirical research to determine the effectiveness of Blockchain technology in addressing COVID-19 issues. There is an urgent need to do empirical research to determine the effectiveness of Blockchain technology in addressing COVID-19 issues. Contact tracing was the most important application of Blockchain technology. This might be explained by the fact that tracing COVID-19 possible patients in the community was a top priority for assisting authorities in controlling viral outbreaks. Individuals in close proximity to those who tested positive for COVID-19 can be tracked, public health strategists may immediately identify "hotspot" regions and focus their efforts on eradicating the virus more efficiently.

The early stages of development of technology were not privacy-preserving, having a centralized architecture that enabled governments to conduct widespread monitoring. To address privacy problems, Blockchain technology is utilized to create a completely decentralized system that does not rely on a trusted third party. Immunity passports and COVID-19 diagnostics make use of the Blockchain to securely store and distribute patient data while guaranteeing that it is only available to authorized parties.

Smart contracts offer an additional degree of automation to the management of sensitive data access. It is worth noting that immunity passports may not be useful at the moment for two reasons:

1. vaccinations for COVID-19 had not been produced at the time of this investigation, and
2. an individual who has already been infected with COVID-19 is still at danger of reinfection.

Other applications, such as remote monitoring, status tracking, and identity verification, are generic Blockchain health applications that predate the current pandemic epidemic, and so will be used for COVID-19.

6.2 Big Data Analytics

The term "Big Data" was used by computer scientists to describe the ever-increasing volume of data that is both large and diverse, as well as relevant for a wide range of purposes. A huge or sophisticated data set is referred to as "Big Data" when traditional data processing tools and methodologies are unable to analyze it efficiently. There is a lot of volume (measured in terms of data) and high velocity (measured in terms of the pace at which data is entered and departed) associated with Big Data, as well as a wide variety of data types and sources and a high degree of authenticity (in terms of accuracy and correctness).

As a result of this, the phrase "Big Data Analytics" refers to the techniques used to analyze large amounts of Big Data in order to uncover new, useful information. For example, compared to known techniques such as regression-based models and other statistical models, this one has improved accuracy and scalability.

6.3 Artificial Intelligence and Machine Learning

"Artificial Intelligence" has been recognized as one of these advanced techniques because of the roles it may play in several application domains, including public health disciplines focusing on infectious disease prevention and treatment.

Supervised and unsupervised machine learning are two categories of artificial intelligence and machine learning methods based on their learning techniques. The technique of inferring a function using labelled training data is known as supervised learning. SVMs, Decision Trees, Random Forests, Naive Bayes (NB), Artificial Neural Networks (ANN), and Bootstrap Aggregating and AdaBoost are just some of the tools available to help with classification and regression difficulties in medical data.

All of these approaches have the potential to improve diagnostic precision and provide patients with more personalized treatment options. Other uses include warning authorities and citizens of impending disasters and recommending preventive and control measures that will help mitigate the effects. The dimensionality of data may be reduced using unsupervised learning techniques such as Principal Component Analysis (PCA). This makes it easier for researchers to pinpoint the exact cause of an infectious disease.

If researchers use other unsupervised learning approaches, such as *K*-means, they may sort patients into subgroups and spot outliers, which will help them focus their research efforts. Topic modelling approaches like Latent Dirichlet Allocation (LDA) may also be used to extract topics from medical text data, for example. Recently, deep learning architectures have been widely used to classification and prediction, social network filtering, and bioinformatics, and are considered as powerful tools for infectious disease analytics. Deep learning architectures have been successfully applied to these fields.

The amount of data gathered through public health monitoring has increased dramatically since the turn of the twenty-first century, thanks to advances in information and communication technology and the deployment of new data collection methodologies. The research of multiple infectious disease outbreaks will probably definitely be made possible via the use of machine learning and data management technologies. Governmental agencies, healthcare service providers, and healthcare specialists will benefit from new developments in syndromic surveillance for risk analysis and resource allocation.

Improved diagnosis and transmission prevention: Fear of infectious disease transmission has prompted authorities to establish procedures for identifying persons at risk. As such, temperature checks are conducted routinely in Singapore airport terminals using a thermal camera to identify persons with elevated temperatures. This basic check is one of the procedures taken ahead to prevent illness spread. Recent advances in surveillance through the use of mathematical modelling are enhancing this sort of surveillance.

A similar method has been developed to identify infected patients using vital sign categorization. Thus, utilizing a neural network and fuzzy clustering approach, we were able to correctly categorize patients at increased risk of influenza based on their respiration rate, heart rate, and face temperature. Fuzzy clustering methods differ from *k*-means clustering in that they incorporate membership values (a measure of an individual's desire to join a cluster based on their edge/centroid position inside the cluster) and a fuzzifier. As a result, unlike with non-fuzzy clustering techniques, one point might belong to many clusters. This indicates a capacity for developing effective approaches for identifying vulnerable groups.

6.4 Internet of Things (IoT)

The Internet of Things (IoT) is made up of three critical components: perception or idea creation, safe data transfer, and intelligent data analysis. These fundamental components can be used in a variety of strategies to minimize and control infectious diseases. The process is based on the use of sensors, artificial intelligence (AI), information technology, and dynamic networking devices that are already accessible.

The Internet of Things networks enable long-distance communication between hospitals, patients, and medical equipment, therefore improving existing medical conditions. The Internet of Things has found several uses in infectious disease management, including early prediction, accurate diagnosis, therapeutic intervention recommendations, and data sharing and policymaking. The IoT network's components are combined into a skeleton structure, which aids in the preventive and control of infectious illnesses.

7 Conclusion

History shows that communicable diseases have had a significant influence on humanity and have grown more dangerous as time has passed. Two-thirds of Athens' population died in the first known pandemic, which occurred during the Peloponnesian War in 430 B.C. The Covid-19 Virus spread the epidemic, as a result 237,383,711 confirmed cases and 4,842,716 people have died throughout the world as on Oct 11th 2021. In future, Geospatial technology is utilized in conjunction with more modern technologies such as Artificial Intelligence and Machine Learning, Big Data Analytics, the Internet of Things, and Blockchain Technology a significant spread of infectious diseases would be minimized.

While the onset of infectious diseases cannot be entirely prevented, different actions may be done to mitigate its impact on human existence via the use of Modern Technologies. Recent advances in disease monitoring through the use of mathematical modelling are enhancing disease surveillance. In conclusion, it is advised that modern technology be used for contact tracing, disease surveillance, and other purposes. As a result, the rapid disease spread and illness outbreak's toll may have been significantly reduced, saving the community from the threat of a global pandemic.

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Chapter 6
Internet of Things in Healthcare

Loveleen Gaur

1 Introduction

"E-Health refers to the collaboration of telecommunication techniques with healthcare" [1]. It is done with the help of a technology known as Wireless Sensor Network (WSN). WSN helps people monitor personal health using sensors to monitor physical or environmental parameters and pass the data through a network to a particular destination [2]. This idea helps develop small devices that can transfer patients' vital parameters to a remote location wirelessly [3]. Hence reducing the challenge faced by the doctors in monitoring multiple patients simultaneously [4, 5]. Sensors are deployed in the human body, which practically detects any abnormality at an early stage. The sensors are always sensing changes in vital measurements and environmental surroundings and continuously gather information in real-time. It assists in decision-making for the treatment [6] and increases any patient's survival rate.

The wireless sensors help in:

- Gathering data in real-time about an object being monitored or its surroundings.
- Increasing the mobility of the patients without limitations or wired cables [7, 8].
- Giving the doctors a break as they need not be physically present to track down the vitals.

The entire system is scalable, portable, user-friendly, and discreet. Many project designs have been suggested for patient monitoring wirelessly by Shin et al. [9], encompassing Wireless WAN, Bluetooth, and ZIGBEE as the emerging technologies for wireless transmission. The healthcare IoT systems also come with their own set of security challenges, including possible harm to the patient's safety and health, loss of PHI (protected health information) or ePHI, and unauthorized access to devices (Mike Nelson, vice president of healthcare solutions at DigiCert) [10, 11]. One problem

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
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https://doi.org/10.1007/978-981-16-9476-9_6

is devices entering hospitals through various channels. Some of these avenues are unknown, making it challenging to figure out the lifecycle management of that device and identify the operating system. Hospitals use the internet of medical things to optimize surgical workflow and alert families to when loved ones are out of surgery, boosting patient satisfaction. The adoption of wearable has encouraged physicians to use the Internet of Things for patient engagement, including medication adherence and home monitoring. The Internet of Things can be used to collect data that would usually be taken at a doctor's office, which doctors can use to get a complete view of a patient's health. A proposed system by Singh [5] suggests monitoring the patient's parameters and transmitting the report using Zigbee technology. The system enables the patient to move around freely and not be restricted to a single location. According to the author, data transfer using Bluetooth becomes limited, whereas Zigbee covers a larger area. The protocol consumes low power, is smaller in size, and does not require any transmission cables. The work stated by Autee et al. [12] deals with monitoring the patient's blood pressure (BP), heart rate, temperature, and body position. Another architecture presented by Mankar et al. [4] consists of a wireless biomedical sensor network. This architecture monitors the temperature and heart rate, processes the values using an ARM7 processor. A similar module implemented a non-invasive system to track the vitals (temperature, heartbeat, ECG, blood sugar) of a patient, analyze them using ARM TDMI processor, wirelessly transfer using Zigbee module which is connected to every patient, notify the doctors with an alarm in case of an emergency. It stated that the transmission range implemented in the system is about 400 m [13]. A method was developed to monitor the physiological parameters, analyze using ARM7, and transfer using Zigbee protocol [14].

The doctor can view the results either on his mobile or the PC. Furthermore, the relatives are also notified in case of any emergency. According to ABI Research, the sale of wearable wireless medical devices will bloom and reach more than 100 million devices annually. Another report by IMS Research, the research partner of Wearable Technologies, states that wearable devices or are close to the body produce more realistic results. There has been clinical evidence that wireless devices' physiological data has been a valuable contributor for managing or preventing chronic diseases and monitoring patients post-hospitalization. As a result, a growing number of medical devices are becoming wearable nowadays, including glucose monitors, ECG monitors, pulse oximeters, blood pressure monitors, etc. The Internet of Things enables health organizations to achieve superior technology interoperability, lift critical data from multiple sources in real-time, and a better decision-making capability. This trend is transforming the healthcare sector, increasing its efficiency, lowering costs, and providing better patient care avenues [15, 16].

2 Current Areas of IoT Application

Areas where IoT are getting used worldwide, are as follows:

Tracking patients' staff and medical device equipment—Outpatient clinics are complex environments with many moving parts and people. Powered by IoT sensors, hospitals are now automatically monitoring the status and location of patients, staff, rooms, and other resources with automated tracking boards, operational alerts and notifications, room visibility, and robust, visually-driven analytics. Clinics can now reduce patient wait times, serve more patients, and improve staff communication and efficiency using IoT sensors.

Understanding patient traffic flow—This can be used to design new layouts for effortless movements and assisted movements across a hospital layout.

Environmental monitoring of temperature and humidity or refrigeration units such as blood banks requires a controlled environment—IoT-powered temperature sensors eliminate manual temperature monitoring and enable staff to focus on clinical tasks. It facilitates regulatory compliance by automating accurate collection and logging of temperature data via 24/7/365 monitoring of critical storage items such as blood, tissues, drugs, vaccines, and organs. It also automates reports of logged data to help identify trends. Humidity monitoring reduces the risk of healthcare-associated infections by monitoring humidity levels in endoscopy cabinets and other storage units. It maintains operating room comfort and safety by alerting staff in real-time if moisture levels are too high or too low and can immediately adjust to stop humidity from causing condensation. With sensors in place, facilities managers know in real-time if document or storage rooms take on too much moisture, allowing staff to quickly take proactive measures to contain and stop water from causing damage.

Hygiene management to prevent hospital-acquired diseases—IoT sensors automatically detect when staff members wash their hands as they enter and exit patient rooms. Automating hand hygiene monitoring delivers reliable, objective data—providing the best input for analysis and reporting.

Infant Security—The infant security system includes tamper alarms, exit alarms, and out-of-unit alerts that allow staff to act quickly. The system sends signals directly to caregivers and automates infants' transfer between hospital areas for a smoother workflow and uninterrupted security. It provides tangible proof to parents that their infants are safe and secure.

Digital Wayfinding and Indoor Navigation—A medical campus is a big layout with many departments and functions. Hospitals and health systems are adding more beds, operating rooms, outpatient and ambulatory facilities, and medical office space to meet an aging population's needs. IoT enabled GPS tracker/powered by Bluetooth Low Energy (BLE) Beacons with indoor tracking integrated with scheduling systems to reduce missed or late appointments and drive a personalized patient experience. This end-to-end management of the patient journey enables hospitals to address some of the most common complaints directly.

Fall Management for older adults—When a resident falls, a healthcare facility can be negligent and responsible for the consequences. Falls can change a person's physical and mental health and can cause their health to decline rapidly. IoT Shock or tilt Sensors integrated with alarms can help detect falls and alert support staff for immediate relief and rehabilitation.

Equipment and Asset Tracking—Manual processes to manage capital and rental equipment are inefficient, labor-intensive, and error-prone. If staff finds it difficult to locate the portable equipment they need, they may stockpile it when they discover it and can be stressful and dangerous for patients. It also increases equipment utilization and lowers shrinkage rates while decreasing rental fees and penalties. By providing immediate access to equipment, it helps to improve patient outcomes and experiences. The system reduces the time and effort spent on maintaining par levels. Location history that pinpoints equipment associated with an infectious patient helps prevent the spread of infection.

Medicines and implants with inbuilt sensors—Today, healthcare pharma companies' most significant challenge are to test the efficacy of medicines on a real-time basis; usually, companies deploy hundreds of clinical trials to obtain results from before and after trials. It is set to change with IoT as companies are doing trials of building sensors within medicinal capsules and implants. Smart pills are ingestible medical devices consisting of sensors, cameras, patches, and trackers that help improve diagnostics and monitoring. A capsule being developed in Ireland aims to contain no medicine but process analytical technology. These unique devices can be easily swallowed and offer a non-invasive thorough examination of the gastrointestinal (GI) tract. The intelligent pills also enable comprehensive health monitoring of various physiological metrics and measuring medication adherence in patients.

Wander management for the mentally challenged—Senior living communities struggle to keep wandering residents safe without compromising their independence, dignity, and freedom. Wandering can have many dangerous outcomes, such as becoming lost to fracturing a bone in a fall. According to the Alzheimer's Association, six in 10 people with dementia will wander. Each resident wears door controllers to protect a small radio transmitter and exits. When a resident approaches an exit, the door controller locks the door to prevent the resident from leaving; if the door is opened, an alarm sound. Even when residents loiter near a door, which could be predictive of an exit, a notification can be generated.

Disposal of Bio-Waste—Bio wastes, including waste blood or blood products, Human organ waste, etc., need to be carefully disposed of and a proper track record kept for ensuring compliance with different legal regulations. These can be monitored using IoT sensors, which can segregate other types of waste and monitor incinerators meant to dispose these wastes, thereby maintaining proper audit trails.

3 Case Studies

Memorial Hermann Hospital, USA has multiple floors to deploy its safety protocols, including Labor and Delivery on the 3rd floor, Well-Baby Nursery and Postpartum on a different floor, and Level III Neonatal Intensive Care Unit (NICU) and Pediatrics on another floor. Each floor's systems needed to be fully integrated with the others. Using IoT based infant tracking system, the staff sees alarms or events each time their attention is required. Powerful reports with complete information on everything that's happening in the system are at caregivers' fingertips. The staff has confidence in the care they provide, knowing that their most minor patients are safe.

Barnes-Jewish Hospital

Patient falls are the largest category of adverse events reported at Barnes-Jewish Hospital. Progress in meeting targets for reducing falls and fall injury rates was static despite multiple efforts. Using IoT-powered patient fall detection systems in six months, the fall rate on one intervention unit decreased from 4.48 to 1.96. The other intervention unit saw a slight decrease in their fall rate during the same period (3.89–3.68); however, their injury rate decreased from 1.56 to 0.

Saint Alexius Medical Center

Saint Alexius was concerned about the risks of a patient or resident fall, including medical, financial, legal, and patient comfort issues associated with falls. After implementing the Bed-Check Fall Management system powered by IoT sensors, Saint Alexius had a reduction in falls and a reduction in restraint use and concluded the new prevention program was successful in meeting the resident's needs.

Huntsville Hospital

In Huntsville, Ala. has deployed an IoT-powered hand hygiene system in its nine cardiac units; accurate, comprehensive, and near real-time data on hand hygiene compliance aided the nurturing of a hand hygiene compliance culture. During the pilot run, the unit accomplished individual compliance rates of greater than 90% and a 58% relative improvement in overall compliance. The solution automatically detects when staff members wash their hands as they enter and exit patient rooms, with no extra steps for staff that could interfere with workflow; they use the hand sanitizer dispenser as usual, which gets recorded for compliances.

Given Imaging Ltd

In 2014, Given Imaging Ltd, a capsule endoscopy pioneer, received FDA clearance for PillCam COLON. The device provides a new modality to ensure clear visualization of the colon in patients following incomplete colonoscopy. According to some recent studies, incomplete colonoscopies occur in approximately 750,000 patients in the United States alone every year. The number is further higher in women due to an increase in past pelvic surgeries. There is a growing demand for such devices among patients with a long-case history of abdominal surgery or advanced diverticular disease. This non-invasive test enabled by PillCam COLON allows more people to get screened for colorectal cancer and gives a minimally invasive, radiation-free option. These devices have revolutionized the colorectal cancer diagnostics and screening in worldwide market.

Treatment of COPD and Way Finding

Healthcare is one of the wealthiest areas of opportunity for the Internet of Things. The next wave of the Internet of Things is going to have a significant impact on healthcare. For example, health sensing in the home is critical for managing chronic diseases such as chronic obstructive pulmonary disease or COPD. Once called chronic bronchitis or emphysema, it is a progressive lung condition that causes shortness of breath and coughing. Five percent of the world's population suffers from COPD, and three million people die of it each year. For example, in the United States, COPD accounts for three-quarters of a million hospitalizations annually and is the third most significant cause of death. The disease is diagnosed and treated using spirometers, which measure airflow in and out of the lungs. Spirometers cost thousands of dollars, are only available in hospitals and occasionally at doctor's offices, and many COPD sufferers do not have easy access to them.

To solve this problem, scientists have created an Internet of Things-based alternative to spirometers, using the most abundant networked sensors in the world: the microphones in telephones. There were less than a billion phones in the world twenty years ago. Today there are nearly nine billion phones, most of the cell phones. Scientists developed an algorithm that measures lung health by analyzing the sound of someone blowing on a phone's microphone. It replicates a spirometer without the expense and hospital visit. All a COPD sufferer has to do is call a toll-free number and blow on their phone. Networked computers take care of the rest by performing complex calculations, then delivering the results a few seconds later via a voice or text message. The early versions of the algorithm only worked on 216 expensive smartphones, but with refinement now, it could work on any phone over time. The approach now has 95 percent accuracy across all types of phones, including landlines. Diagnosing and treating COPD provides a glimpse of how the Internet of Things will improve healthcare in the future.

Wayfinding is a big problem in hospitals. When people get lost in a hospital, it causes them stress and costs the hospital money. Outpatients and people visiting sick family members are both unfamiliar with the hospital and already under duress—a condition that makes it harder to process information. A study at Emory University Hospital, an acute care facility in Atlanta, found that wayfinding problems cost that hospital US$400,000 per year—over US$800 per bed—the equivalent of at least two full-time staff (Table 1). Most of this expense comes from interruption and distraction when people ask staff for directions. This problem is terrible at pediatric hospitals, where visitors are worried parents and the outpatients are children.

Table 1 Pediatric hospital staff asked for directions by visitors at Emory

Visitors often ask pediatric hospital staff for directions	
Destination	Request for directions per week
Pediatric intensive care unit	223
Medical imaging	115
Outpatient clinics	107
Cardiology	83
School-age/Toddler units	70
Total	598

Table 2 Average age of Boston's Major Hospitals

	Year built/Founded	Age
Beth Israel Deaconess Medical Center	1973	44
Boston Children's Hospital	1871	146
Boston Medical Center	1855	162
Brigham and Women's Hospital	1980	37
Carney Hospital	1853	164
Dana-Farber Cancer Institute	1947	70
Faulkner Hospital	1900	117
Joslin Diabetes Center	1952	65
Lemuel Shattuck Hospital	1974	43
Massachusette Eye and Ear	1824	193
Massachusette General Hospital	1811	206
New England Baptist Hospital	1893	124
Shriners Hospitals for Children	1999	18
Spaulding Rehabilitation Hospital	2013	4
St. Elizabeth's Medical Center	1868	149
Tufts Medical Center	1950	67
Average age		101

The costs and harm of wayfinding problems in hospitals have received a lot of attention in the medical community in recent decades. As a result, new hospitals are often designed to be easy to navigate. But few hospitals are new. Most are very old. For example, in Boston, Massachusetts, most hospitals have roots in the late eighteenth or early nineteenth century (Table 2). Some have moved to new sites relatively recently, but others have not added new buildings to old buildings and grow incrementally with little thought to wayfinding. It is not possible to redesign these hospitals for easy navigation: they need another solution.

Boston Children's Hospital has already created one, using the Internet of Things. The hospital was founded in 1869 and moved to its present location in 1871. Today it is widely regarded as one of the world's leading pediatric hospitals. It treats around 25,000 inpatients and 500,000 outpatients each year in more than 300,000 square feet of space spread over twelve buildings and five floors, accessed via five elevators.

In 2012, to make wayfinding simple in its complicated building, Boston Children's Hospital developed a free smartphone app called My Way. My Way uses GPS to sense where a visitor or patient is and guide them to their destination. The app can also show the quickest route to facilities like restrooms, parking, and information desks. It took the hospital only a few months to build the app using Meridian, made by Aruba. One of the app's most important features is that hospital staff can update it instantly whenever things change in the hospital. If an elevator is out of order or a corridor is closed because of construction, My Way can automatically select another route. In its first six months alone, the app was downloaded 4500 times, and 65% of patients said it improved their experience at the hospital [17, 18].

4 Conclusion

Patients and providers both stand to benefit from the IoT in healthcare, whether they're using mobile medical applications or wearable devices to capture health data or keeping tabs on the location of medical devices, personnel, and patients. IoT can improve patient outcomes, but a lack of EHR (Electronic Health Record) integration and concerns about data security may prevent healthcare from fully adopting the technology [19–21]. IoT medical devices increase in hospitals, but IT may struggle to keep the devices patched and updated, especially once they leave the hospital network. While the Internet of Things makes interoperability possible, users must focus on cybersecurity when using IoT devices [22–24]. Finally, there's also the danger of overloading physicians with too much data, which the human brain cannot comprehend, leading to critical errors. However, as a significant benefit in the future, IoT will supplement patient treatment through remote monitoring and communication and keep track of patients as they move through a healthcare facility or their residences. Several hospitals have already adopted IoT to track the location of assets and collect other data elements such as temperature in areas where it is critical to stay in a specific temperature range. However, some technology analysts consider IoT a disruptive technology and are concerned with its level of data security and its ability to meet healthcare compliance requirements, such as those regulated by the FDA. The future of IoT in healthcare may hinge on resolving those concerns and maximizing IoT's core benefits, such as immediacy, transparency, and price point [25]. Smart Pills can help reach places in the human body that is traditionally not reachable, thereby revolutionizing GI diagnosis. Smart Pills are likely to replace conventional diagnostic techniques such as endoscopy and colonoscopy. Capsule endoscopy is regarded as a significant technical innovation, influencing the investigation and management of various minor bowel diseases, esophageal disorders, colonic disorders, etc. Capsule endoscopes are designed to provide complete gastrointestinal tract examination, including images of esophagus, stomach, small intestine, and large intestine. Smart Pills are also introducing patient monitoring as an add-on feature that includes monitoring parameters such as pH, temperature, and pressure and drug adherence. There are still many unresolved challenges like data accuracy, including calibration and capabilities of endpoint sensor devices, lack of interoperability between systems and manufacturers; these would be addressed as the IoT standards evolution and adoption increases soon.

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Chapter 7
IoT Empowered Smart Health Cities

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1 Introduction to Internet of Things (IoT)

The Internet of Things (IoT) is a standard prototype which establishes a dynamic medium of connected devices where data can be shared /transferred freely. Researchers had defined IoT in various perspectives. It's known as network system that bridges the gap among virtual and physical domain. The key concept of IoT is securely connecting prevalent things approaching us viz, mobiles, switches, fridge, sensors etc. to internet with wired or wireless network. Therefore, it permits the devices to communicate among themselves and with surrounding devices to strengthen the system proficiency. Techniques and methods deployed along with IoT are Machine-to-Machine (M2M) communication. Devices connected through IoT can exchange data to enormous number of devices throughout the world.

IoT is the framework which comprises of various "things" like phones, buildings, hospital equipments, vehicles, and power-driven equipments connected together through internet to exchange and acquire data among them. Above mentioned "things" possess the proficiency to assemble themselves and they can communicate with each other automatically. The main aim of IoT is to advance the "internet" further pervasive and further immersive. Since last few decades IoT has been enhanced in its techniques and had been extended over various devices like vehicles, hospital devices, electronics, surveillance cameras, controllers, sensors, and so on. IoT had been applied to various areas and various applications had been developed till now viz smart building (home appliances automation, smart switches, smart lockers, smart parking, smart lighting), smart hospitals (patient monitoring, emergency alarming, smart diagnosis, elderly assistance, disease monitoring), smart agriculture, smart grids, smart vehicles, traffic management, manufacturing, supply chain, industrial and commercial management etc.

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_7

IoT framework provides smart and automatic device modelling which forms a global network web and this will enhance the possibilities of new technologies for Information and Communication Technologies sector (ICT).

Smart cities use ICT to improve the life of citizens. Primary goal of smart cities is to optimize the functionality of city and to promote the economic growth.

2 IoT Architecture

Various researchers follow different architectures according to the requirement of the model, i.e. multiple architectures had been deployed for IoT applications. It had been observed that all this architectures doesn't meet up the security and privacy challenges. Therefore "Centripetal" IoT architecture is required to be designed which address all the security and privacy issues. The prime architecture is the one which addresses all the requisite factors such as privacy, confidentiality, security, integrity, and reliability. Since numerous devices are connected in IoT framework; layered architecture is effective as it is flexible and responsive. The essential factor to be considered while deploying the architecture is data repository should be large enough since it's flexible in nature if devices count raises it must be spacious enough to store new data.

Among all the evolved architectures the basic traditional adapted model is "three layered architecture" enclosing application layer, network layer, and perception layer. Apart from this the remaining are: middle-ware architecture, five-layered architecture, SOA-based (Service Oriented Architecture), and Fog and Cloud based Architecture. In this section the basic architectures of IoT i.e. three and five layered are explained.

- **Three-Layered Architecture:** Is the basic IoT architecture; as its name implies it comprises of three layers via application layer, network layer, and perception layer. Figure 1 explains the three layered architecture and responsibility of each layer. The perception layer is also referred as physical layer as it contains physical devices and sensors which sense the other devices and acquire data from them through sensing and transfer it to above layer; it is the lowest layer of the network. Network layer also known as transmission layer because of its ability to process the data and transmit (wired or wireless medium can be employed for transmission) it to above layers. This layer is considered as bridge between top most layers and lowest layer. Whereas the application layer i.e. the topmost layer is responsible to supervise all applications according to input received from network layer i.e. its responsible to deliver services to the connected applications; these applications can include smart homes, smart cities, smart health care, smart agriculture, smart business etc.

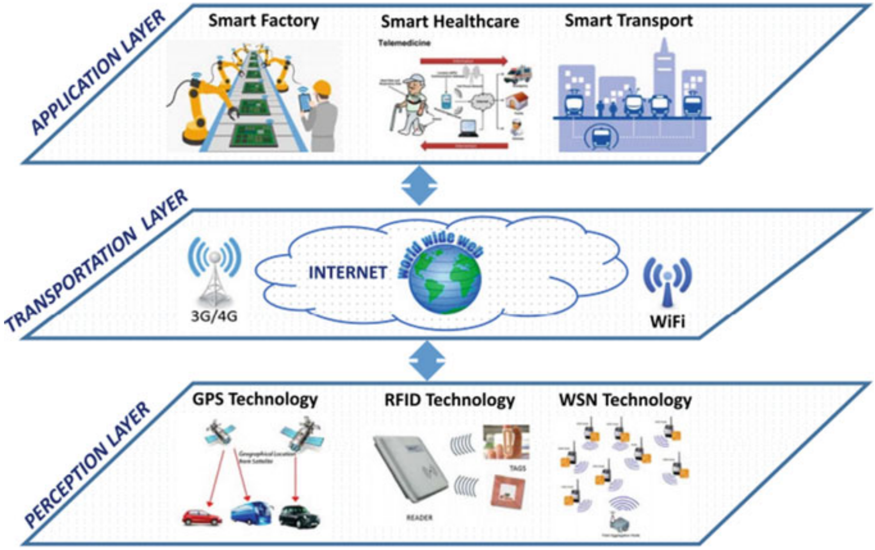

Fig. 1 Three-layered IoT architecture [1]

- **Five-Layered Architecture:** It consists of similar three layers as discussed above and works for the same functionality. The two additional layers are namely middleware layer and business layer. Middle ware layer also referred as processing layer is responsible for communication and to transfer data among connected devices (Table 1). It possesses the ability to store the data, data processing, and computation. It even has the proficiency of decision making out of computations. The business layer also referred as gateway layer or management layer is responsible to manage the other four layers. The key factor of this layer is privacy is managed here. Figure 2 explains the responsibilities and devices of five layered IoT architecture.

Table 1 Communication protocols

Communication protocols	Range	Topology	Band of operation
Zigbee	30 m	Mesh	2.4 GHz
Z-Wave	100 m	Mesh	908.4 MHz
LoRa	7.2 km	Star-of-stars	868 MHz
6LoWPAN	10-100 m	Mesh	868 and 915 MHz, 2.4 GHz
Bluetooth	150 m	Star	2.4 GHz

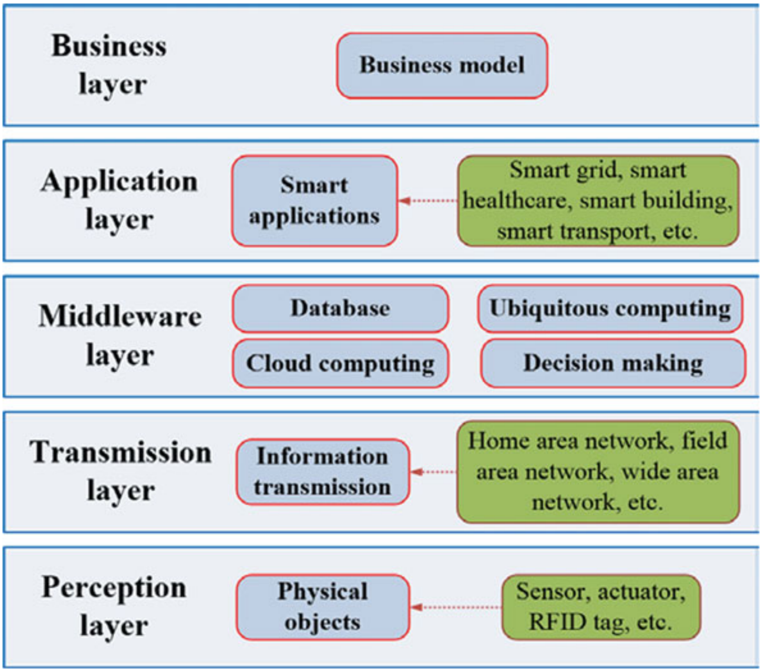

Fig. 2 Five-layered IoT architecture [2]

3 Applications of IOT

The IoT is applied almost in all the fields like transportation, business, retail, agriculture, manufacturing industries, health care, building, parking, cities, etc. Smart cities, smart homes, smart hospitals, smart industries, smart parking, etc. are some among the best applications of IoT, Fig. 3 presents the various applications. All this IoT related applications works flawlessly by means of "Internet" as this technology integrated various devices together while these devices collaborate with each other by communicating and sharing information among themselves i.e. diversified devices are integrated through Internet. Whereas all this integrated devices need to be actively connected to Internet to assist the accessibility. This objective is addressed by sensing devices, actuators, and other technologies to deploy the application at different locations, to acquire and review data (technologies, like Machine Learning (ML), AI, data science, Cloud, and fog computing). Applications of IoT in various domains have been shown in Table 2.

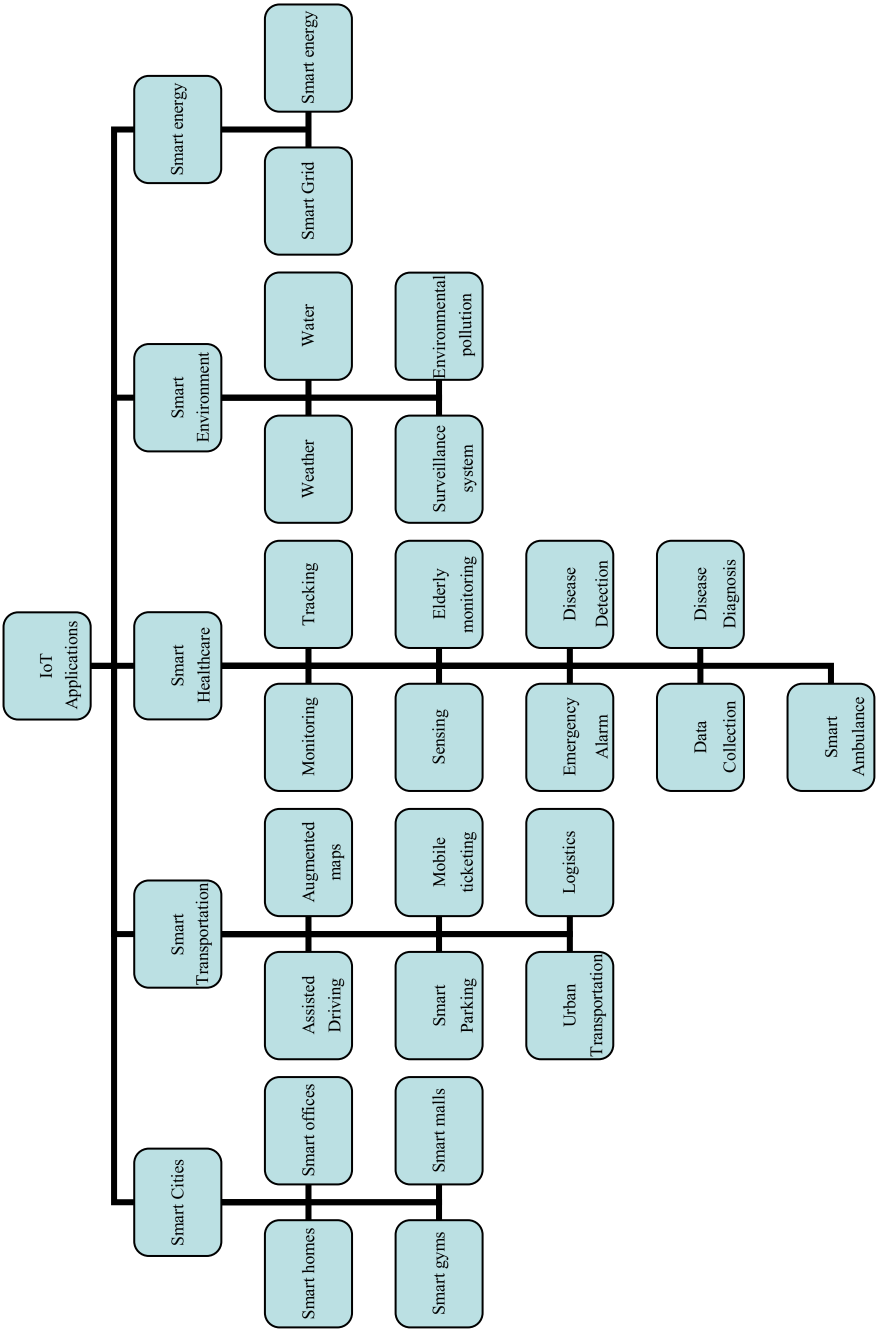

Fig. 3 Applications of IoT

Table 2 Applications of IoT in smart cities/Smart Villages

Sl. no	Name of the application	Reference
1	Smart energy	[3, 4, 5, 6]
2	Smart weather, smart agriculture	[7–17]
3	Smart transportation	[3, 4, 5]
4	Smart mobility	[18]
5	Smart buildings	[3, 4, 19]
6	Daily life	[20-21]
7	Smart governance	[4]
8	Smart elections	[22]
9	Smart economy and society	[23-24]

Table 3 Challenges for IoT in smart cities

Sl no	Challenges
1	Security and privacy
2	Smart sensors
3	Networking
4	Intelligent data analytics

4 Smart Cities

From the last few decades, we have witnessed the tremendous growth of population density in cities. Due to rapid urbanization, there is an increase in the steadily aging population, rise in chronic illness. This poses various challenges on existing health care systems. In order to improve the health care services, smart technologies needs to be adopted in health care system. IoT empowered smart health care systems will enhance the health care of citizens. While adopting the IoT in smart cities there are few challenges faced, which are shown in Table 3.

5 Role of IoT in Smart Health

IoT plays an important role in health care. IoT can be used effectively in health care. IoT is used to sense and record the data from the patient and upload in cloud for further processing. IoT/wearable devices will also help the elderly people to communicate with the doctors. IoT in health care using 5G, AI and could, will transform the way patients are treated and monitored remotely. IoT in health care is widely used in patient monitoring and smart ambulance system. Various applications of IoT in health care is shown in Table 4.

Table 4 Summary of applications of IoT in health care

Sl no	Applications domain	References
1	M- IoT	[25]
2	IoT architecture for health	[26]
3	IoT for diabetes	[27]
4	PPHM	[28]
5	Patient monitoring systems	[29]
6	IoT in medicine	[30]
7	Health observing using IoT	[31]
8	Personal and M- health	[32]
9	Security In IoT	[33]
10	Diet Related chronic diseases	[34]
11	Health care applications	[35]
12	Wearable IoT data	[36]
13	IoT Clinical mechanism	[37]
14	Smart Ambulance	[38]
15	online prognosis and health	[39]
16	Remote patient monitoring	[40]
17	chronic disease	[41-42]
18	Mental disorder	[43]
19	Elderly people	[44-52]
20	ECG monitoring	[53-55]
21	Patient monitoring	[56-58]

6 Challenges in Applying IoT in Smart Health

IoT is the most flourishing technology used in health care. These technologies have also met several challenges while adopting in health acre sector. Due to connecting a wide variety of devices under one common network, we may face bandwidth problem. When large number of devices generates unstructured data, analyzing these unstructured data is also a challenging task. Many devices which are connected to IoT network may not have same standard. This may lead to some issues. Challenges faced when we apply IoT in health care are shown in Table 5.

7 Conclusion

This chapter investigates various applications and challenges of IoT in health care. This chapter explains various application domains, where IoT is feasible to apply in health care. IoT empowered health care system has enormous benefits when

Table 5 Challenges in applying of IoT in health care

Sl no	Challenge
1	Requirement of suitable infrastructure
2	High network bandwidth
3	No uniform standards
4	Security implications/large attack surface
5	Cost effective mining
6	Integration of multiple devices and protocols
7	Data source management
8	Accuracy and overload

compared with the traditional health care system. Quality and efficiency of health care systems will be enhanced through the acquisition of emerging technologies into health care, proper management, and the use of analyzing the health data using IoT.

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Chapter 8
Geospatial Data in Health Insurance

Alfred Stein

1 Introduction

In recent years, we notice an increased interest in geo-health, in particular governed by increased awareness of aspects of a spatial nature that have an influence on issues of health [19, 22]. Research goes back as far as the early nineteen nineties [20], when the advance of geographical information systems started to facilitate the storage and handling of the spatial data [28]. Health is a rather general concept that on the one hand concerns human beings both in physical and mental health, while in the other hand it may consider environmental health, soil health and crop health. Traditionally, geospatial data are considered as realizations from geovariables, i.e. properties that vary in space and time, while the objects at risk, either the human beings, the crops, the soil, or buildings and other property, are either at fixed locations, or are moving through space.

Examples in the literature on spatially varying diseases are abundant. At the city level, Hur et al. [13] studied geographic health disparities in the Los Angeles pediatric esophageal foreign body population, while recently Samuels-Kalow et al. [26] considered COVID-19 cases in Boston. At a larger level of scale, Salmeron et al. [25] spatially assessed the incidence burden of breast cancer in Tennessee. At the national scale Hart et al. [12] studied the effects of major US sewage treatment plants in wastewater-based epidemiology. A typical example of a mental disease that shows spatial variation is autism [7]. In developing countries, epidemiological studies are either carried out to find and explore relations of diseases with environmental factors [1], or—most prominently—on the effects, access and spread of health care facilities [2, 11, 14, 15, 23].

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*, Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_8

So far, health insurance has taken little care of spatial variation [18]. This is somewhat remarkable as other types of insurance have taken care of spatially changing risks. For example, bicycle theft insurance in the Netherlands has a different premium setting in the major urban regions than in rural communities, simply because the risk of theft is much higher in urban cities. At present, with the advent of geo-health, it is of particular interest to also consider spatially varying health insurances.

In this paper, we define risk as the expected loss [3]. The loss is usually based on a well-defined loss function. The basic idea is that an insurance takes care of the expected loss. In order to be able to handle insurance questions, the expected loss is translated into the probability that a threshold is exceeded. We will consider in this paper that the exceedance of the threshold can occur both in space and in time: hence the time *when* and the location *where* it occurs is important. As there is a clear stochastic component to insurance, we will consider here spatial statistics to quantify those risks.

The basic ideas of spatially varying health insurance are that living in particular areas could be much less risky than living on other areas. Although the distinction between healthy rural areas and polluted urban areas seems to be relevant, one may question whether the effects of pollen should be considered, while forest areas can have a negative on for instance asthma. Still, a solid way ahead may be to develop health indicators that signify the healthiness of individual locations. Aspects of insurance are reported in several studies. De Bie et al. [5], De Oto et al. [6] and Vrieling et al. [31] considered insurance against drought by inspecting the NDVI.

In this paper, the objective will be to provide an overview on how geovariables can be used in insurance issues.

2 Geospatial Data

Geospatial data are data that are essentially tied to their location. As in much of statistics, we will consider the data to be generated by a variable, in this case termed a geovariable. We will denote the geovariable by $Y(s)$, where Y is the variable, and with s the location is denoted. For the moment we will take $s \in A$, where A is a spatial area, in 1, 2 or 3 dimensions. Extension toward the time domain can be done as well, and further on in the paper we will pay attention to this. Geovariables that are relevant for human health insurance are incidence to a disease like cholera or Covid, and related variables like rainfall, the NDVI, PM10 and depth to groundwater. For soil health, there is not yet a generally accepted indicator, but the health is considered in relation with for instance the pH and OC—content. The variable $Y(s)$ is a random variable, and we can therefore speak about probabilities, expectations, distribution functions of $Y(s)$. All geovariables have several aspects in common: they are all measured in space (and time), the support in space is restricted as the observations on the variables are commonly of a point type, and the observations are likely to be spatially (and temporally) dependent. The last aspect means that data close to each other are more similar than data at a larger distance. Spatial independence means lack of spatial dependence. Dependence is commonly quantified using the covariance. We will now show how the covariance can be handled for geovariables. To do so, we have tome several assumptions. We consider the expectation. For a continuous random variable Y with probability density function $f(y)$ the expectation is equal to $E(Y) = \int y \cdot f(y)\mathrm{d}y = \mu$, with integration over the possible realizations of y. For a discrete variable, the expectation is expressed as $E(Y) = \sum y_k \cdot p_k = \mu$, where p_k indicates the probability that the value the variable y takes the value k.

We now turn to the general model for geovariables:

$$Y(s) = \mu(s) + S(s) + e(s) \tag{1}$$

where $\mu(s)$ is the deterministic trend, $S(s)$ is a spatially dependent stochastic part, with $E(S(s)) = 0]$, and $e(s)$ is the spatially independent part, also with $E(e(s)) = 0]$. We thus have that $Y(s)$ is a geovariable with a location dependent expectation $\mu(s)$, that we consider to be deterministic, i.e. not depending upon random influences. The terms $S(s)$ and $e(s)$ take care of the random aspects of $Y(s)$. Such a model applies to both continuous and discrete data. Of particular interest in (1) is the role of $\mu(s)$. One could assume that it is constant, i.e. $\mu(s) = \mu$, i.e. without the location specific variable s. Alternatively, we may recognize that the term $\mu(s)$ is dependent upon other geovariables, e.g. like a regression model. Taking the explanatory equal to $Z_k(s)$, one then has that $\mu(s) = \sum_k \beta_k Z_k(s)$, where the parameters β_k are to be estimated from the data.

Next, we turn to the dependence structure that is inherently present in geovariables as is expressed by the spatially dependent variable $S(s)$. Recall, that for two non-spatial variables Z_1 and Z_2, the covariance is defined as $\mathrm{Cov}(Z_1, Z_2) = E[Z_1 \cdot Z_2] - E[Z_1] \cdot E[Z_2]$, i.e. the expectation of the product, minus the product of the expectations. This concept is now generalized to spatial variables. First, we consider the variable $Y(s)$, and realize that it is a variable at each location s. Hence, we can consider first the two locations s_1 and s_2, where we then have two variables $Y(s_1)$ and $Y(s_2)$. For those two variables,

$$\mathrm{Cov}(Y(s_1), Y(s_2)) = E[Y(s_1) \cdot Y(s_2)] - E[Y(s_1)] \cdot E[Y(s_2)] \tag{2a}$$

If $E[Y(s_1)]$ and $E[Y(s_2)]$ are independent of the location, this expression can be simplified as

$$\mathrm{Cov}(Y(s_1), Y(s_2)) = E[Y(s_1) \cdot Y(s_2)] - \mu^2 \tag{2b}$$

Note that both expressions (2a) and (2b) apply to any two locations, of which there are usually infinitely many in any area A. For instance, the temperature is a variable that is defined at each and every location in an area, although measured at only a limited number of locations. When it comes to estimation, one then runs into the problem that no replicates exist: the temperature is measured once, and a later measurement is usually not taken as a replicate but as an observation at a different point in space and time. To overcome this problem, a common assumption is that $\mathrm{Cov}(Y(s_1), Y(s_2)$ depends upon the distance h between s_1 and s_2 only, and not upon the locations s_1 and s_2 themselves:

$$C(h) = E[Y(s) \cdot Y(s+h)] - m^2 \tag{3}$$

where $s + h$ is a location at a distance h from s. We call $C(h)$ the covariance function.

We mention the following properties of $C(h)$:

- $C(h)$ is a well-structured function: it decreases as h increases, i.e. $C(h) \rightarrow 0$ if $h \rightarrow \infty$;
- Taking $h = 0$, we note that $C(0) = E[Y(s) \cdot Y(s+0)] - \mu^2 = \sigma^2$, the ordinary variance.
- In the case of the absence of spatial independence: $C(h) = 0$ for $h \neq 0$, and $C(0)$, as $C(0) = \sigma^2$.

Equations (2) and (3) are expressed for the variable $Y(s)$; however replacing $Y(s)$ by $S(s)$, we have that similar expressions for the spatially dependent part of $Y(s)$ as in (1).

Of interest in spatial studies as well is the semi-variogram. It serves as a—more often—used alternative to the covariance function. Under the same condition that the spatial dependence depends only upon the distance between locations, and not upon the locations themselves, the semi-variogram $\gamma(h)$ is defined as

$$\gamma(h) = 1/2E(Y(s) - Y(s+h))^2$$

It is related to the covariance $C(h)$ as $\gamma(h) = C(0) - C(h)$, hence the use of the scalar ½. It has as a property that $\gamma(h)$ increases with increasing h, and that if σ^2 exists, that then $\gamma(h) \rightarrow \sigma^2$ if $h \rightarrow \infty$. Note that there are random variables for which σ^2 does not exist. An example is a variable that follows the Cauchy distribution. Hence, in that sense the semi-variogram is (slightly) more general than the covariance function, as it requires the intrinsic hypothesis, and not necessarily second order stationarity.

Spatial variables can be mapped, and these maps than show the values at both observed and unobserved locations. The widely used technique to do so is a form of kriging. If the mean is constant, but unknown, the technique to be used is ordinary kriging, while if the mean is constant but known, it is simple kriging. For the general case of (1), typically ordinary kriging will be used, while in the case that we only consider $S(s)$, we will be using simple kriging. In the elaborate case where the mean is a combination of other geovariables, we will be using regression kriging.

For insurance aspects, we have to turn now to probabilities. The basic idea is that the probability of an event is determined. That probability is related to a threshold value. For instance, an insurance can be made for the temperature to exceed 40 °C or to become below 0 °C, a rainfall event to exceed 90 mm h^{-1}, or that rainfall stays away for three weeks or more, or that soil has to be removed if an environmental threshold value is exceeded with 98%. These examples all apply to a geovariable, as the events are supposed to occur at a specific location s. In order to handle these, we are creating maps showing varying risks.

In order to generate maps with varying risks, there are different ways to proceed. We will first describe the use of the kriging predictor and the associated standard deviation. Secondly, we will use indicator kriging, and third we will briefly turn toward spatial simulations.

1. Probability mapping with ordinary kriging.

The first possibility to generate probabilities that a threshold is exceeded in a location s_0, would be to use the ordinary kriging predictor denoted by $Y^*(s_0)$ and the kriging standard deviation $s(s_0)$ [4]. The two-sided confidence interval would be $(Y*(s_0) - t_{0.95} \cdot s(s_0), Y*(s_0) + t_{0.975} \cdot s(s_0))$, where $t_{0.975}$ is the 0.975% critical point of the t-distribution. As a two-sided interval is not very realistic for most insurance issues, the one-sided confidence region $(0, Y*(s_0) + t_{0.95} \cdot s(s_0))$ could be used instead. If the threshold value is outside the confidence interval, or region, then there is no statistical evidence that it is exceeded. Drawbacks of this solution are that (a) the determination of the confidence region and interval is based upon normality, (b) the choice the 0.975 (or 0.95) value is arbitrary and (c) spatial interpolation is a smoothing method. The first issue can be overcome by adjusting the interval (or region) using for instance the much more realistic log-normal distribution, the second can be overcome by displaying the p-value of exceeding the threshold, while the last issue can only be overcome using simulations.

2. Probability mapping with indicator kriging.

In order to advance toward non-parametric estimation, we now turn toward indicator kriging [16]. In indicator kriging we consider a spatial variable $Y(s)$ and we turn it into an indicator variable $1(s)$, being are defined as 0–1 variables, that takes the value 1 if an observation is below the threshold value and 0 if it is above that value: Hence, an indicator variable for the threshold value y_c is defined as

$$1(s; y_c) = 1 \text{ if } y \leq y_c \text{ and } 1(s; y_c) = 0 \text{ if } y > y_c$$

Indicator variables play an important role if probabilities of exceeding threshold values have to be determined. Indicator variables may be used to calculate probabilities that threshold values are exceeded. This activity is termed indicator kriging. In fact, the expectation of an indicator variable equals the probability that this variable does not exceed the threshold value:

$$\begin{aligned} E[1(s; y_c)] &= 0 \times \Pr(1(s; y_c) = 0) + 1 \times \Pr(1(s; y_c) = 1) \\ &= \Pr(1(s; y_c) = 1) \\ &= \Pr(Y(s) \leq y_c) \end{aligned}$$

Therefore, given a threshold value, one can determine the probability that this threshold value is exceeded. There is no further need to expand the above with the kriging standard deviation, and the procedure is entirely distribution-free. For the example of the rainfall data, one may observe from the weather stations whether the threshold of 40 °C is exceeded (receiving the value 0), or not (receiving the value), then construct the covariance function or the variogram for these observations, and then use simple kriging to predict the value at location s_0. As all observations are either 0 or 1, a predicted value between 0 and 1 is most likely to be expected. However, kriging may also result in predictions above 1 and below 0—these have to be treated in an ad-hoc way, like for instance reducing predictions above 1 to 1 and increasing predictions below 0 to 0.

Interestingly, as pointed out by Deutsch and Journel [8], multiple indicator variables can be applied as well, for several, say p, threshold values, $y_1, \ldots, y_p$. These are denoted as $1(s; y_1), \ldots, 1(s; y_p)$. In an unvisited location prediction on each of the indicator variables may be obtained. Combining these predictions results in an approximation of the full distribution curve in an unvisited location, from $\Pr(Y(s_0) \leq y_c)$ can be obtained for an arbitrary threshold y_c.

3. Probability mapping with disjunctive kriging

An estimate of the probabilities that a variable exceeds a threshold value may as well be obtained by means of disjunctive kriging [10, 24, 32, 33]. Essentially, the observed distribution of the variables is transformed into a normal distribution by means of so-called Hermite polynomials. These are used to predict the distribution in a prediction location, followed by back-transformation. Hermite polynomials $H_k(y)$ of order k are defined as:

$$H_k(y) = (-1)^k e^{\frac{x^2}{2}} \frac{\mathrm{d}^k}{\mathrm{d}y^k} e^{-\frac{x^2}{2}}$$

It is easily seen that $H_0(y) = 1$ and $H_1(y) = y$. A simple relation exists between $H_{k-1}(y)$, $H_k(y)$ and $H_{k+1}(y)$ for $k \geq 2$: $H_{k+1}(y) = -y \cdot H_k(y) - k \cdot H_{k-1}(y)$. Hermite polynomials are orthogonal with respect to the weighting function $e^{-\frac{x^2}{2}}$ on the interval $(-\infty, \infty)$:

$$\frac{\int_{-\infty}^{\infty} H_i(y) H_j(y) e^{-\frac{y^2}{2}} \mathrm{d}y}{i! \sqrt{2\pi}} = \delta_{ij}$$

with $\delta_{ij} = 0$ if $i \neq j$ and δ_{ij}=1 if $i = j$. Many functions can be approximated by a finite series of Hermite polynomials:

$$f(y) = \sum_k C_k H_k(y)$$

where fitting the coefficients C_k is based upon the orthogonality relationship.

Note that an estimator of the conditional probability that a variable $Y(s)$ at location s_0 exceeds a cut-off level y_c is based on the indicator function $1(s; z_c) = 1$ if $Z > z_c$ and

$1(s; z_c) = 0$ if $Z \leq z_c$, where, z_c is the transformed cut-off level related to the actual cut-off level y_c and Z is the transformed variable related to Y. The conditional expectation of $1(s_0; z_c)$ in s_0 is as before given by $E[1(s; z_c)|Z(s_i)] = P[1(s; z_c) = 1|Z(s_i)]$. The conditional probability of $Y(s_0)$ exceeding y_c is thus estimated by the conditional expectation of the indicator function $1(s; z_c)$ in location s_0. Now, $1(s; z_c)$ in s_0 can be estimated when it is expanded in Hermite polynomials as:

$$P^*(x_0) = 1 - \Phi(z_c) + \varphi(z_c) \sum_{k=1}^{K} H_{k-1}(z_c) H_k^*(Z(s_0))/k!$$

where the Hermite coefficients C_k for order k are determined using the orthogonality relations:

$$C_0 = 1 - \Phi(z_c)$$

$$C_k = \varphi(z_c) \frac{H_{k-1}(z_c)}{k!}$$

Here $\Phi(z_c)$ is the cumulative standard normal probability distribution evaluated in the threshold value z_c, and $\varphi(z_c)$ is the normal probability density function, also evaluated in z_c. Combination of the DK predictor gives the conditional probability that $Y(x_0) < y_c$. It is estimated by the sum of the predictions of the Hermite polynomials that describe $I(x_0; y_c)$.

4. Spatial simulations.

The third possibility is to use spatial simulations of the random field. There are many ways to generate such realizations, typical examples include the turning bands method, simulated annealing, and Gaussian simulations. Such simulations present the random field as it could have occurred, hence not affected by the smoothing properties of kriging. Generating N of these simulations provides hence values at each location s. The simulations then provide the degree of evidence that a threshold value is exceeded. Spatial simulations do not necessarily require any distribution, while aspects of non-stationarity can be included.

3 Illustration

We illustrate the use of geovariables for insurance in the following example. A set of data is generated in the [0, 1] × [0, 1] square, with values that range between 0 and 15 (Fig. 1). Typically, the value 15 exceeds a threshold value, which we set at 5. One could take these values as disease incidences in locations or settlements, and the question is then to generate a map with incidences in this region. It could be the case that an incidence of more than five cases in a settlement should alarm the authorities.

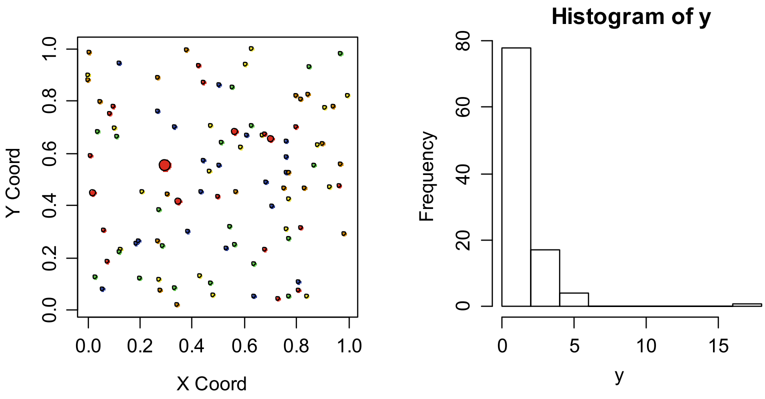
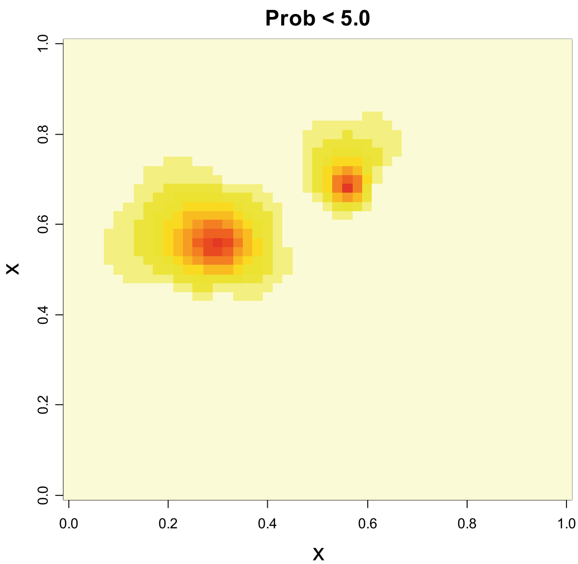


Fig. 1 Random variables generated in a square region. These values could be interpreted as disease cases. On the right a histogram of the cases is given

The probability map that the threshold value is not exceed is shown in Fig. 2. We notice from Fig. 2 a relatively low value (indicated with the red color) at the single large observation and in its vicinity, as well as in the vicinity of the second larger point, slight further to the west. At those two vicinities, the probabilities are low that the value of 5 is not exceeded, hence the probability is relatively high that the threshold value *is* exceeded.

Changing the threshold value to values equal to 1.3, 1.7 and 2.5 (Fig. 3) shows probabilities that these thresholds are not exceeded. One may notice that lighter (less

Fig. 2 A map showing the probabilities that the threshold 5 is not exceeded. The dark red color shows a low probability (and hence a high probability that it is exceeded, the light yellow color shows high probabilities that this threhsold is not exceeded



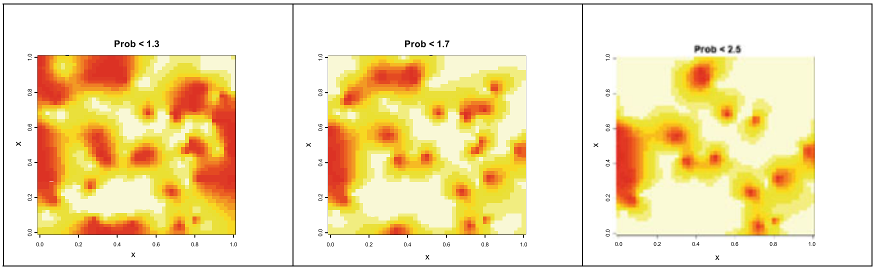


Fig. 3 Maps showing the probabilities that the thresholds 1.3 (left), 1.7 (middle) and 2, 0.5 (right) are not exceeded

red) colors for increasing threshold values—the probability that an increasingly high threshold value is not exceeded becomes increasingly high.

4 Aspects of Threshold Values

As concerns the threshold value, in essence a single threshold is applied. Some attention has been paid as well to spatially varying threshold values, for instance in making the soil quality measurement related to the clay and organic carbon contents of the soils. Also aspects of land use have been applied, where interest was whether the future of a sanitated area would be used by playing children or as a parking lot—in the first instance a much safer environment is required as in the second instance.

Spatial variation of threshold values has been recognized in insurance policies. Provided that there are sufficient data within individual regions, a stratification of an area is possible, without major modification of the above ideas, as the example of bike theft insurance shows. We would then have threshold values $y_c^{A_1}, y_c^{A_2}, \ldots$ for each of the strata $A_1, A_2, \ldots$. A threshold could also vary by allowing it to be dependent upon another geovariable, like the example of the environmental pollution where it is dependent upon the clay content: soils with a high clay percentage have higher threshold values than soils with a low clay percentage. The threshold value would then be denoted by $y_c(s)$, i.e. as a geo-threshold. A geo-threshold could be stochastic, hence following the same spatial model (1) as above, but it might be more practical to have it as a location dependent fixed value.

Of related interest would be dynamics in time. In the past, we have noticed that fire occurrence at the city level [27] is varying in time, with different rates of occurrence during the time of the day, and at different days of the week, separating weekend days from week days. The stratified threshold $y_c^A(t)$ is then defined, where t takes wither values as a discrete time interval (for instance like $t = t_1$ for weekdays and $t = t_2$ for weekend days) or as a continuous one where it may vary according to a sine function. Similar remarks apply to a continuous geo-threshold, which is then denoted as $y_c(s, t)$.

The third aspect to be mentioned is the relation of threshold values to climate change. Climate change may result in risks that increase or decrease over long periods of time [29]. Typical aspects concern the occurrence of droughts, flooding and the occurrence of diseases that were so far absent. This may be addressed by adjusting threshold values either continuously, or stepwise following the most recent insights.

5 Discussion

Much of the above depends upon the quality of the data, and their relation to the problem at hand. A problem that is commonly encountered in environmental thresholds is the limited number of samples. In studies on soils that were carried out in the past, a fixed threshold was used that is relevant for estimating the risk. It is related to health effects of human beings, either directly by children who put contaminated soil into their mouth, through vegetables or through the meat and milk of cows who digest grass from contaminated soil. All these pathways lead to thresholds that express the target level (below which the area is considered to be safe) or the intervention level (above which the government has to clean the soil). A similar approach applies to water bodies as well as to urban air. Judgment on the quality is based upon the limited number of samples taken. We usually assume that these measurements are of a good quality. It has been shown, however, that the quality of the sensors deteriorates in time [30], and that air quality and soil samples can thus be of a limited quality.

In order to increase healthy environments, more attention should be paid to social aspects of health facilities. Social acceptance is an issue that was addressed in several studies in the past [17], while Park et al. [21] and Drake [9] also addressed socio economic aspects of spatial variability. We see these issues also coming back to important questions in developing countries. In the end, this may lead to a further diversification of premiums to be paid for health insurance. At the moment, most premiums are nation-wide the same and are based largely upon covering the expected costs. However, a scaling of the premium setting may be far more realistic.

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Chapter 9
Epidemic Incidence Modeling and Forecasting Geospatially Using Machine Learning

Nitin Kumar Tripathi and Pallavi Mohapatra

1 Introduction

Climatic parameters, such as rainfall, humidity, and temperature, influence ILI and represent crucial information for control of this disease, the relation between the disease and these variables is not clearly understood on Influenza-like illness (ILI). Nimbalkar and Tripathi [1] have conducted a study on space–time epidemiology and effect of meteorological parameters on influenza-like illness (ILI) in Thailand. They analyzed the epidemiology of ILI cases using integrated methods (space–time analysis, spatial autocorrelation, and other correlation statistics). Comprehensive methodology was developed to analyze the global and local patterns of the spread of the disease. Significant space–time clusters were detected over the study region during eight different periods. ILI cases showed seasonal clustered patterns with a peak in 2010 ($P > 0.05$–9.999 iterations). Local indicators of spatial association identified hotspots for each year. Statistically, the weather pattern showed a clear influence on ILI cases and it strongly correlated with humidity at a lag of 1 month, while temperature had a weaker correlation. Furthermore, high negative correlation was observed with regard to change in temperature. However, while maximum temperature affected the one-month time lag cases negatively, no significant relation was revealed with mean temperature. Rainfall correlated strongly without time shift. The study found overall significant influence of climatic parameters specially rainfall and average humidity on ILI but in one year it was not so strong. Therefore, results of spatial statistical analysis in many ways may give a general idea but exceptions remain.

The World Health Organization (WHO) estimated in 2005 that the warming and rainfall patterns due to anthropogenic climate change of the past 30 years already

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_9

claimed more than 150,000 lives annually. Most of the recurrent diseases are associated with climate variability. Uncertainty remains in attributing the expansion or resurgence of diseases to climate change, owing to lack of long-term, high-quality data sets as well as the large influence of socio-economic factors and changes in immunity and drug resistance. Here we review the growing evidence that climate–health relationships pose increasing health risks under future projections of climate change and that the warming trend over recent decades has already contributed to increased morbidity and mortality in many regions of the world. Potentially vulnerable regions include the temperate latitudes, which are projected to warm disproportionately, the regions around the Pacific and Indian oceans that are currently subjected to large rainfall variability due to the El Nin˜o/Southern Oscillation Sub-Saharan Africa and sprawling cities where the urban heat island effect could intensify extreme climatic events [2].

Despite claims that Malaria is eradicated, it remains a major concern in many countries and is still considered a life-threatening disease. Malaria is associated with high mortality rates and often grips the areas away from cities and mainly in the villages located new dense forests or wetlands. In this chapter, we included a case study of Malaria incidence and how the cases in areas affected continuously every year may be modeled for better preparedness of public Health Departments.

On a global scale, malaria's impact has been significant, with social, economic, physical, and many other effects. Malaria, along with other diseases such as diarrhea, HIV, TB, is responsible for 85% of the global disease burden. Malaria is impacting nearly a hundred countries globally, with about half of them being in Africa and some across parts of Asia [3]. As per Ceccato et al. [4], nearly 40% of the global population is exposed to malaria, which has serious implications right from the onset. People living in remote areas or areas affected by poverty and without access to health care services are at a higher risk of morbidity from malaria. The World Health Organization (WHO) has concentrated its efforts in poverty-stricken areas and introduced preventive measures to reduce malaria vulnerability. This includes understanding the mosquito breeding patterns in these areas concerning the weather and climatic characteristics [5].

According to [6], at least 1.4 billion people living in South East Asia are exposed to malaria, with about 1.2 billion living in India alone. While the region contributes nearly 3 million cases to the global malaria burden, more than 75% of this area's burden is from India alone. India's tropical climatic conditions, geographic and ecological diversity contribute to a unique environment that attracts mosquitoes' survival and, thus, spreads malaria at a higher rate [7]. According to [4], Odisha, a coastal state of India, contributes to nearly 27% of India's malaria cases, from which 17% of deaths from malaria cases.

In areas with malaria outbreaks, there is a significant correlation with high mosquito density, an increased bite rate, and a higher rate of transmission of the vector from one host to another. In such areas with a high incidence of malaria, the climatic conditions and weather patterns play a significant role.

Countries prone to the malaria epidemic report low economic growth compared to the average growth of other countries free from malaria. India's efforts to eradicate malaria started in the mid-twentieth century, with control measures developed by the National Vector Borne Disease Control Programme (NVBDCP). The approaches included introducing malaria technical supervisors (MTS) to track malaria's progress at a district level, introducing the Artemisinin-based therapy (ATP), which is meant to delay the resistance of *P*. Falciparum, and implementing rapid diagnostic tests. Many experts and researchers advise proactive measures versus reactive measures to prevent malaria occurrence rather than deal with epidemics after they have occurred. One way of doing it is by creating an early warning system that can test and detect weather patterns and other factors. It will be able to foretell the possible risk of malaria. An early warning system has a critical role in mobilizing the right resources to prevent epidemics; the same is critical across malaria-prone regions.

Hemingway et al. [7] suggested that the malaria warning system can help identify who is most at risk, when they are at risk, the population's size at risk, and thus plan exactly for what type of response is needed. Again, the early warning system can be a critical and useful method of systematically informing where logistics are most needed and where they can be spared.

2 Malaria Overview

According to Kimbi et al. [8], malaria is a protozoan disease. Hemingway et al. [7] explained that malaria is frequently transmitted through 5 types of parasites after the mosquitoes' bite humans. The female mosquito known as Anopheles is the vector directly responsible for transmitting malaria after biting. The malaria life cycle is complex as shown in the Fig. 1. According to [9], human beings are known as intermediate hosts, while mosquitoes are the definitive hosts. As mentioned, sporozoites are fully grown infective worms found in the Anopheles and are delivered into the human body through the bite.

For mosquitoes to complete their life cycle, it must go through four different stages. These stages of a mosquito life cycle are the larva, egg, pupa, and adult. Upon completing the first three stages, a mosquito develops into an adult, a flying insect living out of the water. This mosquito feeds on either nectar from plants or blood from animals and humans [11]. The life cycle stages start with the eggs laid by the female mosquito on the surface of water or moist surfaces with water underneath. The eggs hatch into a larva after a maximum of 48 h and a minimum of 24 h [12]. The larva takes about ten days to mature into a pupa. The pupa is a transitional stage where internal changes occur in the mosquitoes in approximately 48 h to form a fully-grown mosquito. Given that female mosquitoes feed on sugar from surrounding vegetation, one aspect that would support the prevention of the spread of malaria is clearing out any unnecessary bushes. Removal of stagnant water eliminates the breeding ground, while further clearing of vegetation reduces the mosquitoes' safety zone to develop further [13].

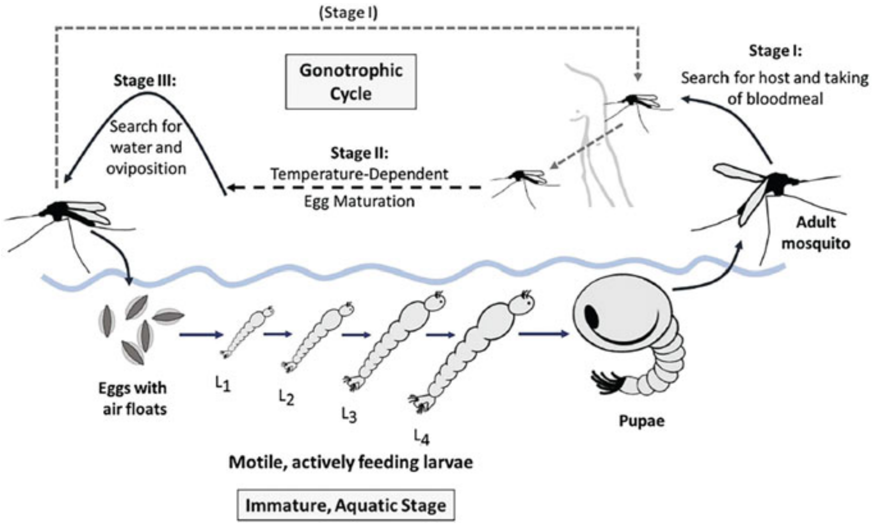

Fig. 1 Mosquito life cycle. *Source* Okuneye et al. [10]

3 Malaria Incidence Modeling Using ML

This study investigated the climatic conditions' sensitivity to the spreading of Malaria incidents in the Sundargarh district, Odissa, India. The district under investigation has 17 blocks analyzed using an advanced machine learning approach and proposed an early warning system for potential malaria risk in the region and population, based on real-time weather forecast information. This research's primary objective is to investigate the linkage between climate conditions and malaria incidents in the study area. This study would encourage better utilization of weather forecasts to predict malaria risk and in the public health sector in general. The objectives of the study were focused on the analysis of different machine learning classifiers to establish a relation between localized climatic conditions and malaria incidents and identify a suitable classifier for malaria hazard prediction.

This study covers a research gap in the literature to understand weather parameters and their effect on the spreading of malaria vectors, specifically in Sundargarh, Odisha. This region has never been under comprehensive study before, and thus with the high rates of malaria, the understanding of weather patterns would help design an early warning system. Several kinds of literature have focused on explaining the importance of an early warning system. However, very few have focused on demonstrating a model that could be applied to real-life circumstances and critical decision-making. The researcher firmly believes that establishing such a study and mechanism would greatly assist the local public health department and communities in general.

4 Determinants of Malaria Transmission

The risk factors of the occurrence and transmission of malaria are permeated by the physical environment, such as weather and climatic conditions and socio-economic factors carried out by human beings. Environmental factors such as the surrounding temperature, humidity, and rainfall play a significant role in both the aquatic and adult stages of the anopheles' mosquitoes transmitting malaria. Recent studies show that climatic conditions strongly influence malaria transmission by determining the abundance and seasonal-related dynamics of the anopheles' vector [14]. Malaria vector species profusions are also driven by rainfall patterns and highly dependent on the temperatures and humidity for complex influences on the parasites' population and development.

5 The Malaria Burden in the World and India

Malaria constitutes a global threat; it merely is a preventable and curable disease spread by mosquitoes. It is a common disease that is highly distributed in certain parts of the world and has a significant health burden. The spatial limits of its distribution are attached to climatic aspects. Research shows that the condition is highly prevalent in Sub-Saharan Africa and South Asia regions. About ninety percent of deaths occur in Africa in the southern Sahara since most of the malaria infections in Africa result from Plasmodium falciparum, one of the most dangerous human parasites in the region. It is also because of the predominance of the deadly malaria vector (Anopheles gambiae) in Africa. The WHO estimates that over 300 million incidences and 1.5–2.7 million deaths occur annually, in which Africa reports ninety percent of mortality alone. A global map of malaria incidence would show that there was a widespread transmission of malaria across regions. The recent WHO published report suggests that there were 219 million malaria cases globally in 2017, which reduced 18% of malaria cases and 28% of death rates since 2010 [15]. The burden was most substantial in the African Region, where an estimated 93% of all malaria deaths occurred, and in children aged under five years, who accounted for 61% of all deaths. According to WHO reports, 306,000 children below five died from malaria; 67% of total deaths were reported in Africa alone.

In areas where malaria transmission is stable, the population groups at higher risk of morbidity and mortality are children and pregnant women. Most children experience their first malaria infections at the age of one or two, making these early years most dangerous. Moreover, persistent malaria infections make infants more vulnerable to other infections such as respiratory diseases, thus indirectly contributing to mortality [16].

Malaria remains a public health challenge in India and contributes to two-thirds of parasitological confirmed cases in the South Asia region [17]. Malaria is the primary cause of mortality and morbidity rates in India, where children and pregnant

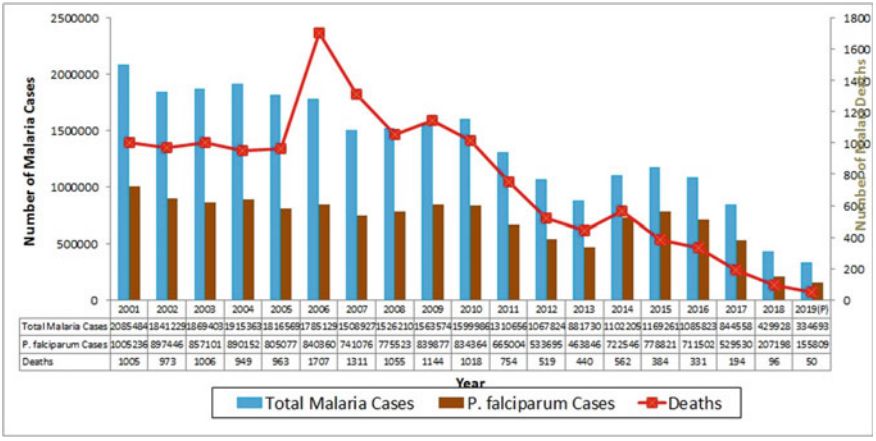

Fig. 2 Trends in malaria incidents in India from 2001 to 2019. *Source* https://nvbdcp.gov.in

women are highly susceptible to the disease. The report indicated that 42% of the world population at risk of Plasmodium vivax is from India and countries such as Indonesia, Philippines, Thailand, Vietnam, China, and Pakistan and 61% of malaria cases are from India, and 41% of deaths are from SEAR countries [18]. In India, an estimate of 539 million individuals resides in areas of high transmission, described as more than a single case per 1000 people. Figure 2 shows that the Annual Parasite Incidence (API) rate has consistently come down from 2001 and confirmed deaths due to malaria have been consistently declining as well. This reflects the malaria prevention and control activities conducted, monitored, and evaluated across the country. Slide Positivity Rate (SPR) and Slide Falciparum Rate (SFR) have reduced over the years 2001–2019(P) [19].

In India, malaria transmission is comparatively high in rural and tribal areas than in urban areas due to higher vector density, poor housing, and inadequate drainage systems in a rural setting [20]. It is especially prevalent in eastern, central, and north-eastern states of the country, especially in Chhattisgarh, Madhya Pradesh, Odisha, West Bengal, and Jharkhand. The tribal populations in India often reside in remote areas which are not easily accessible due to the typical geographical situation with valleys, forest, and hills [21]. Odisha, a state with only 4% of the Indian population, records a maximum malaria burden. Additionally, Odisha experiences further challenges. They incorporate inaccessibility to healthcare services, construction activities that support the breeding of mosquitoes and vector density, inaccessible areas, cultural and language barriers in tribal areas, and ethnic groups usually dominating these tribal areas remotely, finally, inadequate health care staff.

Figure 3 shows only the States with the Highest Number of Incidents (Source: NVBDCP Malaria Situation Reports). Figure shows the statistics published by the NVBDCP and the six most affected states in the country regarding the reported malaria incidents since 2014, where Odisha tops the list.

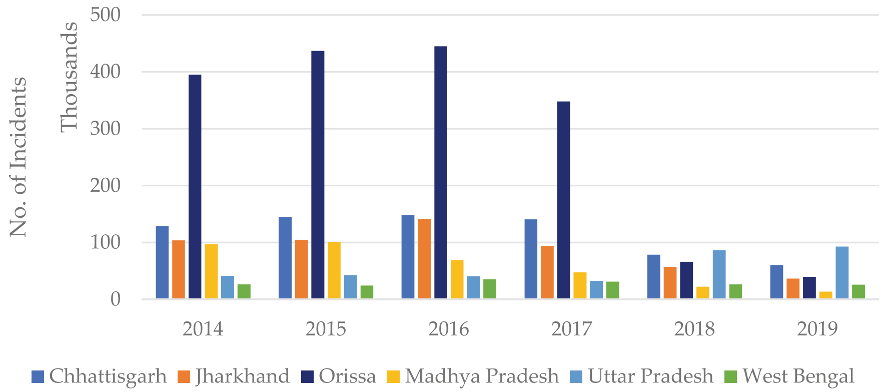

Fig. 3 Malaria incidents across six different states of India for the period of 2014–2019

6 Use of Statistical Regression Methods for Prediction of Malaria

World Health Organization [22] investigated how climate variables can predict infectious diseases by precisely pointing out the pathogens' exact behavior. One of the most effective ways of doing this would be to predict the pathogens' behavior related to the weather variables. Myers et al. [23] emphasized the need to use specified analytical methods associated with accuracy measures. Abeku et al. [24] used regression techniques to achieve predictive accuracy in determining infectious epidemics in different parts of the world. This is a deliberate attempt by the researchers to be able to predict a future epidemic. It is also found that if using the same data in the building and the model's testing tends to exaggerate the prediction accuracy.

Thapen et al. [25] used Generalized Linear Models (GLMs) to predict the Ebola epidemic using simulated data, and the other data used in the analysis was the data between 2014 and 2016 during the Ebola crisis in different parts of West Africa. Time to event data was analyzed using the generalized linear models. In all these GLMs, the systematic component used was $\beta_0 + \beta_1 x + \beta_2 \times 2$ and used to model the data. In the model, x was used to represent the cumulative number of events, while x^2 the square of this value. Different probability distributions were also incorporated, for example, the Poisson distribution, or in the case of the study by Thapen et al. [25], it was referred to as the Poisson GLM.

Kaur and Chhabra [26] evaluated how improved J48 can be used to predict the presence of diabetes. They claimed that decision trees in two phases calculate patterns among patients: data pre-processing where significant aspects are determined, and the second is the establishment of diabetes prediction with the help of a decision tree approach. The comparison of performance between artificial Neural Networks and Decision tree algorithms on medical data was evaluated based on mean absolute error, time to model, kappa statistics, and relative squad error.

Hypertension has been predicted using Naïve Bayesian and J48 in WEKA due to their purity, sensitivity, and accuracy. Analysis of diabetes is performed using artificial meta plasticity on multilayer perception. They claimed that J48, Naïve Bayesians, and Random Forest algorithms are employed in heart disease diagnosis since they result in accuracy and predictions. In the early stages, cardiac diseases and diabetes can be predicted using incremental learning and decision tree. These approaches can easily handle new aspects without influencing the learning process. They further proposed a method that could be used to detect a disease in retinal image analysis. J48 has been used to classify normal correctly, Retinopathy diabetic, and Glaucoma affected retinal images.

Tuberculosis diagnosis and prediction using Artificial Neural Networks (ANN) were conducted earlier. In this research, tuberculosis prediction and the diagnosis were recognized using multilayer neural networks (MLNN). As a result, two different MLNN structures were used: the first with one hidden layer and the other with two hidden layers. A general regression neural network was also employed to predict the presence of tuberculosis for comparison. Adrien and Giovanni [27] used deep learning approaches, specifically sparse autoencoders, and 3D convolutional neural networks, to generate an algorithm that predicts disease status based on magnetic resonance imaging (MRI) scans the brain. They revealed that 3D convolutional neural networks are more efficient than other classifiers and usually produce state-of-art results. Abraham et al. [28] evaluates the use of statistical learning to predict celiac disease accurately.

Salama et al. [29] examined the performance of multilayer perceptron, J48, and Naïve Bayes in investigating breast cancer using WEKA and, using these machine learning algorithms, can predict breast cancer behavior cancer. The experimental results revealed that J48 tends to give the best accuracy in making predictions in the breast cancer dataset than the Multilayer Perceptron (MLP), which fell short for accuracy in the prediction. It should be noted that MLP has its advantages, for example, as [30] points out, MLP is preferable for data that has real value or numerical attributes. Kirmani and Ansarullah [31] investigated heart disease prediction using MLP algorithms, and in doing so, they emphasized how data mining has become a relevant tool in building predictive models to solve an array of problems in different contexts. Other studies such as Adeyemo et al. [32] and Chiroma et al. [33] also studied the use of neural networks to predict various diseases such as malaria, typhoid, and heart disease.

Dhamodharan [34] investigated liver disease using the Bayesian classification technique, and in their investigation, they emphasize the importance of data mining, especially in the extraction of meaningful data from large databases using MLP, J48, and ANN. He argued that it would be possible to predict most of these liver conditions before reaching levels that are considered untreatable. Jin et al. [35] also investigated liver disease in South Korea, pointing out that irregular eating habits and stress, and toxic substances' inhalation. They proposed different classification algorithms that could be used for better prediction based on data characteristics from the liver disease data sets. The researchers investigated and analyzed various results obtained from a few classification algorithms, such as decision trees, ANN, MLP, and Naïve Bayes. Using different evaluation criteria, for example, accuracy, precision, sensitivity, recall, and specificity, and it was established that Naïve Bayes was preferable to other algorithms in terms of correctness. MLP was preferred over the other algorithms on the performance of the prediction test. Adeyemo et al. [32] compared MLP and decision tree algorithms' accuracy in predicting typhoid fever. Data mining plays a critical role in the extraction of hidden patterns in large datasets. Numerous other research examines the behavior of different statistical methods and their performance in predicting the respective diseases.

7 Malaria Risk Determinants

Determining malaria risk is multi-faceted. In general, risk entails three significant parameters, which include hazard, vulnerability, and exposure. While the hazard in the current context is malaria transmission, there would be multiple dimensions of the vulnerability and exposure elements. As described by the United Nations Office of the Disaster Risk Reduction (UNISDR) (2009), Vulnerability is the conditions determined by physical, social, economic, and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards. Vulnerability in the context of malaria determinants could be associated with poverty, social and economic categories, people of particular age groups, society's immunity, and nutritional status. Furthermore, Exposure is defined as the people, property, systems, or other elements present in hazard zones subject to potential losses. Figure 4 depicts a comprehensive framework for malaria risk estimation.

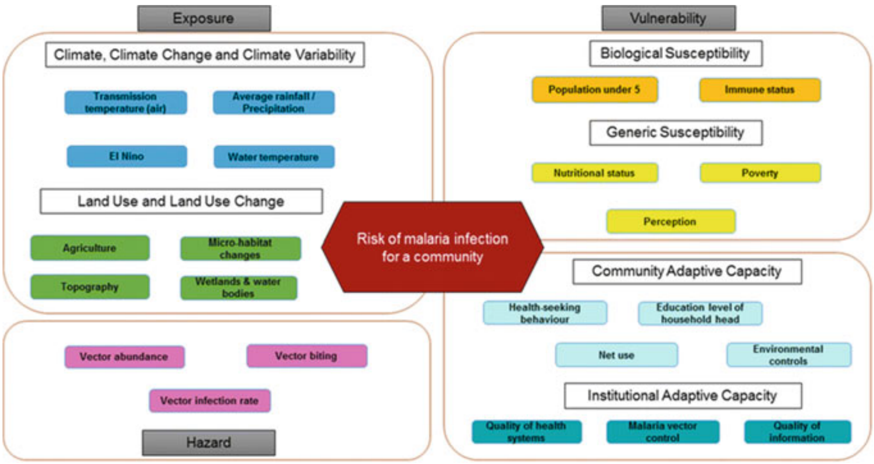

Fig. 4 An integrated assessment framework malaria risk and vulnerability. Extracted from a study conducted in East Africa [36]

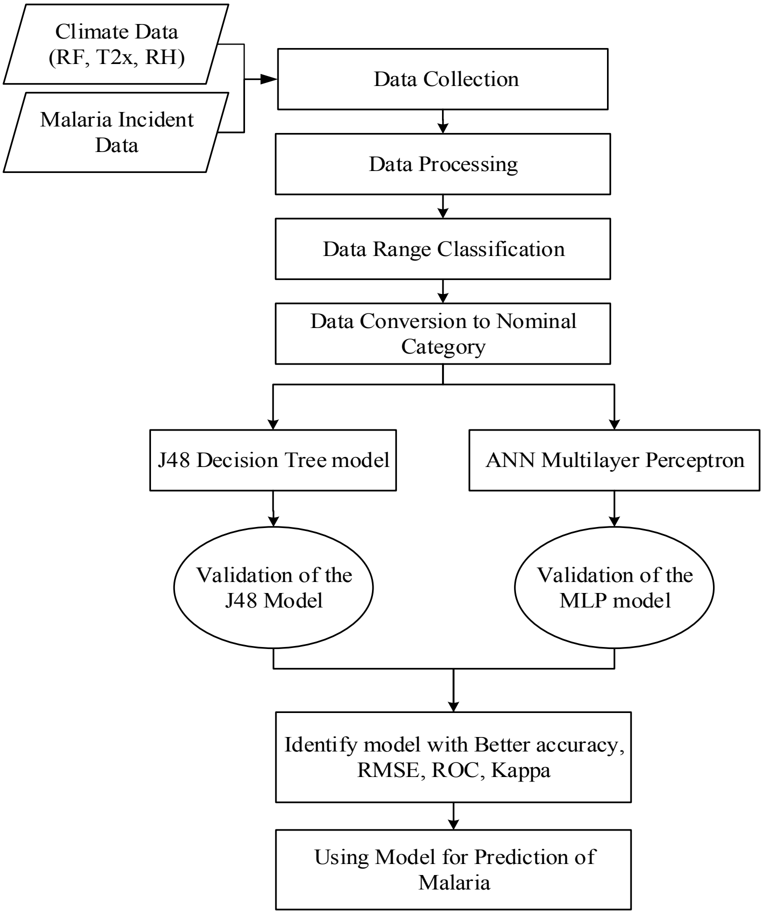

Fig. 5 Machine learning-based modeling of malaria incidence

The other aspect of the risk is the capacity of society to deal with the hazard. A society's capacity is evaluated based on its quality of health facilities, literacy among people, awareness about the hazard (malaria), and control measures. Climatic and other environmental factors, as described earlier in the document, play a crucial role in the risk determination process in terms of hazard detection.

8 Data Collection

Data is required to be collected from two principal sources for conducting analytical research to understand malaria spreading. The data includes meteorological observation data and malaria incident data from the relevant department. Some of the supporting datasets, including the population data, land use, and land cover datasets, would be collected from authentic web sources. The following section discusses the different data sources and lists all data available for the study.

8.1 Primary Data

The research's primary data will be weather data, including rainfall, maximum and minimum temperatures, and humidity for all 17 blocks in the district of the study area. Data from the automatic weather station (AWS) rainfall data were collected from the Odisha state special relief commissioner's (SRC) website, which provides block-wise daily accumulated rainfall for 1988 till 2019. Temperature and Humidity data was also included for the given period. However, considering the unavailability of the station observation data with the India Meteorological Department for the blocks alternate data source was used to complete the analysis. Gridded global reanalysis data from the European Centre for Medium-range Weather Forecasts (ECMWF) was retrieved from the climate data store. Seventeen block malaria incidents were collected for the 2002–2017 period from the Directorate of Public health (DPH). Population census data for the year 2011 was applied for the region, so as the geospatial data.

8.2 Using Reanalysis Datasets as Observation

According to Jolivet et al. [37], reanalysis data is critical in re-assessing recent atmosphere changes. In this process, observation data are assimilated in a model of the atmosphere to produce a complete representation of the atmosphere's state at a time [38]. Parker [39] adds that reanalysis is among the most used data sets, particularly in the study of weather and climate, climate variability, and in the evaluation of climate models. Jolivet et al. [37] and [40] have emphasized the utilization of reanalysis data because of its close representation of the actual observations in the absence of the latter. In the specific context of this research, however, reanalysis data were used primarily because of the unavailability of Indian meteorological departments' observation measurement for temperature and humidity data at the desired scale.

9 Data Analysis with Machine Learning

Monthly averages of the data were used from 2002 till 2017. The data was screened for any quality issues and refined for threshold identification. The analysis is then performed on the data to reveal different patterns and trends in the data. The study results were used to predict disease future incidence.

The data analysis was done through various software relevant to the research, including R statistical software package and WEKA for Machine Learning. WEKA tool was used to perform neural network analysis and J48 analysis. The use of Weka will allow the application of algorithms that use decision trees. The J48 method within Weka will make it possible to predict malaria's future incidence based on previous data. The result realized will be compared against those of another technique for sensitivity, thus increasing the chances of having a more accurate outcome.

9.1 Artificial Neural Network-Based Multiple Layer Perceptron

The study employed a multilayer perceptron (MLP) approach as defined by Dangare and Apte [41], is a class of feedforward artificial neural networks. The configuration constituted three layers of nodes, a hidden layer, an input layer, and an output layer. Each of these nodes, except the input nodes, is a neuron that uses the non-linear activation function. As Korting [42] explained, artificial neural networks have, for a long time, been a robust perceptive classifier for tasks not just in medical diagnosis but also for early detection of diseases. Studies such as Nayeem et al. [43] used ANN to predict diseases such as liver disease, heart disease, and lung cancer demonstrated that forecasts based on ANN of conditions had improved the diagnosis accuracy [44]. Feed-forward neural networks are highly successful in carrying out prediction as models of classification, and the training continues as the network keeps improving on the validation set [45]. MLP uses a supervised learning technique referred to as propagation for training the network [41], it is a modification of the standard linear perceptron. As such, it can distinguish data that is not separable (linearly.

A perceptron produces a single output based on several real-valued inputs by forming a linear combination using its input weights (and sometimes passing the output through a non-linear activation function) [46], which can be represented as:

$$y = \varphi\left(\sum_{i=1}^{n} w_i x_i + b) = \varphi(w^T x + b\right) \tag{1}$$

where w is the vector of weights, x is the vector of inputs, b is the bias, and φ is the non-linear activation function.

A multilayer perceptron (MLP) is a deep, artificial neural network. It is composed of more than one perceptron. They are composed of an input layer to receive the signal, an output layer that decides or predicts the input, and in between those two, an arbitrary number of hidden layers that are the actual computational engine of the MLP. MLPs with one hidden layer can approximate any continuous function. The multilayer perceptron is often applied to supervised learning problems [47]. They train on a set of input–output pairs and learn to model the correlation (or dependencies) between those inputs and outputs. Training involves adjusting the parameters, or the weights and biases, of the model to minimize error. Backpropagation is used to make those weigh and bias adjustments relative to the error, and the error itself can be measured in various ways, including by root mean squared error (RMSE).

9.2 J48 Classifier model—A Decision Tree Method

Dangare and Apte [41] defines J48 classification as building models of classes from records that contain class labels. A decision tree algorithm is used to find how the attribute-vector is likely to behave for an array of instances. According to Korting [42], the decision tree algorithm generates the rules that would be used to predict the targeted variables and accounts for missing values in the model and the output. Some algorithms perform classification recursively until each leaf has been deemed pure. In other words, the classification of data would be as perfect as possible. Korting [42] argues that one of the most critical aspects that contributes to obtaining accurate results, in this case, is pruning, which takes care of the outliers. Some instances in all datasets are not generally well defined and tend to differ from other neighborhood cases. Salama et al. [29] add that pruning minimizes classification errors, which have been produced by specialization in the training set. Al Jarullah [45] used the J48 model to predict diabetes by using decision trees in phases with promising results.

The primary step was to reduce the impurity or uncertainty in the data. A subset of data is pure if all instances belong to the same class. The heuristic is to choose the attribute with the maximum Information Gain or Gain Ratio based on information theory. Entropy is a measure of the uncertainty associated with a random variable. We choose the attribute with the highest gain to branch/split the current tree. Assume attributes are categorical now; the tree is constructed in a top-down recursive manner. All the training examples are at the root Examples are partitioned recursively based on selected attributes. Attributes are selected based on an impurity function (e.g., information gain). This process uses the 'Entropy,' i.e., a measure of the disorder of the data (Quinlan 1993,

$$\text{Entropy}\left(\vec{E}\right) = -\sum_{j=1}^{n} \frac{|E_j|}{\left|\vec{E}\right|} \log \frac{|E_j|}{\left|\vec{E}\right|} \tag{2}$$

, 26, 42]). The Entropy of $\vec{E}$ is calculated by;48

Iterating over all possible values of $\vec{E}$ The conditional Entropy is

$$\text{Entropy}\left(j|\vec{E}\right) = \frac{|E_j|}{\left|\vec{E}\right|} \log \frac{|E_j|}{\left|\vec{E}\right|} \tag{3}$$

and finally, Gain is

$$\mathrm{gain}\left(\vec{E}, j\right) = \mathrm{entropy}\left(\vec{E} - \mathrm{Entropy}\left(j|\vec{E}\right)\right) \tag{4}$$

Further to minimize the inaccuracy the aim was to maximize the Gain, dividing by overall entropy due to split argument $\vec{E}$ by value j.

Evaluation of performance of Machine Learning Methods

The machine learning analysis methods' performance was evaluated through different indicators that were inbuilt in the tool. These include the RMSE, the accuracy, and the kappa values. The detailed methodology can be found in Mohapatra et al. [49].

10 Predictive Analysis of Malaria Using Machine Learning

Primarily two variants of the datasets were used: (1) climate data, and (2) malaria incidents. The task was to establish the best possible relationship between different climatic conditions and their influence on the malaria incidents reported. The analysis was carried out using the *R* statistical software and WEKA machine learning tool. The investigation was conducted for all 17 blocks, and the results were presented at the end of the chapter.

10.1 Hotspot Analysis of Malaria Incidents

Hot spot analysis was done using the hotspot analysis tool, which calculates the Getis-Ord Gi* statistic for each feature in a dataset. The resultant *z*-scores and *p*-values tell where features with either high or low values cluster spatially. This tool works by looking at each feature within the context of neighboring features [50]. Figure 6 show the hotspots on an annual scale from 2002 to 2017.

The Getis-Ord G Z-score in the figure above demonstrates the malaria hotspots for all blocks in the district. It can be noticed that the eastern belt is the frequently affected region compared to the other parts. Gurundia, Bonai, Lahunipara, and Koira are the most severely affected among all others. This is because of the thick forest cover and concentrated tribal population in this area. The mortality rates are also high because of limited access to necessary medical facilities. However, this study focuses on finding the climatic influence of these incidents using some advanced machine learning techniques and possible ways to provide early warning about possible future outbreaks. The subsequent sections would discuss this in detail.

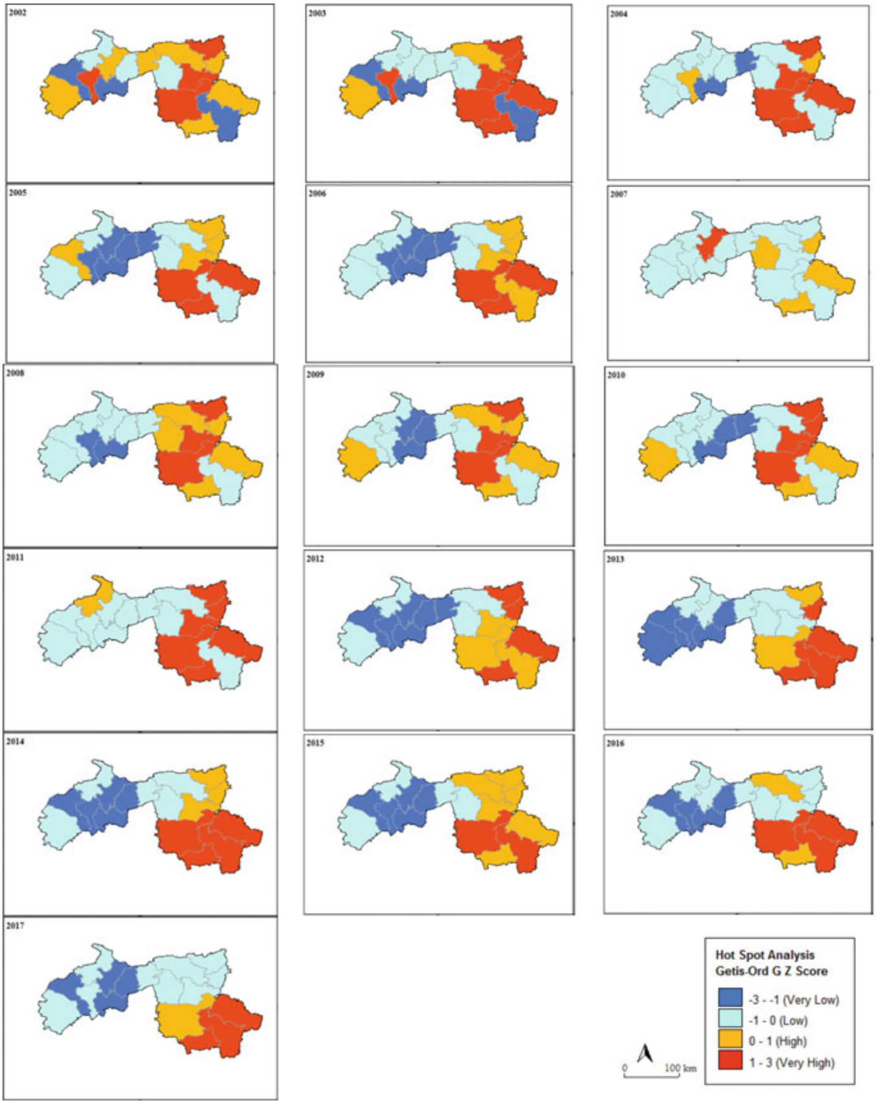

Fig. 6 Map showing hotspots of malaria incidences at block level for all years with the Getis-Ord G Z scores

10.2 Weka Analysis Platform

Waikato Environment for Knowledge Analysis (WEKA), like Holmes, Donkin and Witten [51] defines it, is collecting machine learning algorithms that accurately perform data mining tasks. WEKA contains tools that facilitate data preparation, regression, classification, association rules mining, clustering, and visualization.

WEKA is a machine learning algorithm platform [52], which is simply a category of artificial intelligence that enables computers to learn about data (as samples and with or without the interference of any other explicit programs [53]. More detail about the tool can be found at https://www.cs.waikato.ac.nz/~ml/weka/.

WEKA essentially crawls through the data to find patterns and trends, and upon finding these patterns and trends, the software then adjusts the program actions accordingly. In the current research, just like in data mining, the author analyzes data from different perspectives before summarizing it into parcels of useful information. The collection of data mining algorithms in WEKA is applied directly to the data, or sometimes, they are called from the java code. WEKA uses the Attribute-Relation File Format in the data analysis process by default. Other data formats, also including CSV and database using ODBC, can be imported. The ARFF (Attribute-Relation File Format) has two parts: the header section that defines the data set (the relation) name, the type, and the attribute name, and secondly, the data section that lists the data instances. In most cases, an ARFF file would require the declaration of the relation, the attribute, the data, and a diagrammatic representation of this file. In WEKA, the following data types for different attributes are supported: numeric, nominal, string, and data.

10.2.1 Performing Data Mining

There are six steps to implement machine learning or the data mining process using the platform includes:

1. ***pre-process*** allows users to choose the data file.
2. ***classify*** allows the user to experiment or classify data with different algorithms, particularly on the data files that have been pre-processed.
3. ***The cluster*** allows the user to use or apply different clustering tools to identify homogeneous clusters of data within the data.
4. ***The association*** is responsible for allowing the user to apply the association files, and its role is to identify the association within data.
5. ***Selection attributes*** allow the user to view the inclusion and exclusion of different attributes from the experiment or the data.
6. ***visualize*** tab is responsible for allowing the users to see the possible visualizations that are produced on the data set

10.2.2 Data Pre-processing

Data pre-processing is a must Holmes et al. [51], and in WEKA, there are about three ways that a user can inject the data for pre-processing, and they include:

- *Open file: which enables users the selection of the file from the local machine*
- *Open database: which enables the users to retrieve the data from a source, often a database source*

- *Open URL: It enables the users to select the data to be used from different locations in the analysis process.*

Data is refined by selecting different options after loading it in the explorer. The tool's flexibility allows us to select and remove attributes as per unique requirements and apply filters on the data to refine the results to meet specific needs.

10.2.3 Data Classification

Another essential step in the analysis with WEKA is the classification, and it is at this stage, the analysis predicted the different nominal or numeric quantities. Some of the learning schemes that played a vital role in this analysis included lists and decision trees, instance-based classifiers, support vector machines, logistic regression, and Bayes' nets. It is essential to set test options before running any classification algorithm. Some of the available test options in WEKA include.

- Use training set, wherein; evaluation is based on how well that algorithm can predict the instances trained.
- The supplied training set evaluates how well an algorithm can predict the class of a set of instances loaded from a file.
- Cross-validation is where evaluation is based on cross-validation using the folds entered in the 'folds' text field.
- The split percentage evaluation is done based on how well it can predict given proportions of the data, and this is held out for testing using user-defined values of the '%' field.

10.2.4 Data Clustering

The clustering algorithm is used to identify the similarities of groups within the datasets, and the available clustering schemes include K-Means, X-means, and Farthest First [49].

10.2.5 Data Association

As far as the association is concerned, the handy program in WEKA is the Apriori algorithm, whose role is to identify statistical dependencies between the various clusters of attributes. It is important to note also that it only works with discrete data.

10.2.6 Defining Data Range Through Percentile

The percentile, say, the nth percentile of an observation variable, can be defined as the value that cuts off the first ***n***% of the data's values when the data has been sorted in ascending order. In *R*, obtaining the percentile is done using the quantile function and the descriptive statistics function. An important aspect to note that the data use is all block data, constituting the average monthly historical data and spatially averaged data per block. This data is prepared by converting it into percentiles, and we use the percentile to define the levels of the variables, which is to facilitate better and faster analysis. Table 1 segregates the data using the percentile method and listed the 25th, 50th, 75th, and 95th percentile data points.

10.2.7 Data Conversion from Numeric to Nominal

In some cases, raw data in machine learning could be in a format that is not ideal for modeling, and as such, discretizing the data is necessary. Based on the nature of the data being used in this case, working with discrete data appears to be more accessible, especially as far as addressing the research problem is concerned. As Hornik et al. [53] explain, discrete attributes are used to describe a category, and they are referred to as nominal attributes. During the analysis, it is vital to transform machine learning data into the expectations of an array of machine learning algorithms. To discretize real-valued attributes in WEKA, use the discretized filter. The process of discretizing data is necessary, mainly if the analysis involves using a decision tree type of algorithms. This step would change the historical data into a range and replace it from numerical to nominal (low, medium, high, very high) shown in the output below.

10.2.8 Model Training and Prediction Using MLP and J48 Decision Tree

Both the classifier models were run with the nominal datasets with a different set of data. The total data samples were divided into two sets: (1) a set of training data, and (2) an isolated set of prediction data. The model is then trained with the training data samples and used to predict the remote collection of data that were not part of the model training process.

The classification type includes 10-cross validation; 2) 66% split and supplied test sets. As discussed by the University of Waikato (2011), cross-validation is a standard evaluation technique, is a systematic way of running repeated percentage splits. Divide a dataset into ten items (folds), then hold out each bit successively for testing and train on the remaining nine along. It gives ten evaluation results, which are averaged. After the tenfold cross-validation is processed and the evaluation results are computed, the learning algorithm invoked a final (11th) time on the entire dataset to obtain the model prediction with the corresponding accuracy. While percent split only divides 66% of the total data samples as training datasets and the rest 33% as testing. The supplied test sets work with user-defined supplied training and prediction data sets. In this case, the user has complete control over the process.

Table 1 Percentile calculation of each dataset

Block_id	Block name	Pred$param	P25	P50	P75	P95
All block		malaria$RF	0.00	23.00	178.00	445.00
		malaria$T2	28.33	30.33	33.58	38.34
		malaria$RH	68.27	82.59	93.01	96.66
		malaria$case	35.00	78.00	173.00	460.00
298	Hemgiri	malaria$RF	0.00	25.05	215.50	460.23
		malaria$T2	28.73	30.49	34.09	39.64
		malaria$RH	61.35	80.04	91.53	95.78
		malaria$case	23.50	67.00	147.00	366.45
299	Lephripara	malaria$RF	0.00	24.90	174.25	425.90
		malaria$T2	28.19	30.24	33.67	39.00
		malaria$RH	62.49	80.51	92.48	96.46
		malaria$case	26.75	54.00	108.00	423.45
300	Tangarpali	malaria$RF	0.00	20.00	181.13	425.85
		malaria$T2	28.54	30.54	33.84	39.10
		malaria$RH	63.73	80.95	92.32	96.03
		malaria$case	14.00	31.00	73.00	141.45
301	Sundargarh	malaria$RF	0.00	22.00	179.93	438.49
		malaria$T2	28.54	30.54	33.84	39.10
		malaria$RH	63.73	80.95	92.32	96.03
		malaria$case	12.00	20.00	68.00	671.25
302	Subdega	malaria$RF	0.00	11.00	161.00	400.41
		malaria$T2	28.10	30.25	33.45	38.75
		malaria$T2	63.73	81.35	92.87	96.46
		malaria$case	36.00	63.00	119.00	275.25
303	Baragaon	malaria$RF	0.00	28.00	162.23	467.58
		malaria$T2	28.43	30.40	33.50	38.08
		malaria$T2	68.70	82.38	93.72	96.56
		malaria$case	26.00	50.50	97.25	327.20
304	Balisankara	malaria$RF	0.00	12.50	190.40	413.03
		malaria$T2	28.10	30.25	33.45	38.75
		malaria$RH	63.73	81.35	92.87	96.46
		malaria$case	38.00	61.50	135.25	277.45
305	Kutra	malaria$RF	0.00	22.10	158.30	424.60
		malaria$T2	28.10	30.25	33.45	38.75
		malaria$RH	63.73	80.95	92.32	96.03
		malaria$case	13.00	29.00	52.50	146.50

(continued)

Table 1 (continued)

Block_id	Block name	Pred$param	P25	P50	P75	P95
306	Rajgangpur	malaria$RF	0.00	21.40	145.55	410.37
		malaria$T2	28.12	30.34	33.49	38.22
		malaria$RH	67.18	81.60	93.37	96.48
		malaria$case	30.00	66.50	144.75	327.35
307	Kuanrmunda	malaria$RF	0.00	21.50	170.38	449.98
		malaria$T2	28.11	30.29	33.41	37.98
		malaria$RH	68.22	82.62	93.69	96.77
		malaria$case	34.00	73.00	178.25	370.95
308	Nuagaon	malaria$RF	0.00	18.65	168.60	375.31
		malaria$T2	28.38	30.35	33.33	37.92
		malaria$RH	70.86	83.63	94.53	97.02
		malaria$case	68.50	110.00	199.75	432.00
309	Bisra	malaria$RF	0.00	26.00	183.30	426.92
		malaria$T2	28.07	30.27	33.25	37.79
		malaria$RH	70.34	83.54	94.13	97.02
		malaria$case	70.25	161.00	273.50	700.00
310	Lathikata	malaria$RF	0.00	26.75	176.75	472.10
		malaria$T2	28.07	30.27	33.25	37.79
		malaria$RH	70.34	83.54	94.13	97.02
		malaria$case	102.00	200.50	315.50	693.45
311	Bonai	malaria$RF	0.00	21.00	172.25	465.45
		malaria$T2	28.57	30.37	33.38	37.77
		malaria$RH	74.04	84.65	94.22	96.95
		malaria$case	55.00	94.50	175.25	300.05
312	Lahunipara	malaria$RF	0.00	21.50	191.95	525.10
		malaria$T2	28.38	30.35	33.33	37.92
		malaria$RH	70.86	83.63	94.53	97.02
		malaria$case	119.50	194.00	328.25	584.25
313	Gurundia	malaria$RF	0.00	28.00	197.00	478.93
		malaria$T2	28.63	30.46	33.56	37.96
		malaria$RH	70.11	83.11	93.62	96.39
		malaria$case	56.75	101.00	213.50	493.70
314	Koira	malaria$RF	0.00	25.75	156.13	427.19
		malaria$T2	28.27	30.22	33.04	37.43
		malaria$RH	74.10	84.94	94.95	97.41
		malaria$case	61.75	111.50	186.50	600.45

11 Comparative Analysis of MLP and J48 Models

This section presents the analyzed data, and it constitutes the examination of how different climatic conditions influence the incidence of malaria. The comparisons between the two classifier methods were made for each of the 17 blocks in the district, and performance accuracy was evaluated month-wise. However, this study focuses on finding the climatic influence of these incidents using some advanced machine learning techniques and ways to provide early warning about possible future outbreaks.

All three test options were used to assess MLP and J48 methods' performance, (a) tenfold cross-validation, (b) percent split (66%), and the user-supplied test sets. The following section discussed the outcome of the model prediction.

11.1 Machine Learning Performance

An initial evaluation was completed over the Sundargarh district to investigate which machine learning methods performed better than the others before going for block-wise performance. All evaluations were done for the different months of the year to understand the prediction skill based on the monsoon variation. While the prediction accuracy results show that MLP and J48 are not very different, although J48 shows slightly better performance. In other studies, such as Salama et al. [29] and Gupta et al. [54], where more attributes were analyzed and larger volumes of data used, the prediction using J48 has also turned out to be better in all these cases. However, for both the classifiers, the tenfold cross-validation classification testing option outperforms the percentage split (66%) method for the whole district, as shown in Fig. 7 (accuracy), Fig. 8 (Kappa), and Fig. 9 (RMSE), respectively.

Figure 7 suggests that while the prediction accuracy for both the cross-validation method (J48 and MLP) has improved during the mid-monsoon (July–August period) to late monsoon (September–October), at the same time, the prediction accuracy for the split method has declined. For all models, the dry season has less accuracy.

In terms of KAPPA, to determine which month has a better agreement and which month, the prediction agreement is incorrect or direct disagreement [55]. Low negative values of KAPPA (0 to -0.10) indicate that there is 'no agreement,' and higher positive values indicate higher agreement. In comparison, only the J48 cross-validation method has significantly better Kappa than the other three methods. It shows the superiority of the J48 model with cross-validation over the others (Fig. 9).

The prediction error (in Fig. 9) also depicts that the cross-validation method has much less error than the percentage split method. For this, J48 has better performance during the wet season. Errors are more substantial for both the models during the wet period, and RMSE is low during the dry period. Since the data was analyzed monthly, J48 can be considered a more reliable predictor of malaria for the weather variables. It has comparable RMSE and higher KAPPA (with highest values in September =

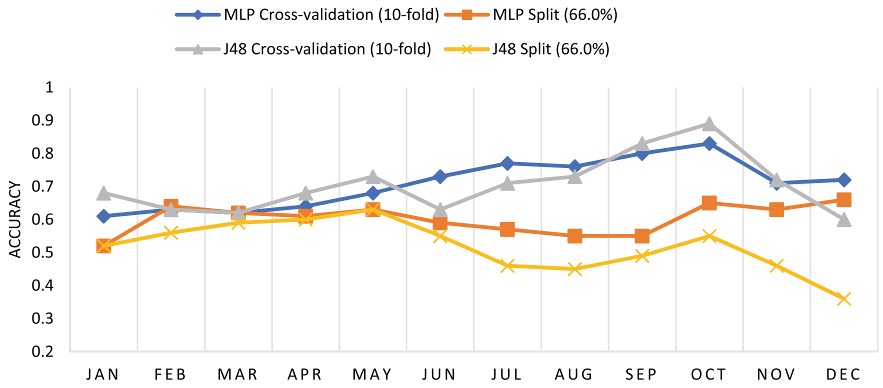

Fig. 7 Month-wise comparison of the accuracy of the J48 (Cross-validation and percent split model) to the multilayer perceptron model for accuracy for Sundargarh District

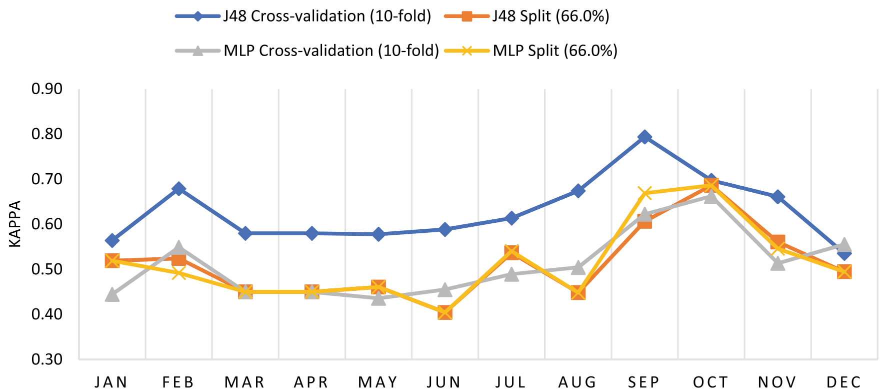

Fig. 8 Month-wise comparison of KAPPA of the J48 (Cross-validation and percent split model) to the multilayer perceptron model for accuracy for Sundargarh District

0.79 and October = 0.70) indicated that it performed better than MLP with Kappa (September = 0.62 and October = 0.66).

11.2 *ROC Scores: Model Prediction Skill Measurement for Sundargarh District*

As explained in the previous chapter, the ROC score is generally a measure of the model's prediction skill and performance. The prediction models must be grouped into three distinct prediction categories called terciles, e.g., (1) High (upper tercile),

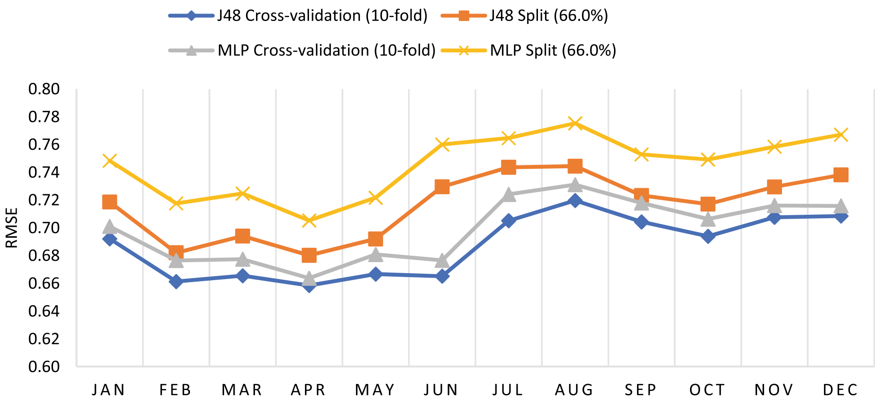

Fig. 9 Month-wise comparison of RMSE of the J48 (Cross-validation and percent split model) to the multilayer perceptron model for accuracy for Sundargarh District

(2) medium (mid tercile), and (3) Low (lower tercile), to evaluate with ROC. The evaluation shows how well the three different categories of events can be predicted.

Figure 10 shows the performance of the three different event categories, and it is evident that the skill of the J48 method is comparatively better than MLP.

The J48 cross-validation method has better performance in predicting high and low events across the year. During the post-monsoon season prediction skill for high events (Sep = 0.89, Oct = 0.84, Nov = 0.80, Dec = 0.85) and (Sep = 0.91, Oct = 0.91, Nov = 0.83, Dec = 0.85) for skill for predicting low events. At the same time, the percent split method has comparatively less skill. This probably could be because of the fewer sample datasets used in the Percent split methods for the model's training, which might not be adequate. MLP has even poorer results depicting skill for high events with ROC = 0.56 for May and consistently poor throughout the year. This shows that the models are generally poor during the early to the mid-monsoon period (May–August), irrespective of the model classifier technique. At the same time, the prediction of the medium category event is challenging for both models. For J48 cross-validation, the lowest value (ROC = 0.65) in September and for percent split method ROC = 0.54 in May. While in the MLP cross-validation, ROC = 0.60 in September and ROC = 0.59 in February month, respectively.

The prediction model's final exercise was to supply the classifiers with a user-defined set of datasets for training and isolate a specific year or years for prediction. This exercise was to monitor the performance of the classifiers in real-time. Data from 2002 till 2015 was used for training and 2016 and 2017 for prediction for this test. The results presented in Table 2 suggest the method has comparable performance to J48 and MLP. It has less RMSE and better accuracy, and higher kappa values. Further investigating the performance of the Supplied test set, it was found that its accuracy of prediction is better compared to the cross-validation method, especially for central and western blocks, including Sundargarh (Accuracy = 1.0, Kappa =

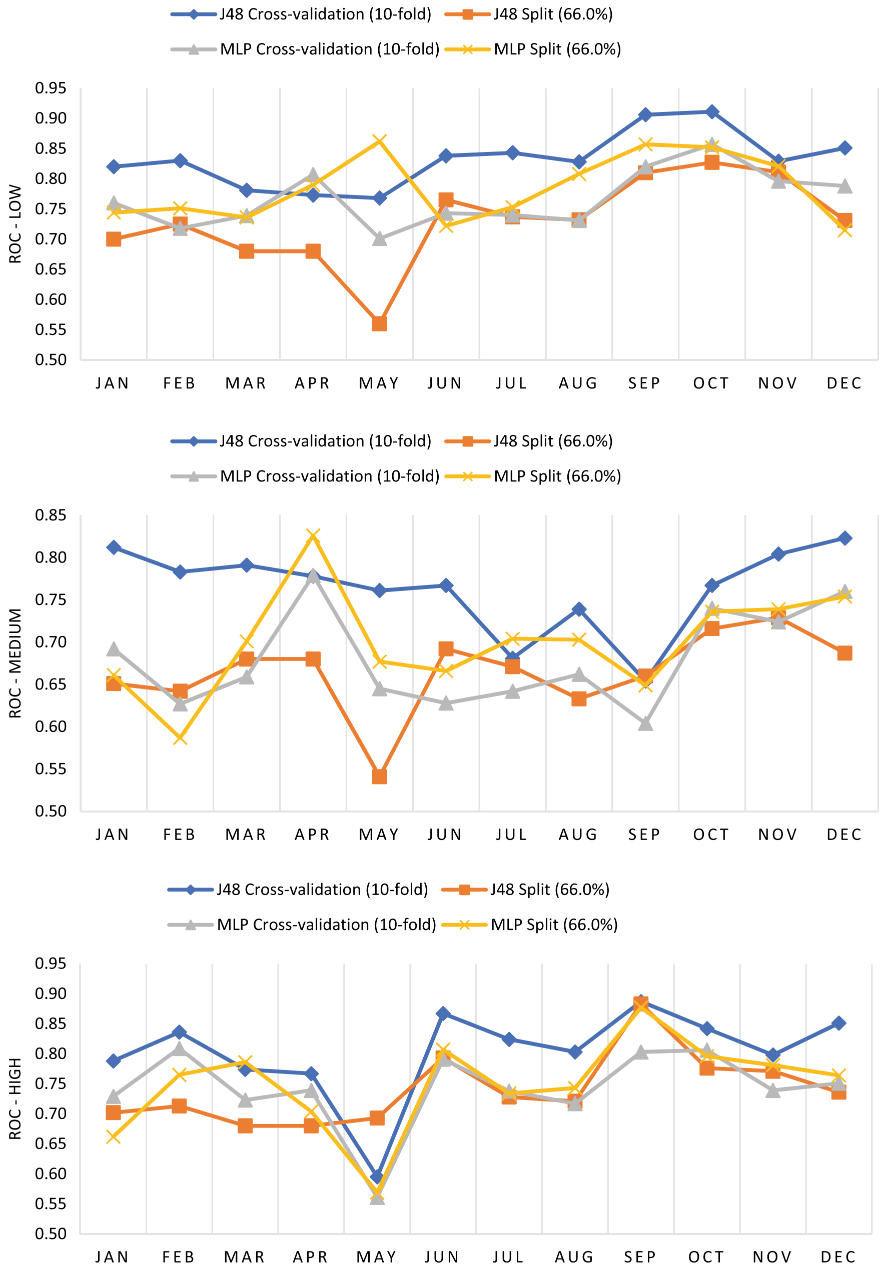

Fig. 10 Month-wise comparison of ROC for (Low, medium, and high prediction category) of the j48 (Cross-validation and percent split model) to the multilayer perceptron

Table 2 Comparisons of accuracy, RMSE, and kappa for all blocks for J48 cross-validation and supplied set test options

Blocks	**J48 Cross-Validation**			**J48 Supplied test set**		
	Accuracy	Kappa	RMSE	Accuracy	Kappa	RMSE
Hemgiri	0.57	0.40	0.89	0.71	0.16	0.37
Lephripara	0.69	0.33	0.88	0.83	0.00	0.34
Tangarpali	0.94	0.55	0.76	1.00	1.00	0.17
Sundargarh	0.88	0.51	0.80	1.00	1.00	0.19
Subdega	0.71	0.60	0.86	0.71	0.26	0.36
Baragaon	0.81	0.63	0.81	0.79	0.17	0.32
Balisankara	0.55	0.31	0.89	0.79	0.00	0.40
Kutra	0.98	0.52	0.72	1.00	1.00	0.16
Rajgangpur	0.69	0.51	0.86	0.63	0.00	0.39
Kuanrmunda	0.63	0.57	0.87	0.63	0.30	0.41
Nuagaon	0.58	0.55	0.90	0.29	0.08	0.53
Bisra	0.53	0.38	0.89	0.58	0.39	0.49
Lathikata	0.72	0.50	0.86	0.42	0.13	0.50
Bonai	0.57	0.50	0.91	0.46	0.18	0.48
Lahunipara	0.70	0.60	0.86	0.54	0.47	0.48
Gurundia	0.53	0.45	0.90	0.17	0.07	0.58
Koira	0.51	0.39	0.90	0.17	0.29	0.58

Highlighted values are for accuracy ≥ 0.70; kappa ≥ 0.55; RMSE ≤ 0.50

1.0, RMSE = 0.19), Tangarpali (Accuracy = 1.0, Kappa = 1.0, RMSE = 0.17), and Kutra (Accuracy = 1.0, Kappa = 1.0, RMSE = 0.16).

ROC scores for both the classifiers of the J48 model were compared, and the results are presented in Table 3. The results suggest that the model performance is satisfactory for the central blocks like Kutra (High = 0.99, Med = 0.80, low = 0.90),

Table 3 Comparative analysis of ROC scores for all blocks in the district for J48 cross-validation and supplied test options

Blocks	**Cross-Validation**			**Supplied Test**		
	High	**Med**	**Low**	**High**	**Med**	**Low**
Hemgiri	0.83	0.73	0.72	0.76	0.74	0.94
Lephripara	0.75	0.76	0.72	0.79	0.61	0.68
Tangarpali	0.69	0.75	0.75	0.81	0.79	0.85
Sundargarh	0.62	0.74	0.70	0.45	0.69	0.81
Subdega	0.91	0.76	0.86	0.98	0.84	0.93
Baragaon	0.93	0.77	0.90	0.73	0.76	0.60
Balisankara	0.73	0.69	0.74	0.12	0.34	0.64
Kutra	0.99	0.80	0.90	0.86	0.94	0.88
Rajgangpur	0.82	0.76	0.84	0.92	0.89	0.77
Kuanrmunda	0.97	0.71	0.84	0.93	0.65	0.83
Nuagaon	0.81	0.67	0.81	0.60	0.71	0.53
Bisra	0.88	0.70	0.84	0.49	0.79	0.73
Lathikata	0.88	0.89	0.66	0.65	0.87	0.43
Bonai	0.76	0.63	0.78	0.46	0.82	0.59
Lahunipara	0.90	0.76	0.94	0.31	0.39	0.39
Gurundia	0.89	0.71	0.76	0.53	0.20	0.33
Koira	0.77	0.75	0.72	0.25	0.21	0.34

Highlighted values are ROC scores ≥ 0.75

Subdega (High = 0.91, Med = 0.76, Low = 0.86), Rajgangpur (High = 0.82, Med = 76, Low = 84). While blocks such as Bonai (High = 0.76, Med = 0.63, Low = 0.78), Koira (High = 0.77, Med = 0.75, Low = 0.72), Gurundia (High = 0.89, Med = 0.71, Low = 0.76), and Balisankara (High = 0.73, Med = 0.69, Low = 0.74), depict considerably lower accuracy and prediction skills. While blocks with plain land and forest cover performed much better compared to the highly elevated regions. Table 3 shows the ROC score analysis.

The probable explanation for the model not performing well for some of the blocks could be a factor that is external to weather influence. Furthermore, mainly to do with the interventions in place in parts of the district and other regions [56] and the socio-economic status of the significant population in the eastern belt, being tribe and access to necessary facilities is limited as also explained by Sundararajan et al. These factors influence the increase or decrease in the cases, and not truly reflect the weather influence. The other reflection from the analysis is that the model's performance dips down significantly, especially during July, August. It picks up during September October and then again shows lower accuracy during November and December months (this is depicted in Fig. 4.4). Again, the possible explanation for the model's poor performance could be the topography and the land use pattern, where the rainfall variation could influence the results. For example, blocks such as Bonai, Koira, Gurundia, and Hemgiri have higher elevation and depict considerably lower accuracy for the prediction. In contrast, blocks with plain land and forest cover performed much better.

11.3 Nominal Climate and Incident Data Range and the Relation

The final exercise presented a relationship between the different nominal climatic conditions for each month and the respective incident condition. The following Table 4 provides the climate data range, and these ranges can be different for different locations, making it a variable indicator. Based on the spectrum, Table 4 summarizes the relationship between the nominal rainfall, temperature, and humidity range to that of the malaria incidents.

From Table 5 periods of low temperature (28°–30°), low rainfall (0–23 mm), and low relative humidity (68–82%) during the drier and cooler months of January and

Table 4 Climate and incident data ranges

Range	Rainfall	Temperature	Humidity	Incidents
Low	0–23	28.3–30.3	68.3–82.6	35–78
Medium	23.1–178	30.4–33.6	82.7–93	78.1–173
High	178.1–445	33.7–38.3	93.1–96.7	173.1–460
Very high	>445	>38.3	>96.7	>460

Table 5 Month-wise nominal relationship between incident data and climate data

Month	RF	$T2_{max}$	RH	Incidents
January	Low	Low	Low	Low
February	Low	Low	Low	Low
March	Low	Medium	Low	Medium
April	Low	Very high	Low	Medium
May	Medium	Very high	Medium	Medium
June	High	High	Medium	Medium
July	High	Medium	High	High
August	Very high	Medium	High	High
September	Very high	Low	High	Medium
October	Medium	Low	Medium	Medium
November	Low	Low	Medium	High
December	Low	Low	Low	High

February are characterized by lower cases of malaria. During the months of March–April–May, a period of low precipitation, medium to higher temperature with lower relative humidity, there is an increase in the number of malaria incidences. This also agrees with Lee et al., a study conducted in the humid Arunachal Pradesh, India, that suggests decreasing precipitation and increasing temperature increase malaria incidence. With the arrival of the monsoon and during the June–July–August–September, the period of high to very high rainfall, higher temperature, and medium to high relative humidity, the malaria incidents were further on the rise. Surprisingly, malaria incidents climbed even after the monsoon's withdrawal, fall in the temperature and humidity significantly during the November–December winter period. So, there is possibly a lag-effect of the climatic phenomenon on the incidents.

Based on the results, it can be concluded that relative humidity and temperature showed a strong association with malaria incidence, which is consistent with the study by Srimath et al. [57] in Vishakhapatnam, in India, which experiences a similar climate compared to Sundargarh. In contrast, rainfall showed a relatively weaker association, which is in line with the study by Bomblies [58], which argues that mosquitoes' breeding habitats are flushed away temporarily during the rainy season. Still, they start breeding again when the rains stop, and water becomes stagnant, and the environmental condition is conducive for breading. This study found that extremely high temperature is a crucial trigger of the higher number of malaria incidents in Sundargarh district. Therefore, this agrees with Smith et al. [59] argument that when the temperatures increase, it reduces the mosquito parasite's time to complete its development. Furthermore, relative humidity also affects the transmission of the malaria vector, in agreement with Goswami et al. [60], who found out that mosquitoes survive better under high humidity conditions. During high humid seasons, the number of malaria incidents increases compared to the less humid conditions.

It is concluded that relative humidity and temperature showed a significant relationship to malaria incidences in the district, especially for some blocks, those are in flat terrain and near dense vegetation like the forest. Additionally, rainfall also affects the transmission of malaria vector incidence. However, the rate of vector transmission during the rainy season is relatively lower, suggesting the influence of rain on malaria incidents may happen in a time lag mode.

11.4 Model Selection and Model Evaluation

Appropriate selection of model, algorithm, and model evaluation techniques are vital in machine learning. The evaluation intends to estimate the performance of a model or algorithm on future data. Running a learning algorithm over a training dataset with different hyperparameter settings will result in different models [61]. Since we are typically interested in selecting the best-performing model, estimation helps in choosing the best model to fit the purpose though, the estimation of the absolute performance of a model is one of the most challenging tasks in machine learning [61].

Working with small sample sizes in machine learning is acceptable but choosing the correct sampling method is vital [62, 63]. Considering the sample size in this study is smaller, and for parameter optimization, tenfold cross-validation and Leave-One-Out cross-validation are recommended as the best sampling mechanisms and generally would yield better results [62].

Though researchers have not explicitly evaluated or discussed why a particular test option performs better over others and instead focused on the overall classifier performance only, this study put an effort to assess the better performing tenfold cross-validation method used in this study. With more in-depth analysis, the reason would be linked to the method's data sampling and training strategy compared to the others. A list of explanations is provided below, which considers the mechanism with which the cross-validation method works.

(a) Utilized all the data samples for training and test and takes care of the multi-class issue in the percentage split method, where the sample sizes are static, and generating multiple classes means a reduction in test sets.
(b) We defined more metrics for the learning algorithm than other methods. If we have, n samples there can $n - 1$ models to predict one instance of the predictand.
(c) Through model stacking and back-propagation, models are processed in a pipeline allowing model prediction by learning from the previous model in the forward direction and feedback and model training in the backward direction. The model bias (error) is also handled better in this process.
(d) Finally, parameter fine-tuning, in which the parameters were tuned with an independent validation set, suggested the ideal number of trees in a classifier, hidden layer size (activation function) in the Neural network.

12 Conclusion

The climatic condition of Odisha, especially the Sundargarh district, makes them the most vulnerable to malaria susceptibility. Monsoon rainfall, maximum surface temperature ranging from 27° to 40° Celsius during the summer, and relative humidity in the range of 60–85% in the region provide a conducive climatic condition for the breeding of the malaria larva during the monsoon and post-monsoon period. As shown in the results, an increase in malaria incidents is specific to temperature, humidity ranges, and monthly rainfall. Among the two classifier models used, J48 has shown comparatively better skills over the MLP. J48 demonstrated less error (RMSE = 0.6), better kappa = 0.63, and higher accuracy = 0.71), suggesting a skilful model.

J48 model has provided a greater insight into the predictability of malaria when compared on a seasonal scale. During the pre-monsoon (Mar–Apr–May) period of the year it has accuracy = 0.68, kappa = 0.58, and RMSE = 0.67, at the same time for monsoon (Jun–July–Aug–Sep) period with accuracy = 0.73, kappa = 0.67, and RMSE = 0.70, post-monsoon (Oct–Nov) period with highest accuracy = 0.81, kappa = 0.68, and RMSE = 0.70 and during the winter (Dec–Jan–Feb) period with lowest accuracy = 0.64, kappa = 0.59 and RMSE = 0.69, respectively. This suggests that the model performance is particularly good during the monsoon and post-monsoon when the events are at the peak, which is an encouraging signal for predicting future malaria incidents, particularly during the rainy and posts rainy seasons. Therefore, it is recommended that the public health department could adopt the J48 classifier machine learning technique for the early detection of malaria for taking corrective measures [64–85].

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Chapter 10
Connected and Smart Medical Devices

Rajat Jain, V. K. Tewari, Yogendra Singh, Nitin Chandola, and Saurabh Badola

1 Introduction

It was not too long ago that the triumphant commencement of the digital era was earmarked as revolutionary by many ingenious people from different sectors. In a short time, it has definitely shown its importance and penetration into every field, be it engineering or medicine. In the present time, the general mass is quite aware of keeping a check on their vital stats with just the help of highly technologically developed machines that can be used anywhere and do not need a doctor or nurse to be monitoring it. In this way, these state-of-the-art wearable medical technologies have not only attracted the attention of companies in the healthcare sphere but have also been recognized by the public eye and hence, are helpful in raising general awareness regarding health care and easy accessibility to it.

According to a recent KPMG report on the global medical devices industry, the US$ 483 billion global annual sales of medical devices in 2020 are expected to grow by over five percent annually to reach around US$ 800 billion in 2030. India and China, as emerging markets of this industry, have huge growth potential. The only way to make maximum use of this opportunity is by stepping up what the manufacturer and distributors of medical devices are offering in terms of innovation, quality, and affordability.

Some recent trends in the medical product-related industry will bring a huge impact not only on the present but the future of the health care sector also. Healthcare devices form one of the fastest-growing sectors of the AI, IoT, and highly technical manufacturing market. In recent times, it is also called the Internet of Medical Things (IOMT), which is predicted to reach US$176 billion by 2026. The IOMT devices can

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Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_10

be used in multiple ways, the most important being used remotely. Apart from these devices being used for remote patient monitoring, these are used mainly for health monitoring, vital monitoring, and hygiene monitoring, etc. Recently these devices have been used for depression monitoring, Parkinson's disease monitoring ingestible sensors, inhalers, robotic surgery, and connected contact lenses.

IOMT-based smart medical devices are the future of healthcare. Their applications are important in remotely placed health centers, aerospace applications, defense applications at high altitudes, etc. These medical devices are much cheaper and can be used by the common man at home also without the need for experts. This is also useful in continuous monitoring for the above applications. Only in serious cases, one has to go to the hospitals for the expert advice of doctors.

Another advantage of connected and IOMT devices is for bulk and big data generation. This huge data generated by these devices help experts to lighten up some grey areas, help in generating health analytics and predictions as well. Some of the important areas of research and applications are as follows.

2 Digital Health

With innovative technology as the driving force, people will have to spend less time in hospitals as they monitor their health with the help of wearable integrated smart devices and other smart online data services. The availability of technology at hand results in the prevention of major, unexpected diseases, making people spend less on expensive treatments and hospital visits, saving valuable time [1]. A range of innovative, non-intrusive, wireless portable monitoring medical devices are becoming common, such as watches, wearable accessories, skin patches, and much more [2]. Other advantages of having digitally integrated medical management are:

- **Distant Data Monitoring, Reporting, and Alerting**: Digitally empowered technologies and products can be used to send key information of patients to doctors and nurses, where no direct contact is required between any of the parties involved. Along with this, the staff also gets alert signals when the conditions get worse for prompt action as shown in Fig. 1 [14, 16].
- **Mass Management of Medical Equipment**: Many medical appliances can be connected to a central control unit, which further facilitates the management and monitoring part, resulting in the reduction of human error and making the whole process more time-efficient and self-running.
- **Coherent Information Distribution Through Automation**: Because the gadget is always recording data, the medical logs are easy to access and the medical officers receive structured data that is ready to use.
- **Medical Apparatus Administration and Remote Configuration**: Tracking the location of equipment as an owner becomes easier, tuning or setting of the devices as per the requirements from a distance is also possible, mitigating the need of visiting hospital now and then.

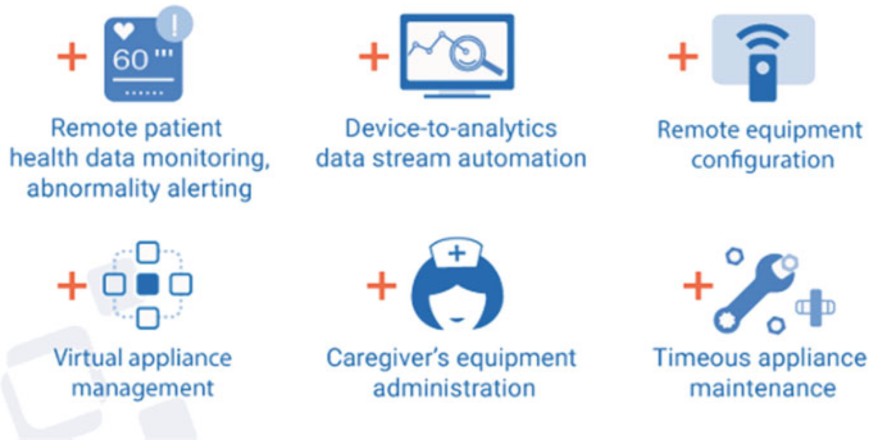

Fig. 1 Example applications of digital health platforms

- **Robust Maintenance System and Budget-Friendly**: If any problems are occurring in the machinery, it can be notified to the manufacturer immediately before it results in severe damage, thus, reducing the overall maintenance cost while optimizing the system. With the same configurations, the patients can also be kept under a watch effectively, which enables prominent home treatment.
- **Daily-use Equipment**: Increasing prevalence of lifestyle diseases coupled with the chronic ailments of a growing aging population and the rise of non-communicable diseases (NCDs) have resulted in huge demand for daily-use medical equipment like blood pressure monitors, nebulizers, digital thermometers, and glucometers that help patients monitor their vital stats every day.

3 Vital Signs Documentation and Health

Vitals such as blood pressure, blood sugar level, heart rate, etc., can be easily recorded by wearable technologies and used not only by the doctors but also by the user. This allows for persistent observation and record-keeping of the patient's health status, transition in condition, and treatment's effectiveness no matter what's the subject's location [7].

Below are the examples of some of the most common DigiTech in this area:

- Blood sugar level and blood flow monitor [23] meters that rate the required marker and alarm in cases of abnormality.
- Fertility monitors help women track their ovulation cycles to increase their chances of getting pregnant, which is especially important at a time when an increasing number of couples have fertility issues.

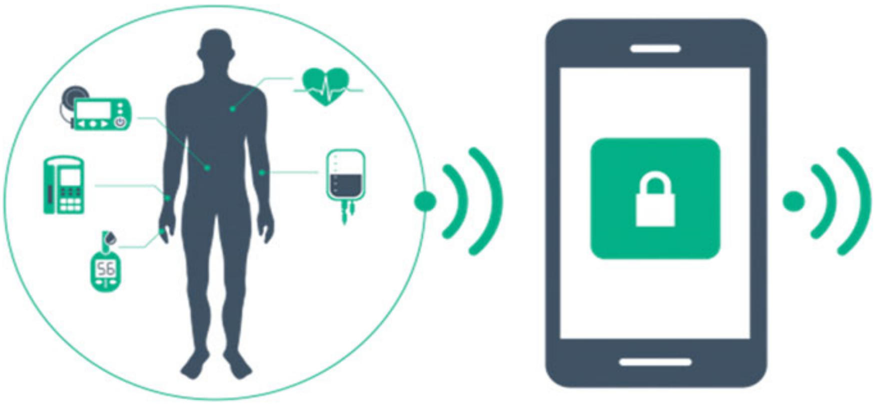

Fig. 2 Example applications of vital monitoring devices

- Pulse oximeters for those who suffer from asthma, as they measure heart rate and blood oxygen levels and report the results to the physicians.
- Vitals sign monitors through wearable ear sensors [22].

All of the above applications and examples of the devices are shown in Fig. 2.

New bacteria detection methods

A lot of emphasis is given to find new ways and means for the rapid detection and identification of microorganisms or bacteria. When patients increasingly start depending on antibiotics, they become resistant to those, making it more difficult to be treated for any or all ailments. As more innovative devices come into the market that detect specific bacteria in a short span of time, only specific antibiotics targeted at a particular part of the body can be prescribed, bringing down resistance to antibiotics considerably. It will go a long way in ensuring patient safety leaving no room for error, especially when it comes to saving lives.

4 Parameters that Can Be Measured with the New Generation of Sensors

The following factors can be captured with the aid of a variety of sensors available today:

- **Quick Pulse/ECG/EKG Reports**: Through modern technology, it has become easier to capture Electrocardiogram (ECG/EKG) even at the comfort of home. Be it for cardiac monitoring or diagnosis application, vivid ECG reports that can be directly shared with the doctors for quick feedback have become readily available through the help of sensory innovations as shown in Figs. 3 and 4.

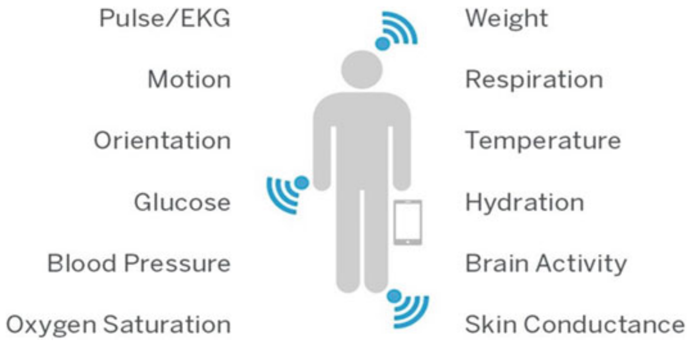

Fig. 3 Example of parameters captured

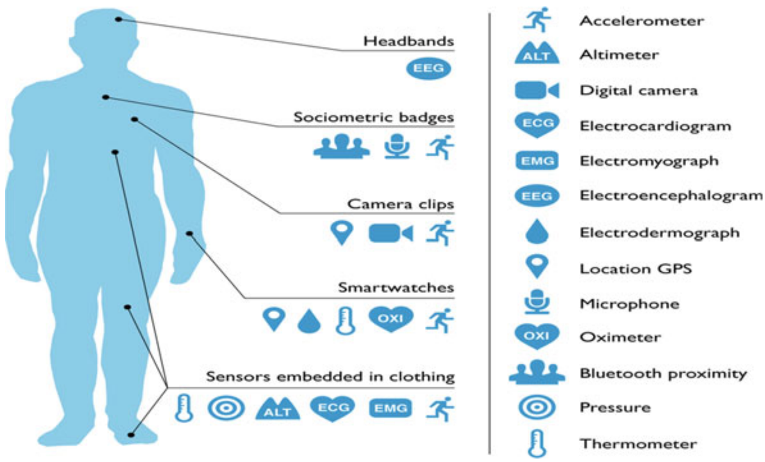

Fig. 4 Example of parameters captured with different wearable sensors

- **Recording Motion, Weight, and Orientation**: With more and more people recognizing the importance of healthy living, devices that can easily measure steps walked, miles ran, and other such parameters, act as a fillip toward a more health-conscious population and also provide on-spot vitals in case of fall or injury as shown in Figs. 3 and 4 [19].
- **General vitals Monitoring**: Glucose, Blood pressure, temperature, Oxygen saturation, and other such stats for general physiological healthcare, applications, and alerts can easily be monitored through sensors that are engulfed in headbands, wristbands, and other smart wearable designs, that are effortless as shown in Figs. 3 and 4 [19].
- **Special Diagnosis**: Hydration, brain activity, anemia, sleep apnea [15], sleep quality, skin conductance [20], cardiac stress, physiological stress [13] etc., are some of the factors that are used for special diagnosis and now can be effectively

calibrated with the help of some sensor-imbibed compact equipment as shown in Figs. 3 and 4.

5 Methods and Type of Sensors

The way sensors are getting unified into our daily wearables showcases how easily these futuristic technologies can be introduced to people in a simple yet effective manner. Given below are some of the most prominent ways in which sensor-infused gadgets have been integrated with the daily lives of the masses [11].

- **Headbands**: Sensors that can easily detect the electrical activity in the brain are used in the form of headbands so that spotting brain disorders becomes easier and no elaborate procedures or operations have to be performed just to get a minor diagnosis [12].
- **Sociometric Badges**: These badges work as the best way to capture body movements accurately with the assistance of Bluetooth proximity and microphone sensors. This information can be further used for understanding the kind of environment the person lives and travels in. These devices can also be used as accelerometers [10].
- **Sensors Embedded in Clothing**: Such type of clothing will be perfect to be employed in sectors like aerospace, marine, sports, and other industries that can benefit a lot from the full-body statistics of a person under varied conditions. Parameters measured by a thermometer, pressure sensor, altimeter, electrocardiogram, electromyograph, accelerometer, can all be measured with the help of fabric [3, 4].
- **Smartwatches and rings**: Such wearables can measure a lot of vitals by just sitting on your wrist or as a ring. They can act as an oximeter, thermometer, and accelerometer, providing important information regarding one's body every minute. Some diseases can be regional, which can only be diagnosed after getting a full travel history of the patient, for such diseases GPS tracking present in such devices work like a charm [5, 7, 9].

All of the above applications are shown in Fig. 4.

6 A Glance at Developments in Cardiology

Background Information/Challenges

According to the World Health Organization (WHO), an estimated 17.9 million people die each year due to Cardiovascular Diseases (CVDs) worldwide. It has become one of the leading causes of global deaths and mostly affects low- and middle-income group countries. One of the major causes of such a high percentage (estimated 32% worldwide) of CVDs deaths can be taken as the unavailability of cardiac monitoring Point of Care (PoC) devices for last-mile users. The PoCs are costly, complex, inefficient, inadequate, inconvenient, and non-portable. Handheld ECGs that are available widely in markets are not ergonomically comfortable to use during severe chest pains. Smartwatches with EKG are prone to baseline wandering and other noises. When we talk about remote areas or hilly regions, the condition worsens. There is no ECG facility available in such places. Patients have to travel at least 20–30 km to reach the primary healthcare facilities, and by the time they reach the hospital, they either collapse or suffer complications during the treatment.

This problem altogether made people realize the need for preliminary cardiac monitoring at primary healthcare facilities all over the globe. For example, a device that is efficient like the bulky ECG devices, but served with the compactness of handheld ECG without compromising on any of its features, can impact billions of underserved. Such devices are now available for the benefit of the common population. ECG data generated with such devices is even used for sleep apnea, sleep quality [6], heart rate variability, cardiac stress monitoring etc.

An ecosystem of connected cardiac devices and wearables

The above problem highlights the importance of creating a medical ecosystem that is prompt and efficient, one that converges with the medical needs of all types of patients, irrespective of their location. By innovating an alliance between networking tools and smart wearable technologies, the sharing of information can be made much more easier and agile [9]. The best part is that this idea of a connected medical framework is no longer a dream but is now being converted into a reality by many inspiring young entrepreneurs, as shown in Fig. 5.

While the basic requirement remains “sharing of information on time” various mediums can be used to communicate the data, be it your phone, laptop, even

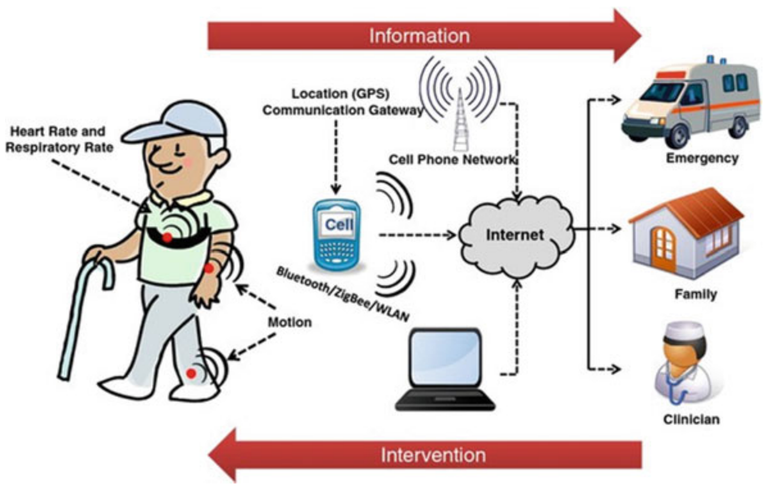

Fig. 5 Ecosystem of connected cardiac devices

your smartwatch or mask [18]. Through this quick sharing of the facts or figures for monitoring and emergency purposes, sharing and receiving of information and intervention becomes much more swift and methodical [14].

7 Modernizing Conventional ECG Monitoring Through Portable ECG Devices

The Future of Cardiac Diagnosis—Overview of Product or Service

The authors have developed the smallest and smartest portable ECG device called Spandan (Fig. 6). Spandan is a device that makes the accessibility and availability of medical-grade ECG to the common public viable. Weighing only 12 g, this device when clubbed with its AI counterpart can identify and monitor 50+ abnormalities without any medical expertise and provides the last mile connectivity to the health workers, paramedic staff, and nurses, through its report sharing feature. In case of an emergency, Spandan can also provide the required assistance to the user if a Cardiologist is not available nearby.

One of the shining features of this device is its portability. Packing into the size of a matchbox, Spandan can reduce the risk of having a cardiac attack up to 80%. The medical equipment vacuum that is present in the primary healthcare sector can easily be filled with this economical device that is also known to reduce the cost per test up to 80% when compared with the traditional test. Due to its digital features, Spandan makes medical procedures easier for patients that require routine monitoring.

The targeted customer segment is cardiac patients, primary health care, small clinics, individual practitioners, cardiologists, nursing homes, GPs, ANMs, health workers, tele-medicines platforms, e-health/m-health platforms, remote health centers, mobile health centers, and ambulances.

Implantable Healthcare Applications

Intelligent and next-generation connected [21] or non-connected devices are seen across multiple applications as shown in Fig. 7. Most valuable health information and assistive technologies can make life easier, simple, productive, and life-saving.

Fig. 6 Spandan ECG Device

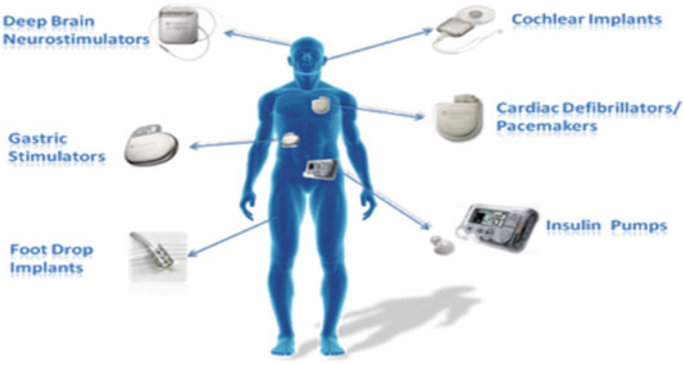

Fig. 7 Wireless Implantable devices

8 AI in Digital Health

It is well known that the medical field highly relies on the amount of information, accuracy, and precision. But when it comes to humans or even digitally empowered diagnostic instruments, significant chances of error still persist, whether it be in data collection, record-keeping, diagnosis, prognosis, etc. To tackle these problems, Artificial Intelligence (AI) is being experimented with and employed in various medical spheres as a tool to mark higher precision in a medical process. From taking care of the patients, workflow optimization, and other non-medical requirements, all can be brought under the sphere of AI [1].

While AI is still in the early stages of implementation in the healthcare field, it has already shown promising results be it in predictive medicine, computer-aided wellness technology, medical decision analysis, bed allocations, virtual assistant, medical research, all can be made simpler and more accessible to the general public with the help of AI.

9 Concluding Remarks

The application of smart technologies such as Artificial Intelligence, the Internet of Medical Things, Connected and non-connected devices built with additive and rapid manufacturing technologies have brought a quick and significant change in managing the day-to-day healthy lifestyle of the people and patients. The rapid advancements have also significantly reduced the product development lifecycle and time to real-life deployment of these innovations too. The millions of applications of these IOMT devices are leading to saving lives, predictions of diseases, management of healthcare discipline, and even reversal of critical diseases in a much more affordable way. Doctors can also manage and treat more patients easily, effectively, and conveniently in less time to create a deeper penetration and for a healthier, happier world. With these effective and handy applications, the future of healthcare services and management seems to be bright.

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Chapter 11
ICT for Real-Time Health Monitoring

Shipra Verma

1 Introduction

The Internet is a friendly and convenient user interface for collecting, sharing, and analyzing information [19]. In a worldwide communication network, the internet is on-demand, and the transfer of data necessitates the integration of technologies [28]. Before the 1990s, the use of such technologies was very limited by an average person due to its cost and complexity [2]. The Internet in particular was mainly used by research professionals and government agencies and its services consisted mainly of e-mail, usenet news, file transfer, and remote access to computers [14]. Information and communications technology (ICT) and public health (PH) integrates and derive meaningful information regarding storage, retrieval and analyze the health data [4].

1.1 Public Health Needs

Public health (PH) can be defined as the collective action for sustained population wide improvement in health. Its mission is to improve the health of populations and reduce health in equalities [12]. A large proportion of the disease burden of the world, India has been estimated to have more than a 16.8% share of the world's population [10]. It is the system which is capable of monitoring, promoting, and protecting the health and safety of the total population and sub-populations [13]. In the health information system, an integrated effort is required to collect, process, report, and use health information and knowledge to impudence policy-making, program action, and research from community to global level [24].

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_11

Fig. 1 The government role in health

The government's role evolved three public health functions at committee levels, namely, assessment, policy development, and assurance (Fig. 1).

Public health faces three main challenges. First, there is an increased recognition of the growing economic and social impact of chronic diseases on the ageing population. Secondly, changing demographics and increased longevity in developing countries have increased the numbers of those at risk for chronic diseases. Third, necessitating of health systems are to evolve in order to meet this new challenge [5].

At district level, health information enables health planners and managers to take decisions regarding the effective functioning of health facilities and of the health system as a whole. In discipline to real-time health informatics integrates the ICT to PH.

The key roles and responsibilities in public health are provided by both private and public sectors [18]. They suggest that nevertheless the absence of basic public health needs will ensure the persistence and re-emergence of the much targeted diseases (e.g. malaria, polio, and tuberculosis) and reviewed the different scenarios in India that mandate a different framework and different solutions. Alongside the rapid advent and innovation of modern ICTs, PH facilitates the health research [25].

For health GIS, disease data is spatial and dynamic. Disease data sharing is important for collaborative preparation, response, and recovery stages of disease control [15]. Web GIS supplies a more efficient platform for timely integration and dissemination of geo-referenced health surveillance data. It supplies and enables efficient data use and effective public health interventions [26].

GIS is a desktop tool and its applications have enabled users to view and analyze spatial data in its proper form [16]. Probably it is analyzed that 80% of the data contains spatial format [22]. Paper maps are an important source of spatial information for centuries. Web-based GIS (referred to as Web GIS) is a form of GIS that is deployed using an Internet Web browser [29]. Web GIS offers some of the same functions as a desktop GIS, but does not require the full suite of (often expensive) specialized software or tools that need to be mastered before one may effectively use the software. It provides a scale-independent tool that allows users to manipulate and analyze very large data sets to discover spatial patterns related to the earth's surface [7].

Web GIS provides GIS users with easy access to geographic data, spatial information, modeling and processing tools. It provides an open and distributed architecture for disseminating geospatial data and web processing tools on the Internet [17]. This makes it easier for larger organizations to distribute maps and tools without the time and cost restrictions to end-user. To provide a successful Web GIS solution, it is required to understand the complexity of the implementation process [1, 8].

The increasing need, popularity and decreasing cost of mobile devices, computer devices, and laptops, changed the lifestyle of using the Internet in our day-to-day activities. This resulted in the widespread use of the internet in Web GIS. Several Web GIS architectures have been proposed to meet the evolving needs. Web GIS is a combination of GIS and the Internet (WWW), the main trend in the future of GIS. It reproduces the main functions of GIS on a Web interface like spatial analysis, navigation (zoom, pan), dynamic creation of maps, layer overlaying, and interactive querying [30].

Nowadays, Web GIS-based applications have been gaining popularity on a large scale. The Web GIS system framework is developed in health by using adopted multi-tier system architectures, which consist of the server tier and the front tire. In present study adopts the server tier used J2EE-based architecture, while the front tier uses GIS maps to show public health information with geo-referenced information. JE is a major epidemic and problem in many parts of India and its demand by research on health planners to spread the disease information and provide facilities at public health spheres [34]. JE disease problems and its GIS Mapping and management have become a necessity utilizing modern technological tools. This study is for Gorakhpur, Uttar Pradesh, India, and the approach, to use customized ERDAS Apollo Server 2010, as an effective bottom-up method, should increase the capabilities of planners to discover and solve JE disease health problems at the district level.

1.2 Web GIS Architectures

The basic three-tier Web GIS architecture performs into the client-side and server-side where a client is a web browser [32]. Figure 1 shows a typical Web GIS-based architecture.

The features of the architecture of Web GIS are represented in Fig. 2. The server-side consists of a web server, Web GIS software, and a database.

1.3 Geospatial Web Services

Geospatial web services have been considered as a promising technology to overcome the non-interoperability problems associated with geospatial processing systems via the internet. These are particularly a type of online services, which can provide access to geospatial information stored in a database, perform simple and complex geospatial analysis [3]. Open Geospatial Consortium (OGC) has defined a comprehensive framework of geospatial web services, and this is known as the OGC Web services (OWS) framework. It allows interaction with HTTP techniques with the

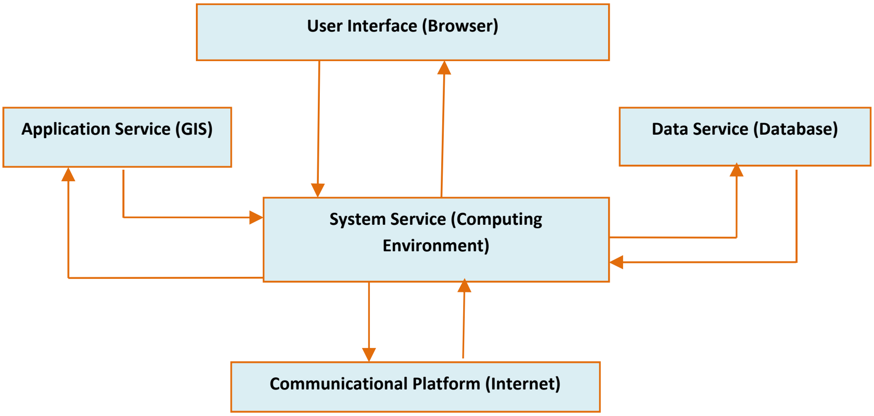

Fig. 2 The main parts of architecture of web GIS

distributed spatial processing system and provides an interoperable framework with implementation and encoding specification.

1.4 Interoperable Geospatial Web Services

The interface specifications make data access independent of underlying data format allowing tools from different GIS and internet mapping to access the same data [31]. The promise of interoperability, whereby geospatial data distributed anywhere on the Web can be searched, located, retrieved, and compiled either by a Web GIS service provider or at an individual's desktop, is becoming reality.

World Wide Web Consortium (W3C) developed interoperable technologies (specifications, guidelines, software, and tools) to facilitate minimal levels of conformity in web standards. Core specifications include Hypertext Transfer Protocol (HTTP), Uniform Resource Locator (URL), and Hypertext Markup Language (HTML) [20]. These have become the building blocks such as Extensible Markup Language (XML), Extensible Style sheet Language Transformation (XSLT), Scalable Vector Graphics (SVG), and Cascading Style Sheets (CSS). The effort to geo-enable the Web is being led by OGC. Web GIS development adopted a web 2.0 core principle platform for user participation, software development lightweight computing and programming. It makes users more customizable, interactive, social, and multimedia intensive (Fu 2011). The development of the web had a major impact on health GIS with simple web mapping, websites and then reached many milestones.

ERDAS Apollo software is interoperable, customizable, rapidly serve and manage large volumes of geospatial data. It provides Service Oriented Architecture and implements an interactively connected framework to support the management and serving of spatial data, meta-data, and maps.

1.5 Open Geospatial Consortium (OGC)

In the process of promoting geographical data sharing, OGC has developed several specifications and standards. In the field of health geography, data heterogeneities, integration, interoperability, and cartographical representation are still major challenges [6]. Several organizations are now actively involved in addressing these challenges and problems of geospatial interoperability. Interoperable systems help ensure such multiple applications. Interoperability can mean different things to different people, but the underlying factors are ease of access using common tools [11].

The OGC introduced standards by publishing specifications for GIS services to solve interoperability problems [35]. OGC is an attempt to create open standards for geospatial data and systems that are the cause of interoperability [27]. OGC web service standards can be arranged into four tiers, namely Clients, Application Services, Processing Services, and Information Management Services [37]. These standards define interfaces for raster, vector, and gridded images. The most used and well-known visualization-related OGC GIS services are GIS Mapping Services and GIS Data Services in different standards. OGC calls map services Web Map Services (WMS) and data services Web Feature Services (WFS) and Web Coverage Services (WCS). WMS returns the corresponding map, WFS supports inserting, updating, deletion, search, and discovery services for geographic elements, WCS provides coverage data in raster format, and all are encoded in GML according to the request of HTTP [38].

1.6 Japanese Encephalitis (JE)

The epidemiology of JE disease is extremely complex and even after 50 years of research; some aspects remain unresolved [33]. JE occurrence causes infection and an impact on humans [36]. The incidence is higher in males but sub-clinical infection has occurred equally in both sexes.

Saxena et al. [34] presented a brief explanation of JE in the Uttar Pradesh paddy growing area near to Terai area. JE is an endemic insignificant number of patients between 5 and 15 years [21]. Uttar Pradesh districts affected by the year 1988 outbreak were Gorakhpur, Deoria, Azamgarh, Basti, Gonda, Bahraich, Ballia, and Faizabad. Out of these districts, in Gorakhpur district, nearly half of the cases and deaths were recorded alone [23]. The viral encephalitis was reported in July through November in the year 2005 in Gorakhpur.

2 Objective

Recently the geographic interfaces, which run on different web search engines like Google https://www.google.com/ and MSN Search https://search.msn.com/ and provide the public with detailed satellite imagery/aerial photography map layers available to users [9]. For a particular field, an effective or efficient approach is needed to communicate the information with the client. The present study collected health data and information for Gorakhpur district that would enable a customized framework in a user-friendly platform, making it easier for easy-to-understand maps with just a few clicks. The online framework also would be able to increase awareness.

3 Methodology

Multiple processes were held with the client to define the functional and non-functional requirements. Software development cycles are designed to identify the data needed to build the database schema. A File geodatabase was created in a GIS environment with coded value domains and stored in ERDAS Apollo Data Manager. The disease data were imported by ERDAS Apollo 2010 cataloging process. The application enables for sharing non-spatial and spatial at online platform including the high incidence of disease risk-prone areas at the web client end and deployed on the same application server. Different steps are considered of ERDAS Apollo Web client customized framework.

3.1 Basic WEB GIS-Based Model

Disease data is spatial and dynamic. For health GIS, disease data sharing is important for collaborative preparation, response, and recovery stages of disease control [15]. A web browser can handle HTML documents and embed in standard formats. This process can utilize HTML forms and CGI with JavaScript to increase user interface capabilities, and Java applets to provide client-side functionality. It enables to share the efficient data effectively at public health interventions.

A basic Web GIS model with high performance can make a system capable of integrating spatial and non-spatial data efficiently, implementing distributed spatial computing and sharing various spatial data sources and provide an application for multiuser (Fig. 3). It also supports the Web GIS development method and distributed geospatial data.

It can be observed from the Fig. 3 that the requests are directed to the JBoss Web Application Server which in turn communicates with the ERDAS APOLLO server for data retrieval. ERDAS APOLLO Server works as the map server in this

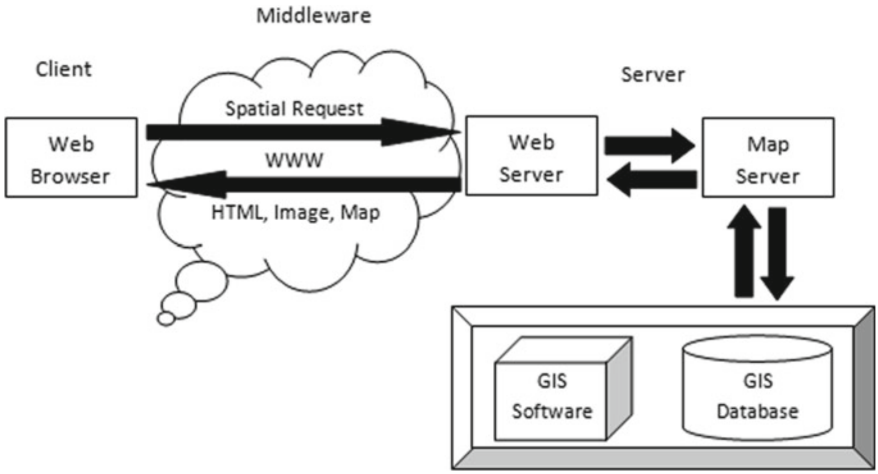

Fig. 3 Basic WEB GIS-based model

architecture. Main function and inquiries are executed at server side as adopts client-side architecture. Client side is only interacted client computer interface. The ERDAS APOLLO Server fetches the stored spatial data via ERDAS APOLLO Data Manager which accesses the geo-database consisting of public health-related spatial information. The required spatial data is retrieved along with the non-spatial attributes and returned to the client.

To develop any online framework, there is required a sequence of software development methods at the final output. The iterative waterfall method is adopted to understand each step (Fig. 4). Initially, the feasibility study is done. Next, collect the required information in terms of requirement analysis, collected non-spatial and spatial data is verified at this stage like system hardware, software, topographical maps, and statistical data. GUI (Graphical User Interface) is designed in the design phase and provides a working platform for the system (Fig. 5).

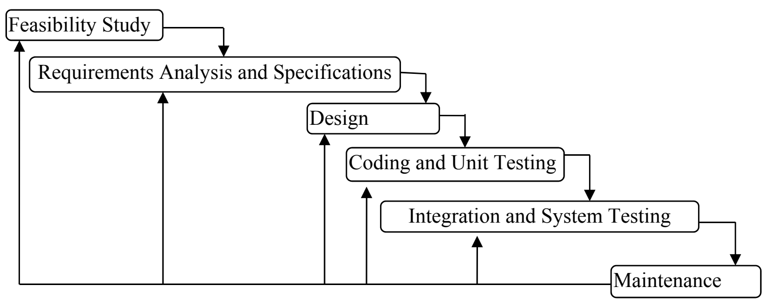

Fig. 4 Software development model

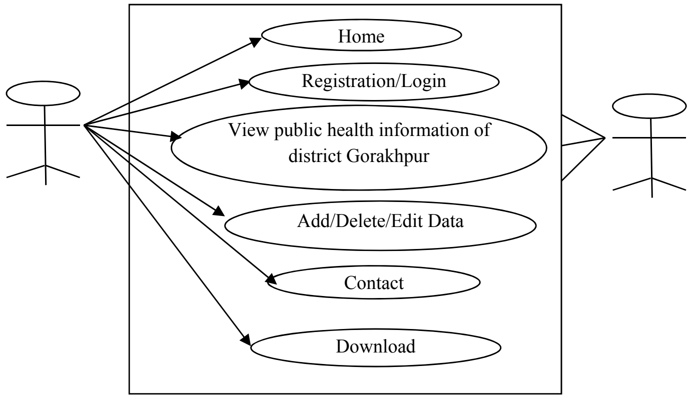

Fig. 5 Shows the design phase

A design framework has performed the relationship between content, connector, and data to reach constrained in their relationships. To achieve a basic sequential model, the main four major elements i.e. the desired set of data, architecture, component, and interface properties. In interface properties, the user interfaces first display page is Home, where the user must get registered and obtained a USERID. These USERID helps to access the system.

Coding and testing are done at ERDAS Apollo Web Client-end on JSP (Java Server Page) for creating GUI. All the modules are coded and tested properly. Every step of the development cycle is, customized and The GUI has five sub-modules which are discussed subsequently. Every module is connected to ERDAS APOLLO Web Client, and the GUI is integrated and connected to ERDAS APOLLO SERVER 2010.

4 Results and Discussion

After starting the Apollo log server, vector services are required. A Service runs via a catalogue of vector and raster services format. All detailed services are registered for the public health domain of the Gorakhpur district on JE disease. The added information shows on the map. It shows the added service as the map. The stored data have been created with the Data Manager tool. Figure 6 shows the Apollo Server Log when it is started. These figures showed the storing information on Data Manager.

After starting the Apollo log server, vector services are required. Once the service is registered and indexing has been done on the server, the data manager asks the user if wishes to see the registered service on the browser. Figures 7 and 8 show the registered service on the browser.

Fig. 6 Apollo server log

The modifying framework and existing tools are modified in the desired field of public health using ERDAS Apollo Software. It expands most specific health information and is modified to make an easy display. The main functioning of user interface was designed and organized by grouping related component based on their clarity and consistency could be done easily. On its developed framework in JSP shows first page Home, five links are available on Home Page, including, Home, Public Health Information, Public Health Management System, Important Links and Contact Us (Fig. 9).

The second link (Fig. 10), after clicking the Public Health Management System link, the login page is opened. The user can view the Interface and complete registration form.

The new user may fill the registration form and get the login id and password to enter the Public. For accessing the collected information and analysis details about JE disease Public Health Information System and various generated links to access customized framework of Web Client display, as shown in Fig. 11.

The present in each block in the study area as well as number of health facility are shown in Figs. 11 and 12.

Figure 13 is the customized framework that shows the disease affected zones.

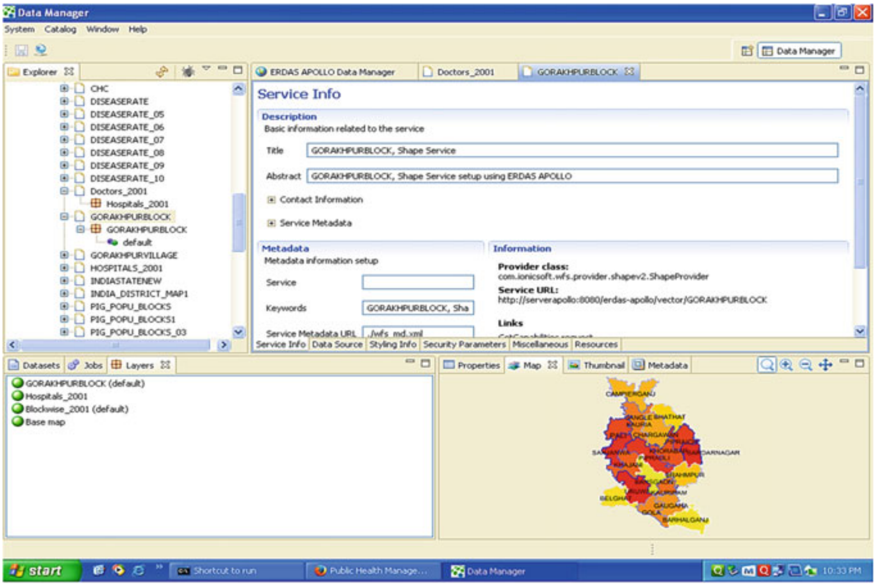

Fig. 7 Storing data on server side

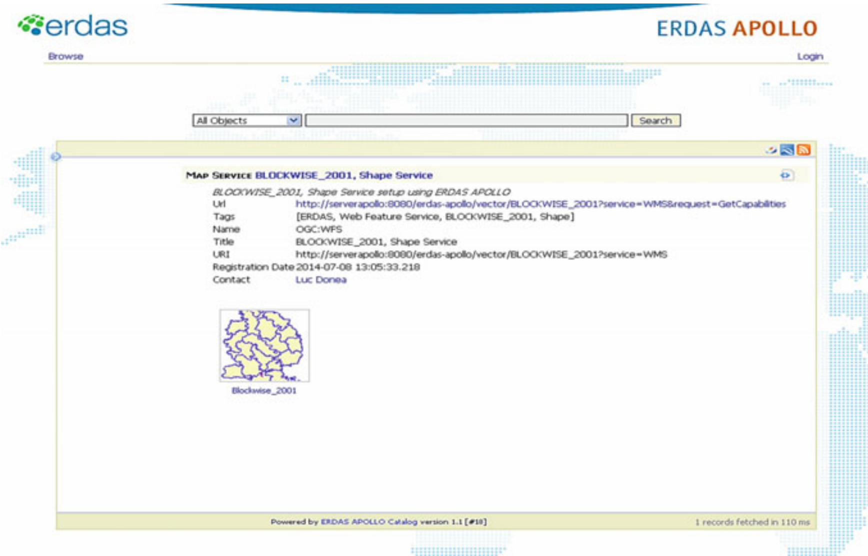

Fig. 8 Viewing the registered service on the browser

Fig. 9 Main window display on Home Page

Fig. 10 Login interface

Fig. 11 Public health information system browser

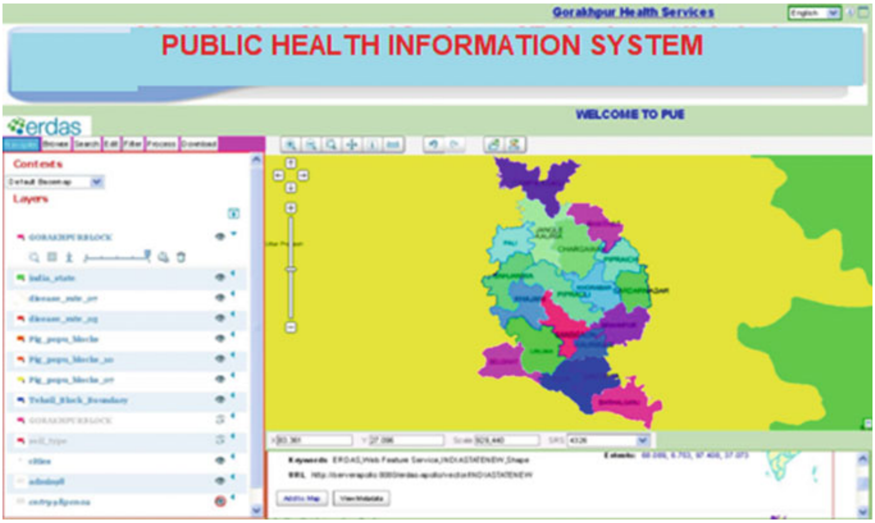

Fig. 12 Showing study area

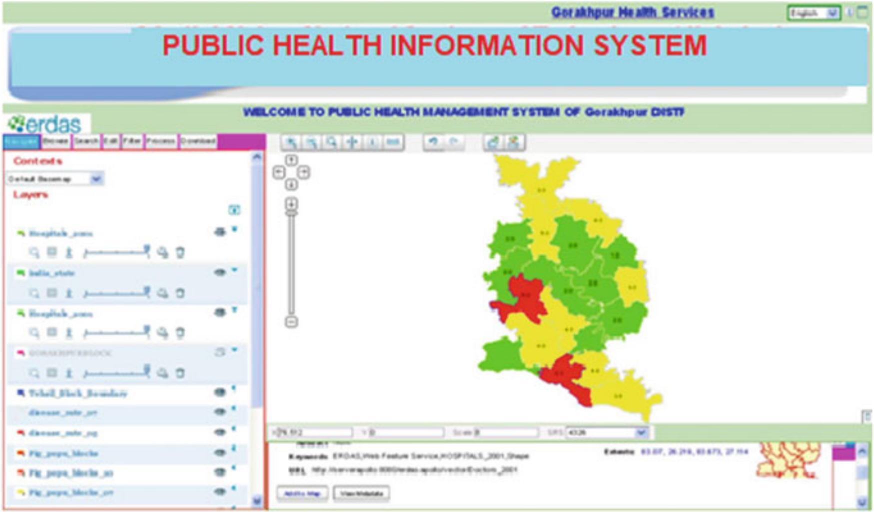

Fig. 13 Number of health facility in blocks

Users can get updated information on locations that are highly affected by JE disease in the Gorakhpur district (Fig. 14).

Integration of all data within a Web GIS framework, therefore, represents a useful approach for performing more complex analyses that can support the decision-making processes during the diffusion of disease. The public health Information

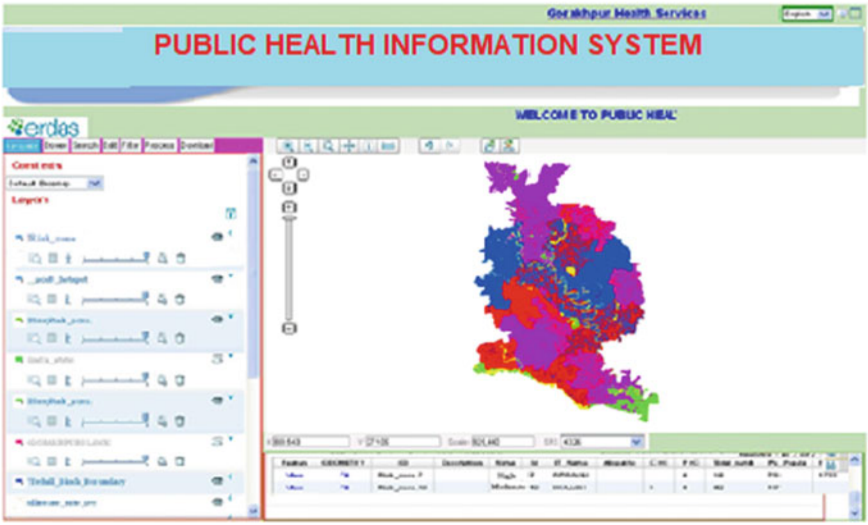

Fig. 14 System interface showing JE disease risk prone zone

system planning, prevention, remedies, and relief require precise maps with spatial and non-spatial data. This includes the development of an integrated geodatabase consisting of various thematic maps of disease incidence areas under the GIS environment. The Web GIS system faces new challenges such as sharing the voluminous data, different technology innovations with users. This customized Public Health Information System overcomes these challenges by innovating on the conventional web GIS architecture and adding client side processing to minimize the volume of data transferred between the browser and the web server.

The system provides the district health planner and managers with an effective tool to access and retrieve spatial information needed to handle JE disease outbreaks. Once a threat to a particular area of the district rapidly increases, the emergency managers can immediately respond and take appropriate action to mitigate the effect of JE disease on public health. The health planners and emergency managers need not be experts in the field of GIS as all the information can be accessed and analyzed through a user-friendly GUI. The government, as well as private sector organizations, is seeking ways to maintain and improve public health in the world and to control the costs at the same time. For achieving this, the internet is serving as a vital source of information at the global to the local level. The use of a Web GIS-based public health information and management system is an important and exciting development for the nation and health agencies.

5 Discussions and Further Work

Public health information system based on Web GIS technology has mainly two components for the platform: server end and the client end. At server-based J2EE framework is used as GIS server while user interface is used at client end to visualize public health information. The user must have enough storage and the bandwidth to transmission data.

Public health domain participated actively with information technology for managing, controlling, and preventing the acute disease. The developed Web GIS-based Public health information system creates interactive environment and will be helpful at public health domain on their initiative. The Java application, GIS technology combined with web-based technology has been applied to the public health information of the geographical distribution and the historical developing tendency. This interactive public health information system will be helpful to track infectious disease-spreading tendency, to build up the immunity isolation mechanism for the infectious disease, establish the best transportation line for the personnel and the equipment supply in the infectious region, and dynamically issue the medical service health device information on the Internet. It will have the important practical value and to protect the life and health. GIS maps used to display data and pattern at local level, with PH additionally Web GIS can perform awareness at minimum time and used. The effect of this combined accessibility into remote area. For looking further some times while in very many situations, the user possibly only needs a small area of the whole map or the partial GIS data, not the complete spatial data. So that network and the bandwidth limit get down, the system performance becomes very slow. These problems are the essential technical problems, which need to be solved in building a Web-GIS, based on the public health information visualization platform.

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Chapter 12
Role of ICT in Telemedicine

M. Ramalingam

Abbreviations

AI	Artificial Intelligence
DICOM	Digital Imaging and Communication in Medicine
ECG	Electro Cardio Graphy
EMR	Electronic Medical Records
EMRS	Electronics Health Record System
EMS	Emergency Medical System
GIS	Geographical Information System
HCX	Health Cloud exchange
HIPAA	Health Insurance Portability and Accountability Act
HIS	Hospital Information System
ICT	Information and Communication Technology
ICU	Intensive Care Unit
IoMT	Internet of Medical Technology
iOS	Iphone Operating System
IoT	Internet of Things
ML	Machine Learning
MMS	Multimedia Messaging System
MTS	Mobile Telemedicine System
NHS	National Health Services
OPD	Out Patient Department
PCP	Primary Care Provider
PHEIC	Public Health Emergency International Concern

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_12

PoC	Print of Contact
PPE	Personal Protective Equipment
RMP	Registered Medical Practitioner
VOCAL	Virtual Online Consultation Advantages and Limitations
VSAT	Very Small Aperture Terminal

1 Introduction of Telemedicine

Telemedicine is the term coined during the 1970s meaning healing at distance. Medical information is transferred via ICT technology. The doctor can use technology to communicate without being in the same room. Telemedicine has a variety of applications used for different services such as wireless, two-way video, Smartphone, and other telecommunication technology.

1.1 Evaluation of Telemedicine

Telemedicine dates back to the nineteenth century. It was initiated by the electric telegraph and the telephone inventions. Telemedicine's commercial application began in 1960. Initially, military and space departments used this. During the Civil War, telegraphs were used to order medical supplies and to report death and wounds on the battlefield. Medical consultations were also conducted through the telegraph. When the telephone arrives, the doctor gives direct medical advice to the patient. Furthermore, telephones are used to consult and exchange information between physicians [1].

Many parameters were described as telemedicine drivers and the new health care facilities are rapidly created by the availability of ICT. The rate of growth of IT and information and communication has grown with the emergence of the Internet. The Telemedicine domain has evolved into web-based apps and multimedia techniques.

1.1.1 Types of Telemedicines

Telemedicine has been divided into 3 Types (i) Store and forward (ii) Remote Monitoring and, (iii) Real-time interactive services. Each type plays a unique role in healthcare in general and offers significant advantages to medical work and patients [2].

1.1.2 Store and Forward

The store and forward telemedicine does not provide the opportunity to the medical practitioner need not meet the patient in person. Instead, medical records and bio signals can be conveyed to the professional and archived. Whenever it is required later which will be retrieved used from the storage for diagnosis with proper care. Store and forward telemedicine can save time and enable the physician to serve the public fully. This type of telemedicine is based on historical reports and verified information. This method is often used by primary care practitioners and rural practitioners in rural areas who can contact a specialist elsewhere.

1.1.3 Remote Monitoring

It uses a spectrum of technology to remotely monitor the health and clinical symptoms of patients. Such a practice is used in chronic disease management, including cardiovascular diseases, diabetes mellitus, etc. Remote monitoring benefits include cost efficiency, higher monitoring, and greater patient satisfaction. The physicians are already widely used in seniors to prevent falling and monitor residents' vital health statistics.

1.1.4 Real-Time Interactive Services

It can give advices immediately to individuals who require medical attention. A variety of media, including telephone, virtual and home visits, are used for this purpose. Providers use video conferencing software for consulting patients using real-time telemedicine. Remote monitoring of patients is effective for chronic diseases such as cardiac disease and asthma, diabetes. Remote medical professionals can automatically transmit basic medical data to physicians.

1.1.5 Examples of Real-Time Interactive Services

Teleneuropsychological consultation and evaluation over the phone with patients suspected of having a cognitive disorder is a sample of this sort of telemedicine. A study held in 2014 showed that this form of telemedicine provided a feasible alternative to a traditional in-person consultation.

Telenursing refers to the use of telecommunication technology in remote nursing. Consultation can be conducted by telephone to diagnose and monitor health concerns. Because of its minimal price and widespread accessibility, telemedicine is rising in popularity. It also reduces patient burden in hospitals by addressing minor ailments and treating patients accordingly.

Telepharmacy gives patients paramedical guidance when a pharmacist cannot be reached. Medication can be tracked and patients can be advised over the phone.

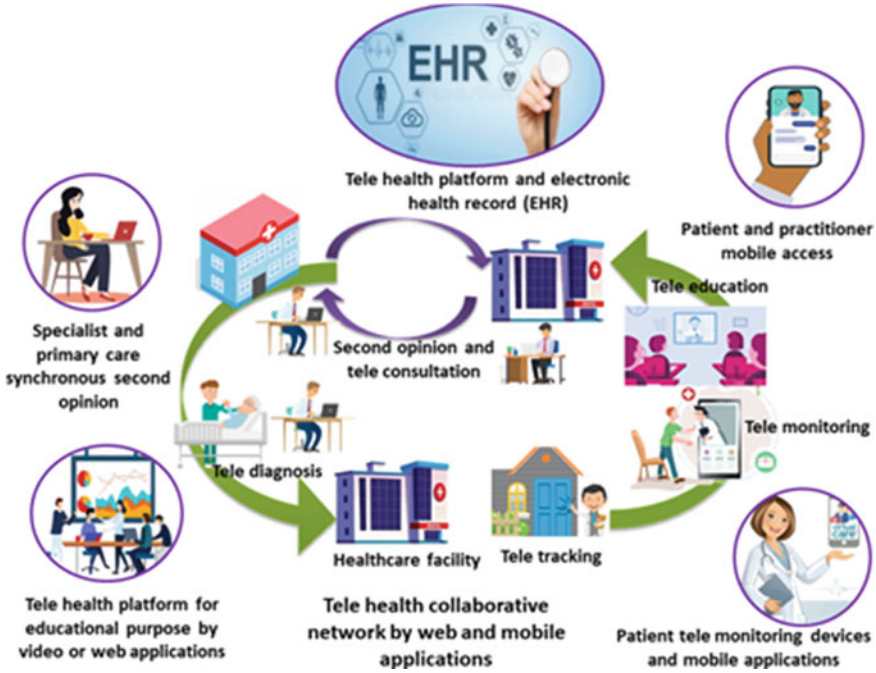


Fig. 1 Telehealth platform used in different health practices

Telerehabilitation uses technology to communicate, assess, and treat patients, with video conferences and webcams, this has significant visual aspects to enhance communication and clinical progress.

Telehealth platform used in different health practices is presented in Fig. 1

1.2 Telemedicine Today

Today, the overall number of telemedicine practices is rising at an amazing rate. Most of the researchers said that telemedicine comes into the picture during 2018. Above 60% of healthcare practitioners are already utilizing telemedicine services. Telemedicine and related services which including teleradiology are so essential for such healthcare providers [3].

The followings are the 8 Top Telemedicine trends in 2018 and beyond.

1. Telemedicine parity becomes a norm
2. Take data security more seriously
3. Better Investment opportunities
4. Increases in Consolidation of Telemedicine
5. Decentralized care

6. Patient-centred medical homes to become reality
7. Proprietary hardware expirations
8. Advanced Healthcare and Technology apps.

1.3 Advantages and Disadvantages of Telemedicine

Telemedicine is effective if the patient must be physically distanced or cannot go to the healthcare centre in person. There are several pros and downsides to the system. The following paragraphs will discuss the advantages (benefits) for the patients as well as for healthcare providers. Likewise, there will be certain drawbacks for both patients and healthcare practitioners.

1.3.1 Advantages for Patients

The following are some of the benefits to patients.

Low cast: using telemedicine patients spend less time in hospital, which saves in healthcare costs. Also, less commuting time will save some secondary expenses related to travel etc.

Improved access to care: Telemedicine facilitates access for persons with disabilities. In addition, those with disabilities can now benefit from telemedicine. As a result, other populations, including older folks and those who are physically isolated, will have easier access.

Preventive care: Telemedicine makes things simpler for consumers to receive preventive care that will aid in their long-term health.

Convenience: Telemedicine enables consumers to access comfortable care and privacy at home. This enables the person not to take time off on the job.

Slowing down infection speed: Some persons near the doctor's office can be unwell and often close to them. This can be harmful for persons who have a higher risk of infection.

Advantages for health care providers: Medical practitioners offering telemedicine services can profit from many perks as indicated below.

Reduced overhead costs: Providers of telemedicine services may incur less overhead costs.

Additional revenue stream: Telemedicine may complement the income of health care providers by allowing them to deliver care to a greater number of patients.

Reduced risk of illness and infection: When health care providers see patients remotely, they are not at risk of contracting any pathogens carried by the patient.

Patient satisfaction: When patients are not required to meet and wait, they are likely to be more satisfied with their health care provider.

1.3.2 Disadvantages

To some extent, Telemedicine may not be suitable for everyone. There are some possible drawbacks to adopting telemedicine instead of more traditional means of therapy. Several disadvantages are listed below.

Disadvantages for patients: Telemedicine is not appropriate for all patients. The following are some drawbacks they come across.

- **Insurance Coverage**: Not all insurance cover telemedicine. Only a few insurance companies currently cover or reimburse the cost of telemedicine. However, laws are always changing.
- **Protecting medical data**: When a patient accesses telemedicine through a public network or an unencrypted channel, the medical data of the patient may be accessible to scammers and criminals.
- **Delays in care**: When a person requires emergency care, telemedicine might cause a delay in treatment, especially because a doctor cannot give life-saving care or do laboratory testing digitally.

1.3.3 Disadvantages of Health Care Providers

Additionally, healthcare professionals may encounter several downsides associated with telemedicine, including the following.

- **Licensing issues**: Because state regulations vary, doctors may be unable to practice medicine in multiple states. They may practice in the state of patient resides and in Physician licences issued state.
- **Technological concerns**: Choosing the appropriate digital device can be difficult. A shaky connection can make providing quality care challenging. In addition, practitioners must guarantee that their telemedicine equipment is safe and compliant with the applicable privacy requirements.
- **Inability to examine**: Health practitioners must rely on self-reporting patients during telemedicine encounters. This may necessitate professionals asking additional questions of patients to obtain a complete health history. If a patient suffers from some major symptoms that may have arisen during personal care, treatment may be compromised.

2 ICT Operating Telemedicine System

2.1 Telemedicine System

A patient who requires medical attention comes to the neighbourhood health centre, where a local health care worker (may not be a registered doctor) takes care of the patient and does primary health inspections. This facility has the basic diagnostic equipment and teleconsultation gadgets linked to the town hospital through the PC and the internet. The local health unit is responsible for acquiring the patient's vital stability about physiological data (such as blood, urine), and images (such as ultrasound), and for transferring the data to remote urban hospitals [4]. The remote doctor examines the main vital signs in every detail once the records are received, before starting a live interaction with patients, and the meeting is organized online between patients and healthcare professionals in the remote medical unit. The doctor uses audio and video conference technology to interact with the patient live.

The general architecture of a telemedicine system is presented in Fig. 2

These remote hospitals are interconnected to a centralized database that also stores all patient records and documents, even the recorded audio–video dialogue between the doctor and the patient.

One can access the stored information via mobile apps or web-based interfaces.

The major hospitals are also connected to speciality hospitals, to support patients in emergencies, and the same teleconferencing devices are available to support remote patients in these specialized hospitals.

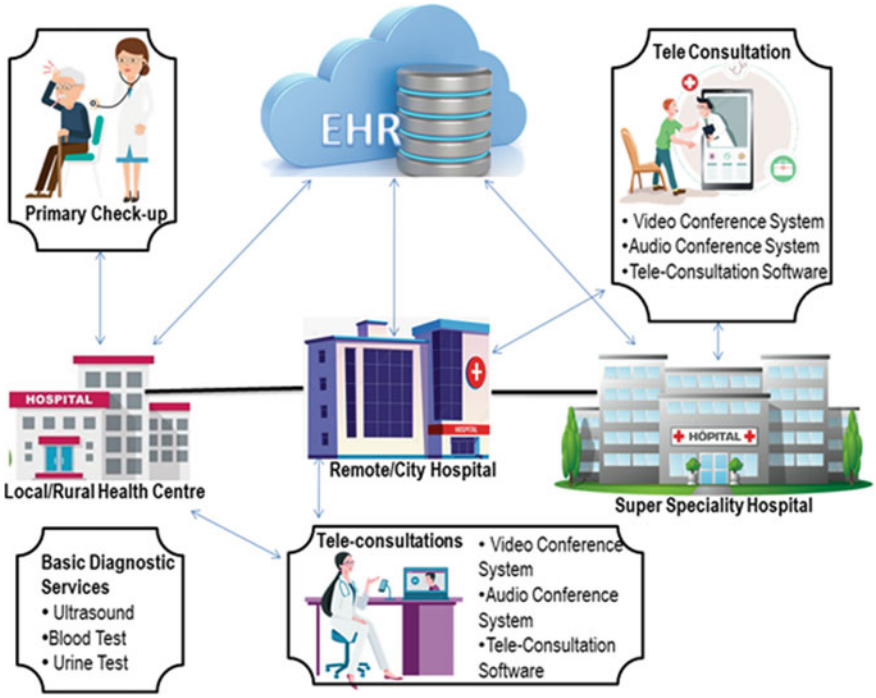


Fig. 2 General architecture of telemedicine

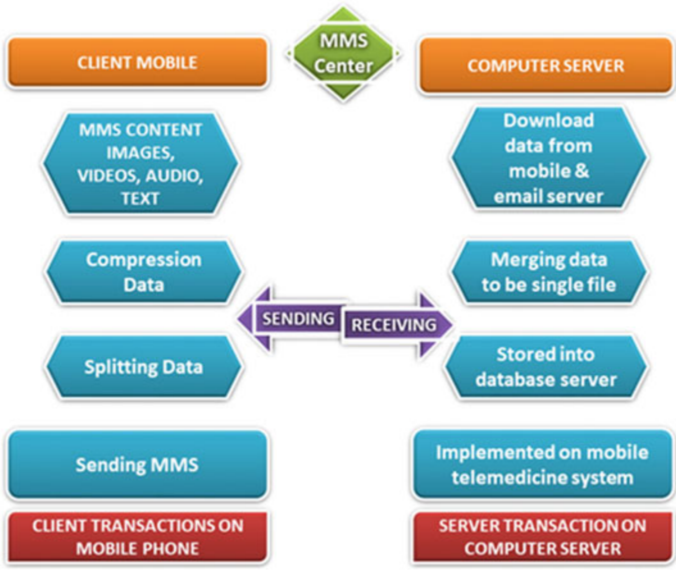


Fig. 3 Telediagnosis architecture of MMS

2.1.1 Telediagnosis to Teletreatment

Telediagnosis is the concept of diagnosing a patient's ailment from a distance using telehealth technology. Telediagnosis is described as remote access to a patient's testing results and medical history without physically interacting with the physician. There are various ways to do it.

Telemedicine supports data collection from multiple sources, transmission to social insurance, and healthcare providers over 3G/4G networks. Users can identify chronic diseases such as diabetes, skin diseases, and ECG with 3G/4G technology and web applications. The architecture is shown in Fig. 3

2.1.2 Machine Learning Approach for Telediagnosis

Machine learning, particularly deep neural networks, has shown promise in disease diagnosis.

Parkinson's disease, a central nervous system's neurodegenerative disorder, is a type of tele-based machine learning diagnosis. A smartphone-based Telediagnostic technique using a deep neural network is proposed.

The idea of classifying Parkinson's disease is based on reading and acknowledging the content after these steps.

- In smartphone applications, patients provide personal information, such as age, sex, medical records, and speech recordings.

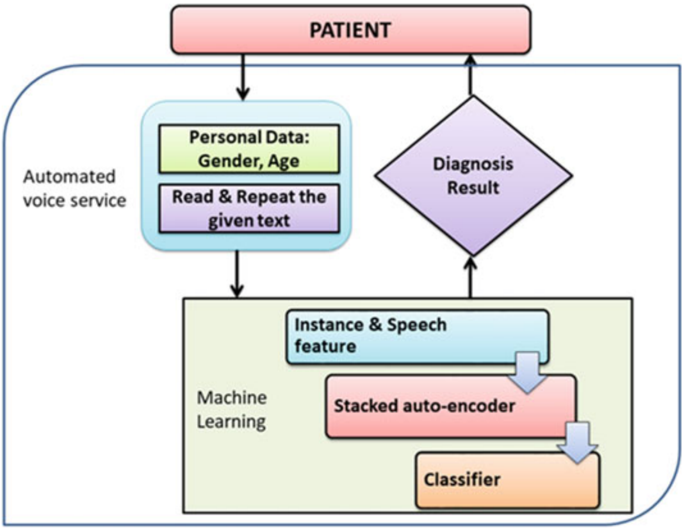


Fig. 4 Deep learning architecture for tele diagnosis

- Patient access is required to validate the information.
- Time recurrence-based features are used to assess the record of speech from the voice sample captured.
- Encode and minimize the future dimension of the stacked autoencoder (SAE) and multiple-layer encoders.
- The patients can then acquire diagnostic results.

The architecture of the deep learning method for the above telediagnosis is shown in Fig. 4

2.2 *Wireless Emergency Telemedicine System for Monitoring Patients*

ECG, recorders have an enhancer tool, a microprocessor with configurable read-only memory and a mobile phone with low transit power. The chest electrode monitored ECG recorder can be accessed via the doctor's personal computer notebook. This recording device captures ECG continuously and if the doctor wants to track the patient's ECG, one may dial straight from the laptop to the ECG recorder and send ECG to the laptop [5]. Where the patient suffers chest discomfort, the waveform of the ECG recorded is relayed to the doctor's laptop 2 min before and 2 min after switching on. The technology is wireless and the patient can be adjusted to examine the irregular pattern.

2.3 Hardware and Software Required for Telemedicine

Most people with access to basic technologies such as phone, Web, and computers. But solutions in telemedicine demand more equipment than the basic ones. Required equipment for telemedicine is stated below [6].

2.3.1 Telemedicine Carts

Most extensive telemedicine requires a cart. The telemedicine device provides a movable frame and storage system for transporting cameras, computer monitors, keyboards, computers, and mobile medical equipment. The carts look like standing work stations with computer monitors on top and wheels at bottom for easier movement. Doctors can roll these carts room to room when they meet patients and have to record and transmit patient medical data or provide a consulting doctor at another patient's visiting site. These carts are generally used in hospitals or other major healthcare facilities. In other circumstances, however, a patient could have a telemedicine station for simple access in his home.

2.3.2 Telemedicine Kiosks

Since more companies and retail clinics provide telemedicine options, many add telemedicine kiosks on site. These kiosks appear like a picture booth and are usually fitted with all the mobile medical devices and equipment needed for a telemedicine visit. These kiosks are costly and frequently only by major businesses or retail clinics used to provide healthcare services to employees and drugstore clients.

2.3.3 Digital Cameras

The suppliers of telemedicine offer high-resolution digital cameras to capture crystal clear videos. Medical practitioners utilize integrated cameras to obtain thorough medical photos and to share them with another local physician. Since this kind of equipment is expensive and often used by medical professionals. It is mainly used to store and forward biomedicine solutions.

2.3.4 Telemedicine Kit

Health care providers in the U.S. and around the world need compact, affordable telemedicine kits. These kits are like a strong portable case or a large medical kit. This system has an incorporated screen, a camcorder, and modest medical gadgets in a compact computer.

2.3.5 Portable Medical Devices

Mobile medical devices are used by either healthcare professionals or patients themselves capture medical data send it to the medical professional in a different location. In the case of a patient with a cardiac attack, a mobile ECG gadget may be needed to track his heart's functioning after hospital discharge.

Some telemedicine services include mobile medical devices or patient monitoring systems. An electronic hand-held console that asks patients questions, records their replies, and sends data to doctors through the internet. Other mobile medical devices included a vital signs monitor or ECG device.

For example, a doctor in one area has to share visual medical information with another doctor in another location, this type of equipment is more sophisticated. Some telemedicine companies offer a range of medical applications with built-in visual and audio recording equipment. Some healthcare providers exchange captured images on a USB port with other devices. Healthcare providers may utilize the digital stethoscope, record, and distribute the heart and lung sounds of a patient.

2.3.6 Telemedicine Software

Recently more telemedicine solutions moved into the cloud, certain telemedicine providers still wish to buy a software system to be installed on the computers of medical practitioners. These software solutions require additional devices such as data storage hardware and servers. All software must be tested for compatibility with a computer operating system of a healthcare provider.

Some healthcare providers also purchase multiple telemedicine software solutions for a different purpose. Rather than just one integrated software, a doctor must acquire and install software for live video conferencing and another for storing and forwarding telemedicine patient data, and collecting and monitoring patient data remotely. It is always better to go for an integrated solution that has everything in one place.

2.4 Telemedicine Using a Computer Communication Network

A VSAT-based telemedicine network has a hierarchical structure. The following is required for rural telemedicine.

(i) Network division
(ii) Legal documents from network foundation
(iii) V-Satellite communication
(iv) bandwidth allocation
(v) High cost for maintenance for TM division
(vi) High filter section circuit for transmission and receiving signal.

2.4.1 Computer Communication Network

Figure 5 shows the architecture model of logical linkages of telemedicine applications through CCN.

In this communication service architecture, distributed sharing is employed to provide an efficient service for all customers. Telemedicine users, displays of medical information, archiving and recovery systems constitute the distribution network for communication sharing. The communication between them is all depicted in Fig. 5 in the central network service. The communication network service is responsible for receiving, transferring, and distributing medical information and for managing the directions, priority, and streaming rate of information exchange. Since a network may interchange data, each customer can send and receive information over the network. To meet the special need in telemedicine application, three operation modes are defined [7].

Mode 1 is the central communication mode for setting the users communication condition.
Mode 2 is a point-to-point function that allows users to communicate point-to-point.
Mode 3 is a working method group that supports multi-point communication.

Fig. 5 Computer communication network for telemedicine

2.4.2 Application of Grid in Telemedicine Network

Grid technology is an innovative use of information technology for broad access to quick, cost-effective, and high-quality medical care. The recent rise of grid technology is providing a new way to telemedicine and medical research with underdeveloped countries, particularly to prepare a medical mission, but also to support teleconsulting, telediagnosis, and patient follow-up to the local medical centre. The grid masks the complexity of handling distributed in such a way that the physician does not know where the data is stored.

GRID technology enables the interactivity and data access of existing telemedicine systems. The benefits of the grid in telemedicine networks include, the diverse and advanced global environment uses several open standards and protocols in a wide range of systems. Grid Computing adds an endless number of computer devices in all grid environments.

Better computing and problem-solving operations within the operational grid environment.

The grid collects, 1) Drug designer for identification of new medicines. 2) Healthcare centres involved in clinical tests. 3) Healthcare centres collecting patient information. 4) Structures that participate in the distribution of current treatments. 5) Developers of IT technology. 6) Centres for computing. 7) Biomedical laboratories looking for vaccinations which operate like virus genomes.

The following services should be offered under a specified condition by a grid for research and development.

1. Large computing resources search for a new target and virtual docking
2. A large storage capacity for post-genomics and virtual docking data output
3. Grid portal for post-genomics and virtual docking data access
4. Grid gateway for medical information (clinical tests, drug distribution, etc.)
5. A collaborative environment for the participants

3 Recent Technologies and Its Impact on Telemedicine

3.1 Artificial Intelligence (AI)

Artificial Intelligence has improved many telemedicine aspects by using broadband technology and electronic data to coordinate remote healthcare services [8].

3.1.1 Artificial Intelligence Application

This technology can be used in a lot of different areas of telemedicine. Diverse artificial intelligence applications are used through the application of various neural networks, machine learning, furious logic etc. Below are some of the telemedicine applications enabled by AI.

3.1.2 Monitoring of Patients

Telemedicine is one of the first and most widespread uses in patient surveillance. This enables a more efficient and cost-effective method of conducting regular doctor–patient consults using teleconferencing and the connection of virtual medical devices to capture and record clinical data from patients. Recent telepresence robot designs are capable of walking autonomously around halls and rooms when directed remotely via a software interface that connects the user to the robot over Wi-Fi connections. This technology was recently created for navigation and obstacle detection by integrating artificial intelligence and a visual system. The implementation of artificial intelligence will fit into the concepts of machine learning equipped with sensor-based interior navigation and synchronized mopping.

3.1.3 Health Care Information Technology

With large health care data being captured in hospitals, not just through manual registration but also the use of self-diagnosis technologies, medical data will be difficult to obtain and retain. Given the purpose of telemedicine, which is to connect physicians and patients from all over the world, there is a need to develop a universal record system. The use of big data analytics and artificial neural to manage and retrieve electronic health records is a popular trend nowadays. Artificial intelligence-based data retrieval and analysis also tackles challenges encountered during healthcare treatments. This is a system that successfully handles patient records by replacing the manual procedure and making a prompt choice to begin treatment. Another trend in the evolution of monitoring patients is the use of cloud-based solutions to tackle electronic infrastructural challenges in specific sectors, such as bandwidth and implementation complexity. This advancement intends to improve the efficiency of collecting and distributing patient information by utilizing data centre services and a webserver to store and maintain the information.

Because the telemedicine procedure relies on wireless connections and the frequent transfer of patient information, there was a security and confidentiality risk. This was one of the most common reasons for people's hesitation to use Telemedicine. Several studies including image processing and AI have developed methods for securing data utilizing wavelet-based watermarking. The construction of device-to-device communications for a comprehensive security-aware transmission method by including authentication and assessing the device demonstration.

3.1.4 Intelligent Assistance and Diagnosis

Another element of robotic technology is the incorporation of aiding mechanical components, as well as the use of gathered medical data and findings for intelligent diagnosis. Both characteristics attempt to help patients physically or by evaluating early patient evaluations to help the current hospital system. These tools can be used in conjunction with a pre-programmed neural network and machine learning application. Existing technologies are introducing the usage of intelligent diagnosis in many types of software and Smartphone applications for self-diagnosis. With the known trends in medical devices, there has been a development in the market of self-diagnosing applications and devices that are quick evaluations of vital signs such as a pulse, heart rate, breathing, and so on. Doctors will assess the case and may perform telephonic consultations before issuing medications. Emergencies such as exchanging ambulance medical data with a nearby healthcare facility to collaborate and provide high-quality, timely assistance to the incoming patients can also be addressed through wireless telemedicine.

3.1.5 Information Analysis and Collaboration

In addition to collaboration, perspective, and diagnostic information, medical data will be exchanged via technology. This will change the use of large data analysis in clinical test findings in pharmaceutical research as well as the use of genetic neural networks for the recognition and analysis of data. This demonstrates the application of artificial intelligence to leverage clinical data in pharmaceutical values and treatment results. This trend will apply artificial intelligence pattern detection since health information will not only be simply stored, but also analysed. The use of computer analysis eliminates prejudices and opinions about the results. The project aims to create predictive tools for better interpretation and understanding of domestic data. The connections in health records or medical diagnostic stored in electronic health records are a major use of the neural network.

3.1.6 Challenges in Implementation

Cost is one of the biggest barriers to the use of telemedicine technology and device. Regardless of the advancement of cost-effective technology, hospitals will need to commit time and resources to properly use them. There is also a problem with a connection that creates bandwidth to provide quality telemedicine information quickly and stably. In the field of health information, there has been a broad range of future instructions on artificial intelligence. Apart from other medical processes and devices, another problem is malpractice that is why training and license are required to efficiently use telemedicine technology.

3.2 *IoT in Telemedicine*

This technology is growing rapidly and benefitting the health care domain through telemedicine. The implementations of the IoT term benefit both professionals and consumers. It's an interconnected network of internet-based physical gadgets. Computer chips and wireless networks can transform everything into IoT, and digital intelligence can be achieved through sensors.

The IoT network is shown in the figure Fig. 6

The IoT is widely used in many approaches of medical services, equipment, IT communication amongst doctors and patients. It also improves the other domain such as mHealth, telehealth, and telemedicine and so on.

3.2.1 Benefits of IoT in Telemedicine

It helps the clinician to get vital medical device data. A doctor can look at the wound, rash or colour of the skin, and assess the patient, but cannot test heartbeat, control blood pressure, and other associated vital factors. In this situation, wearable IoT devices serve a significant role in allowing the doctor to get important information. The IoT devices used by patients during the telemedicine consultation and the virtual conference are oximeters and digital stethoscopes.

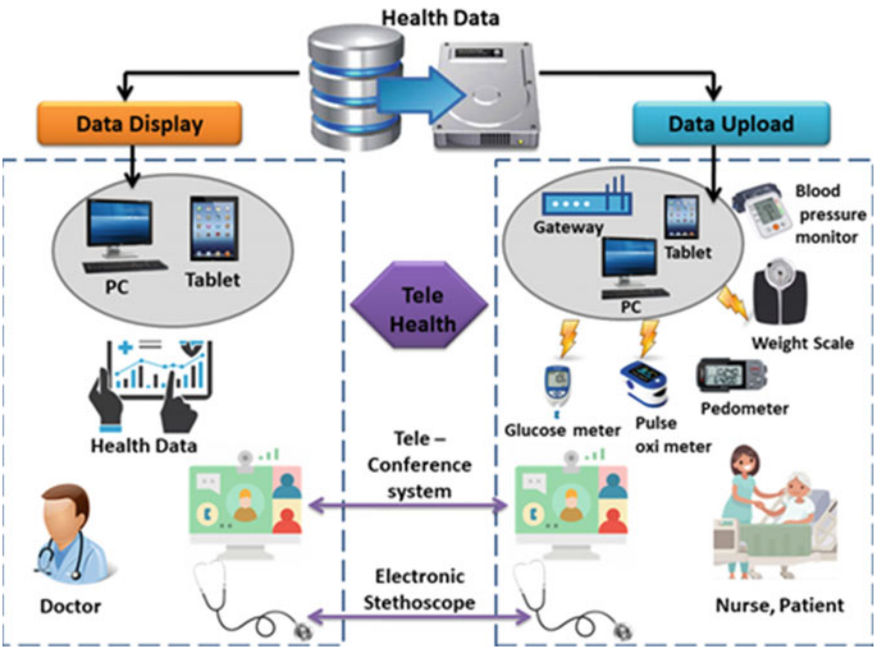


Fig. 6 IoT architecture for telemedicine

The real-time monitoring system permits doctors to obtain patient details every second via IoT devices. Holter monitor is used by patients to detect heartbeat irregularities. The rise of technology has enabled people with IoT and telemedicine to take care of their health. For older people, pray that they will stay at home during their last days instead of moving to aided living facilities. Telemedicine IoT plays an essential role in such circumstances, speech-enabled gadgets such as Alexa, voice-enabled speakers for senior citizens in their homes. These devices are also helpful for those with disabilities.

3.2.2 IoT and Its Use in Telemedicine

IoT has created new possibilities for patient care in telemedicine, including active care, home care, and long-term care. Wearable and intelligent devices, with an enhanced network and internet access, are increasingly being used. Remote patient monitoring in the telemedicine business is one of the most prominent IoT platform applications. The entire target is to reduce hospital stay, in-person visits, and overall healthcare expenditure. The technology lets patients and physicians track the actions of the patient and their impact on the essential indicators. For instance, a healthcare organization has created a remote diabetic solution that keeps track of the level of glucose in the patient's arm. The vital elements can be tracked via the application installed on your ios or Android OS smartphone.

Mobile health is a boon to innovation in the healthcare profession. The convenience of monitoring all the body's needs and obtaining a complete report on intelligent devices is one of the major advances in this area. Many patients tend to forget the doses of the recommended prescription and get carless, making the health condition much worse and the typical therapy for the disorders will take longer than usual, hurting both the expense and criticality of the disease. The ingestible sensors which travel within the human systems and remain in a certain place are detected to avoid this catastrophe. The doses completed and missed can be detected based on the sensors. These intelligent pills also limit the unnecessary use of the medicine, which could prove fatal or life-threatening. In the advanced form, these ingestible gadgets are now equipped with a camera mounted to them that shows the interior view of the parts and bodies.

3.2.3 Drawbacks and Challenges in the Industry

The drawbacks and challenges are presented as.

- Unauthorized access

  If the system has no effective security module, hackers, and other interlopers may get access to the physician and patient data. It can be harmful because the access is based on an erroneous intention.
- Concerns about privacy

If a server computer or even a single patient device gets hacked, all available data might be exploited. This affects not just the treatment of the patient but could also be a very risky factor for investing in the healthcare sector.

- Global Health care policies

  Healthcare policies are currently undergoing a transitional phase around the world. In many states and nations, the health centre and the government continue to obey the obsolete regulations that hinder the use of the right treatment technique [9].
- Regular updates difficulty

  These telemedicine IoT devices frequently demand regular updates as challenges for consumers. Not all the users are technologically knowledgeable, and so older individuals or disabled people find it difficult to remain up to date with the latest edition.

  This finding is incomplete and impedes treatment.
- Lack of sufficient memory in device

  Developers and companies provide enormous storage space on gadgets. Sometimes, lack of memory results in the patient's data being incompletely stored, leading to a diagnostic complication and obstructs further measures.
- Underdeveloped initiatives

  Several IoT concepts in the health sector are battling to achieve correct outcomes in chronic distress and other essential matters, as the industry is in its early phases. With time and additional study and development, this can be avoided. These disadvantages, however, do not outweigh the benefits of IoT in the telemedicine business.

3.2.4 Advantages of IoT in Telemedicine

The advantages of IoT in telemedicine are

(i) Lesser no-show rates: Because patients are not required to visit a hospital in person, no-show rates are reduced as a result of a packed schedule, adverse weather, and bad health.

(ii) Provides businesses with a competitive advantage: Implementing technology and enabling patients to utilize technology improves brand identity and authenticity in both the regional and global markets.

(iii) Increase Revenue: Because the technology has various advantages and requires less investment, it provides a superior ROI to businesses and hospitals.

(iv) Workability: This technology allows patients to access health care services from a remote location whilst also allowing clinicians to work and treat patients without having to be physically present in the hospitals.

(v) Cost-effective: Doctors can increase the number of appointments per day and the patient count in general with less effort and less time. In addition, the patient must pay a lower percentage of the consultation fees when compared to an in-person visit.

(vi) Under access to health care experts: Because the solution provides a list of experts and physicians available for consultation, the patient has a wide variety of healthcare professionals from which to choose and receive numerous opinions in one location.

(vii) Health care professionals are exposed to less illness: Because physicians and nurses do not have to examine patients in person, they avoid direct exposure and maintain their own health.

As new technologies are introduced into the healthcare industry, the IoT in telemedicine is expected to increase significantly. With today's hectic lifestyles and technological breakthroughs, both patients and doctors are looking for ways to improve their comfort and convenience.

3.3 Cloud Computing in Telemedicine

The Internet is such a dynamic and rapidly growing phenomenon that it appears hard for traditional humans, information systems such as libraries, in-person consulting, and peer-reviewed journals to keep up. The use of the internet for health information by both practitioners and patients is increasing at a rapid pace. Cloud computing encompasses both applications delivered as services via the internet and software and hardware in data centres that deliver services. Cloud computing stores and analyses data on remote Internet servers. For example, if a doctor uses a camera to connect the patient, he uses cloud computing. The doctor's computer is accessing software stored on a remote server and that software connects the practitioner's video and audio stream to the patient's computer and their data. This allows you to see and talk to patients in real-time.

Telepsychiatrist was the first medical field to use cloud computing. Normally, a psychiatrist counsel with the patient can be accompanied through video conferencing. In addition, it saves the patient's travel time and expenses. Cloud computing is also employed in the following telehealth fields [10]:

1. Primary care physicians use web-based cloud services in a rudimentary version to allow patients to examine their medical records, communicate with their physician, and track prescriptions and appointment scheduling from the comfort of their own homes.
2. Emergency room physicians use advanced cloud computing (e.g. video conferencing) to transport data to distant areas utilizing real-time technologies such as teleECG.
3. Cloud computing is also being used in surgery to control robotic surgery.
4. Cloud computing might be used for healthcare administration tasks.

Telemedicine and cloud computing has grown exponentially, and they combine and provide a low-cost telemedicine solution for healthcare facilities.

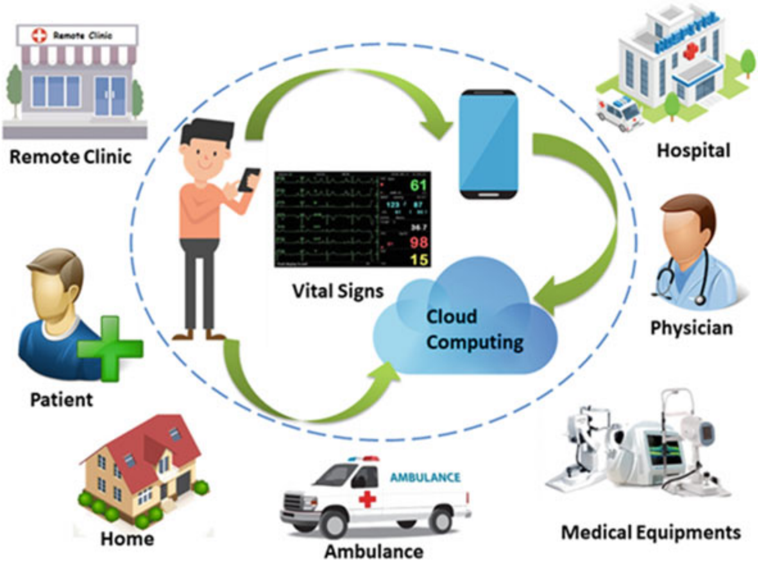


Fig. 7 Cloud computing architecture in telemedicine

3.3.1 Need of Cloud Computing

The government and private have been taken many initiatives to provide better healthcare for every citizen. Whereas in our having more than 130 million population, the scenario of e-healthcare (Telemedicine) is not up to the mark. Cloud Computing Architecture in telemedicine is shown in Fig. 7

According to UNICEF data, over 78,000 mothers die in childbirth and from pregnancy complications in India each year, and the country's efforts to reduce maternal mortality are failing due to a lack of primary medical centres. Client/server architecture has traditionally been used to implement telemedicine initiatives. Data maintenance becomes an issue with typical servers due to the vast volume of health information that accumulates over time.

3.3.2 Benefits of Using Cloud Computing

Cloud computing has surpassed all other computing architectures or mechanisms in terms of both competitive and popularity. In cloud computing, services may be scaled up or down as needed. Cloud computing provides flexibility, a quick to the production model, and capital savings by allowing enterprises to migrate all of their data to off-site providers' hosted premises. Cloud supercomputing of existing technologies as well as a paradigm shift in computing systems that employ multiprocessors, virtualization technology, network-based dispersed data storage, and networking. The advantages are

(1) The elastic nature of cloud permits infinite no. A large number of users use the cloud at the same time without restriction.
(2) Mobile devices need not do a heavy load when it comes to running an application.
(3) The cloud infrastructure is used for storing patient health information and their data.

3.3.3 The Current State of Cloud Computing in Telemedicine

According to the results of the survey, healthcare-related cloud-based applications categorized as Health cloud, Emergency medical system (EMS), health ATM kiosks, health cloud Exchange (HCX), and DICOM-based systems are all examples.

- **EMS** is an emergency medical system that uses patients' health information to deliver prompt care. It is made up of three parts: a personal health record (PHR) platform, an EMS application, and a gateway to access the forms. The PHR platform is made up of an interface that allows individuals to access their medical history data as well as authorized healthcare personnel to access the required data. The EMS application saves emergency medical data as well as application software. It has several web services available to authorized personnel in the emergency department.
- **HCX** is a distributed web interactive system that provides a private cloud data service that discovers different health records and associated health care services dynamically. HCX allows medical files to be shared between various HER systems.
- **Health ATM kiosks** are developed to manage personal health data for patients. It offers patients with rapid access to health data and strengthens the communication of the patient with their health care personnel. Individuals can review personal account information and perform transactions to manage their health care online.
- **DICOM** handles the high volume of medical data in the storage and management of the site images obtained from the intern network of the hospital.
- **@Health cloud** is a cloud-based, android OS-based mobile health information management system. It allows storage, updating, and retrieval of data via Amazon's easy storage service.

3.3.4 Tabs and Smartphones Telemedicine

One of the best ways of using cloud computing in the telemedicine field is to develop software and provide it on the cloud that can be used by doctors and other medical staff to access the medical devices used in the patient room remotely. Cloud computing and telemedicine generally lag behind other technology because some healthcare providers probably use cloud-based applications as software-as-service without thinking it is cloud computing. Recently health professionals are starting to use tablets and smartphones to access patient records. It is seen from the study more than half of the healthcare providers using smartphones, one out of four healthcare providers are using tabs. The application of cloud computing and mobile phone has been of great use in the telemedicine area. When doctors are far apart from the patients or in flight, they could still see the patient's current state through the system. One can combine the concept of video streaming and cloud computing to develop an application circuit complex algorithms Doctors' Smartphones and tablets can access essential data with a single click.

3.3.5 Challenges in the Smartphone Applications

The use of Smartphone applications has been growing over the last few years. Because of the rapid growth of the Smartphone method, many new users may not be aware of the potential risk the devices face. The growth of mobile devices with the internet connections access to the voluminous data even in a smartphone or tablets. Mobile devices have limitations as compared to desktop computers. These limitations are to be taken care of whilst developing mobile applications. Smartphone users and company administrators have a low level of security knowledge. A Smartphone carries sensitive information and because of this greater security is desired for smartphones. Confidentiality, integrity, and authentication are the most desired security services.

Cloud computing can be effectively used in telemedicine to provide great conveniences for both patients and doctors. Healthcare and medical communities that are geographically divided could benefit from the most recent breakthroughs in ICT.

4 Planning and Organization of Telemedicine Consultation

4.1 Telemedicine Session

The doctor uses the internet or other technology to advise, examine, and do procedures. Telemedicine can also be utilized for medication refills, for an appointment and for the physician to discuss the health problem and the therapy with other physicians.

Telemedicine is more than making a phone call, sending a fax, sending an email, or filling out an online questionnaire. Something may need to come to the healthcare facility to use their equipment (TV screen, Camera, and Internet). The health provider may need to use technology tools to check once health regularly. Based on the consent of the patient, part of their health records may be sent to the telemedicine provider before the session. The team and individuals participating in the patient's treatment will develop a telemedicine-based strategy for the patient's care. In the case of Emergency during the telemedicine session suitable plan will be prepared, throughout the telemedicine consultation. The health care providers and employees will make their introductions.

- When the session begins, the patient may be asked to confirm the state from where telemedicine care is being sought.
- The healthcare professional can share his/her health history, examinations, X-rays, and other tests with the patient and other professionals can also participate in a discussion.
- There may be a visual and/or partial physical examination. This may be video, audio, and/or other technology tools. A nurse or healthcare staff may be in the room with the patient to help with the exam.
- Non-medical staff may assist with technology.
- Video, photo, and audio recordings may be made.

The patient can request a copy of the session report from the healthcare professional.

All laws regarding the privacy of patient medical records and information apply to telemedicine, as well as the video, photo, and audio recordings created and stored.

4.1.1 Risks and Common Problems in Telemedicine Sessions

Telemedicine technology makes getting healthcare easy, but there are some problems.

- Diagnosis and treatment may be delayed due to equipment failure.
- Records and images that are taken may be of poor quality which leads to delay or cause some problem with diagnosis or treatment.
- If the records sent for review prior to the session are incomplete, the telemedicine provider may struggle to utilize his or her best judgement on the patient's health problem.
- There may be some problems with internet security and privacy. If the hackers are able to access the data, there may not stay private.
- If there are any technical problems, the session's medical information may be lost. This will be outside the control of doctors and telemedicine providers.
- It can be difficult to diagnose the condition without a hands-on examination.

4.1.2 Telemedicine Consultation Services Need Prerequisites

At the start of the telemedicine consultation, 10 steps are needed (i.e.) to identify the important partners, select a platform, start with a pilot, and design the product and processes. Privacy and security considerations must be ensured before the system is implemented. Consideration regarding who are the participants, payment issues and developing ongoing feedback is important. Finally, if implementation succeeds, prepare for sustainability [11].

4.1.3 Partners- Identify the Key Working Partners

Telemedicine project requires (i) clinical champions, consisting of family physicians and specialists to run the system effectively (ii) There will be infrastructure and human resources provided by the health region (iii) A hospital or local/regional health network can provide technical/e-health support to ease the system's creation, maintenance, and technical support. To reduce the financial and technical load of planning and deploying the infrastructure to host the e-consultation application, consider partnering with another institution.

4.1.4 Decide on a Platform for Your E Consultations

As technology advances, so does the ability for physicians to communicate and collaborate with one another. In order to ensure sustainability and scalability, a system should be chosen based on the local infrastructure. This is made easier by including essential partners in the initial project team. Many health care providers are using different types of computer systems, and they may next lend themselves to collaborate with external partner organizations and individuals. It is often challenging to find an application to integrate seamlessly with diverse systems.

As a result of the extranet's platforms, users have access to a wide range of capabilities, including.

- An easy to use advanced collaboration tools including document reporting, discussion books etc.
- Individually customized workspaces for the team.
- The capacity to develop a wide range of instruments, digital information, and workflows automate a wide range of power.
- Automated outboard emails and notifications delivery.
- Creation of desk base and generation of records.
- Comprehensive and secure email.

4.1.5 Pilot Study

To begin with, a small core group representing the important partners and specialists, starting with a small group, the hurdles will be identified before the system is large enough. A participative technique can be used to design the system iteratively and locally. Starting small and engaging more users early on in the development process will be critical to success. This technique allows users to design and test the system on different versions of the form, access workflows and deal with users' issues, their privacy, responsibilities, and payment.

4.1.6 Product—Design for e-consultation

Participants can utilize an online form anywhere with internet access. Use of the particular form that allows for the secure transmission of data over the internet, which is suitable for both the PCP and the specialist. There are three different forms (viz), free text, addressed form incorporating instructions for further information and existing EMR forms. The e-consultation system can be based on many different forms of consultation. System users both primary care providers and specialists to be consulted before finalizing the forms. The majority of users preferred forms that were closely matched with the way providers allowed for free text questions, the ability to connect files, and the provision of additional patient information in the form of free text. For those already conducting consultations via a computer system, this also enables them to connect a standard consult form or perform a cut and paste from an existing document.

4.1.7 Privacy—Ensure the Privacy and Security of Individuals

When it comes to employing internet-based, information-sharing technologies in the health care system, security is a major problem. Electronic transfer of a patient's information can jeopardize a patient to privacy if the proper safety measures are not taken. An assessment of the privacy impact and threat risk must be conducted in accordance with the personal health information protection act. Collaboration with the health region and partner hospitals may facilitate this endeavour. The majority of health care provider organizations will have a private office/officer can assist with the privacy impact assessment process.

4.1.8 Stages of the Process-Workflow

To ensure participation, the e-consultation workflow should be as smooth as possible with the physician's normal workflow. The description of workflow in an e-consultation system is given below.

The PCP logs into the e-consultation service using his or her username and password on a computer linked to the internet. The PCP will then open and complete the e-consultation request form after logging into the system. PCPs have the option of attaching extra files to the same page, such as images, test results, and so on. After submission of form two automatic notification emails are generated (1) to the requester to confirm the successful submission and (2) to the "Assigns" who will refer the patient to the concerned specialist. It is critical to note that the email has no information on the case other than the PCP's name and the target specialist's name. The project manager will log in to the system and assigns the specialist based on the specialities required and the availability. In other instances, a single specialist is assigned, who receives notifications and has access to cases at any time or location. When there are two or three specialists assignment rotates amongst the specialists, depending upon their availability. Where a longer group is involved, the manager provided updated e-consultation schedules based on the availability from the relevant department. The assignment prompts an automated email to the assigned specialist and to get a response within a weak. The professional logs in with his or her account and password to the e-consultation system. At this stage, the PCP is automatically notified by email of the consultation answer. The PCP would then re-login to the e-consultation system to view the specialist's response, at which point he or she could ask follow-up questions or close the case. Once the survey is completed, the system generates a pdf transcript of the case and makes it accessible to both the PCP and specialist.

4.1.9 Participants- Keep Physical Engagement Simple

Physician participation determines the success of e-consultation and physician recruitment for this project is often challenging. The clinical champions within the project team depend on their contacts and are ready to push for the system. In addition to the recruitment of PCP and specialists, different firms of advertisement including distribution of leaflets organizing medical events at booths and word of mouth also will be used to maximize reach to PCPs, specialists recruited for the purpose will also be utilized for other medical consultation on in-hospital rewards. The choice of the expert type relies on the demands of the primary care community.

In the beginning, e-consultation project managers will meet both PCP and experts to provide personal training in website navigation and the usage of e-consultation forms and also to provide future reference training. System support for troubleshooting and technical assistance should be accessible for the length of the system online. Any online service requires a central hub in which users may receive and respond.

4.1.10 Payments

In consultation with different specialists, the average rate per minute is assessed. The consultant fees are fixed based on the consultation time in the range of 1–10, 10–15, 15–20, and > 20 min.

The expert e-consultation form that ends with asking them show how long they have spent on patient consultation. Accordingly, the payment to the specialist is made.

4.1.11 Provide Feedback

Obtaining feedback was critical to know whether the services provided are satisfied for the patients. This will also enable us to identify the lacuna in patient services. In addition to obtaining physician feedback, the efficiency of the system was constantly examined by the usage and result. The usage was tracked by calculations the number of participating physicians, the number of completed e-consultation processes per registered PCP, and the proportion of requests per speciality. The response time for the appointment request and the doctor's self-request time will also be a tracker. The specialist regularly updates and includes the reference number and summary feedback, including PCP remarks.

4.1.12 Plan the Pilot to Sustainable Service Transition

Three key factors are required to achieve sustainability (1) maintaining service benefits (2) financed infrastructure, and (3) supporting human resources. The pilot project of e-consultation may be start with a seed research grant. This seed money will help to cover the startup costs, including the development of forms, system workflow, user training, and everyday operational cost. The success of the pilot project will exchange the team to seek additional funding from reputed hospitals. With the realization of secured funds, the transformation of e-consultation into a sustainable program occurs.

Access to specialists in this form of e-consultation will remain a difficulty, in addition to critical patient safety concerns. Personal stress and difficulty in transfer require seeking innovative solutions to improve care. This system will boost access to care and PCP-specialist availability. By adhering to the above basic principles, this method can be duplicated in different health regions.

4.2 Electronic Medical Records and Telemedicine Software

Physicians, nurse practitioners, clinical physiological specialists, and physicians employ telemedicine EMR software to assist with medication management, virtual treatment, and chronic disease management. It will provide the top 5 open source Telemedicine software, and EMR software that will provide comprehensive features. These telemedicine software systems will give patients with remote care that is both safe and cost-effective.

Before choosing telemedicine software, it is necessary to understand the key tools and features that should be included in a top-rated telemedicine EMR software.

- Online appointment calendar
- Web video session
- Intuitive dashboard
- Consultation
- Safe data sharing
- HD screen resolution
- HIPAA compliance
- Reporting and analysis

Five finest free telemedicine software for connecting with patients remotely and successfully.

4.2.1 EMR Software for Intel Health Telemedicine

The open-source telemedicine software assists rural health workers in providing treatment to patients in their communities. The telemedicine software system includes a powerful smartphone app for health care practitioners, as well as cloud-based EMR software [12]. The Intel health platform facilitates data reporting and enables the easy transmission of medical data to remote clinicians. The use of video tools, which include live counseling and patient education, aids in the therapy process.

4.2.2 Me EMR Software for Telemedicine

Cloud-based healthcare software enables doctors to connect via video and audio conferencing with their patients. The software also offers group conversations, screen sharing, and capture and transmission of images. Doctors can also use live chat functionality to engage with their patients. By inputting messages, videos, and images, virtual waiting rooms could be customized.

4.2.3 U See Telemedicine EMR Software

U see is a cloud-based telemedicine software platform that allows doctors to effortlessly communicate medical documents and reports during virtual sessions. Other features of the software system are patient self-programming and virtual waiting rooms. The process of setup is easy, and the software is intuitive and easy to use.

4.2.4 Go Telecare Telemedicine EMR Software

Compatible with telemedicine software that provides excellent remote communication through video conferencing. It has set up the software for EMR and medical billing. It is easy to execute and involves minimum to zero expenditure. The software system may be simply adapted to the demands of the physician.

4.2.5 EMR Software for ChARM Health Telemedicine

ChARM Health is a software solution for telemedicine that makes it easy for hospitals and clinics to schedule web-based appointments. The software provides a secure and HIPAA-compliant platform for secure storage and transmission of all data.

The telemedicine software can interface with other technologies to boost functionality easily and can operate the OPD and clinic's whole workflow. Real-time video consultations can link patients in rural locations and remotely extend care.

Those mentioned software solutions for telemedicine offer all-inclusive functions without compromising features. Most of the remedies can be easily adopted at no expense to the practitioner and the patient.

4.3 Advantages and Limitations of Virtual Online Consultation (VOCAL)

Technically available and more acceptable is remote video consultation between clinician and patient. There are a number of video communication platforms accessible for patients and healthcare systems, such as Skype. It is crucial to know how the dynamics will alter with video-based communication tools in consultation.

In a case study, a mixed-method study in a National Health Service (NHS) acute trust, London, UK, based on a Skype video outpatient consultation in two clinical contexts (Diabetes and Cancer Operations). The research consists of thorough examinations of actual consultations (micro-level) integrated into a case study (Meso level) and a national context evaluation (Macro level).

At the macro level, the physician and the patient interaction was examined during the Skype consultations. They combine audio, video, and screen capturing to generate rich multimodal data on 30 Skype-based virtual consultations. They added 17 matched voice recordings face-to-face, and the comparisons were made. The Roter Interaction Analysis System (RIAS) has supported this analysis to code and evaluate different conversation types.

At the meso level, they mapped medical and administrative processes which needed changes whilst consulting and supporting skype. Data were acquired through professional practice interviews and questionnaires, document charts, and other objects used by staff. At the macro level, they interviewed national stakeholders to gain an understanding of the national framework for virtual discussion in NHS, organizations and what actions could stimulate and simplify this.

This study also has a component of action research. They worked with top managers in several departments to identify and implement the organizational change necessary to support virtual consulting.

4.3.1 Study Findings

When clinical, technical, and practical prerequisites were met, video consultations with some patients and employees proved to be safe and popular. Compare to fact-to-face consultations, video consultations seemed to be shorter and patients did slightly more takings. Video consultations seemed to perform better if both the therapist and the patient knew and trusted one another already. In fact, many obstacles to integrating virtual consultation services are needed to build digital alternatives to traditional consulting. In a busy and financially extended hospital, a considerable and constant effort has been made to coordinate and adopt one another. They observed that the exchange of information and practices between inter-organizational collaboration seems to be crucial for service improvement.

4.3.2 The Benefit to the Patients

The use of video-based communication tools is having great potential such as skype, for remote consultation between clinician and patient. This strategy could enhance patient access to medical practitioners and strengthen their commitment to and trust in health management.

They have established considerable expertise in the establishment and training of a virtual clinic, standard operating procedure, information governance, and technical guide materials. This successful virtual consultations program may be extended to other parts of the country.

5 Clinical Guidelines for Telemedicine

All telemedicine consultations should be guided by the professional judgements of a certified medical practitioner. Seven aspects must be examined before initiating any telemedicine consultation in order for the practitioner to exercise sufficient discretion and not compromise the quality of care [13].

- Context
- RMP and patient identification
- Way of communication
- Patient assent
- Consultation Type
- Evaluation of the Patient
- Patient Administration

5.1 Telemedicine Must Be Appropriate and Suitable for the Situation

In the best interests of the patient, the required medical professional should decide if a telemedicine consultation is preferable to an in-person consultation. Before making any decision, they should assess the mode/technologies available as well as the adequacy of diagnosis. They should be comfortable with the telemedicine in the interests of the patient, often taking a holistic picture of the problem. Each patient, scenario, and medical condition may be different, for example a new patient may have a simple headache complaint whilst a known patient may be diabetes, for instance. The RMP should maintain the same level care as in-house, but within the natural restrictions of telemedicine.

5.2 RMP Identification and Patient Identification

The consultation with telemedicine should not be anonymous, but the patient and the RMP must know each other's identities. The RMP should verify and confirm the name, age, residence, email ID, telephone number, and registration ID of the patient. The RMP should ensure that a patient's credentials and contact data of the RMP are verified through a method. For the issue of prescriptions, the RMP must expressly ask the patient's age and, in case of dispute, seek proof of age. When the patient is a minor, teleconsultation will be permitted only if the child is consulting with an adult whose identification must be established following proof of age. An RMP should start each consultation by telling the patient his or her identity and credentials. The registration number assigned to each RMP by the state medical council/MCI must be shown in prescription, website, electronic infraction, should be noted here (WhatsApp/email) and receipts etc., given to his/her patients.

5.3 Mode of Telemedicine

Telemedicine consultations can be delivered using a variety of technologies. All of these technologies have their own strengths and weaknesses, as well as contexts that may be acceptable or insufficient for providing optimal care. There are primarily 3 modes, including video, audio or text (Chat, pictures, email, and fax), etc. Their strength, limits, and suitability must be taken into account by the RMP. Asynchronous exchange of information may be preferred in real-time. Assuming the RMP wishes to hear the patient talk, a voice interaction may be preferable for their diagnosis rather than an email or text. The RMP may recommend the visual examination of the patient and the diagnosis in an RMP. In view of the situation, the RMP can pick the appropriate diagnosis and treatment technology.

5.4 Patient Consent

Patient consent is needed and consent may be implicit or explicit in any telemedicine appointment. If the patient initiates the telemedicine consultation, then consent is implied. A health worker or a caregiver initiates a Telemedicine consultation then it is explicit. Explicit authorization to send an email, word or audio/video communication can be captured in any form. This must be recorded in the RMP's patient record.

5.5 Information Exchange for the Purpose of Patient Evaluation

Before rendering any professional judgement, the RMP should make every effort to gather sufficient medical information on the patient's condition.

An RMP would employ professional judgement in obtaining the sort and extent of patient information (history/examination findings/investigation reports/past records, etc.) necessary to exercise sound clinical judgement. The information can be supplemented through conversations with a health worker/provider by any information supported by technological tools.

If the RMPs believe the information supplied is insufficient, he or she may ask the patient for further information. The information may be shared in real-time or by email/text, depending on the nature of the data. Telemedicine has its own set of constraints when it comes to conducting an adequate examination. If a physical examination is required for consultation, RMP should delay proceeding until an in-person consultation can be arranged. The information requested varies according to the RMP's professional experience and discretion, as well as for various medical conditions based on recognized clinical criteria and conventional treatment protocols. RMP is responsible for maintaining all patient records, including case histories, investigation reports, and pictures, when applicable.

5.6 Consultation Types: First Consultation/Consultation Follow-Up

There are two kinds of patient consultations: first and second. When a patient initially contacts telemedicine and there is no prior consultation in the person, an RMP can only have a limited understanding of the patient. However, if the initial consultation is conducted by video, RMP can make a more informed decision. On the other hand, the patient can be handled in greater depth if the RMP has already been seen in person.

The initial consultation is to consult if a patient is visiting the RMP for the first time or if the patient has visited the RMP early but has passed more than six months after the review consultation was carried out, or the patient has visited the RMP earlier. The workflow for the first consult in Telemedicine is shown in Fig. 8

Follow-up consultations entail that the patient consults with the same RMP for the same health condition in 6 months from his/her personal consultations. It is, however, not taken as a follow-up if the spectrum does not include new symptoms and/or the

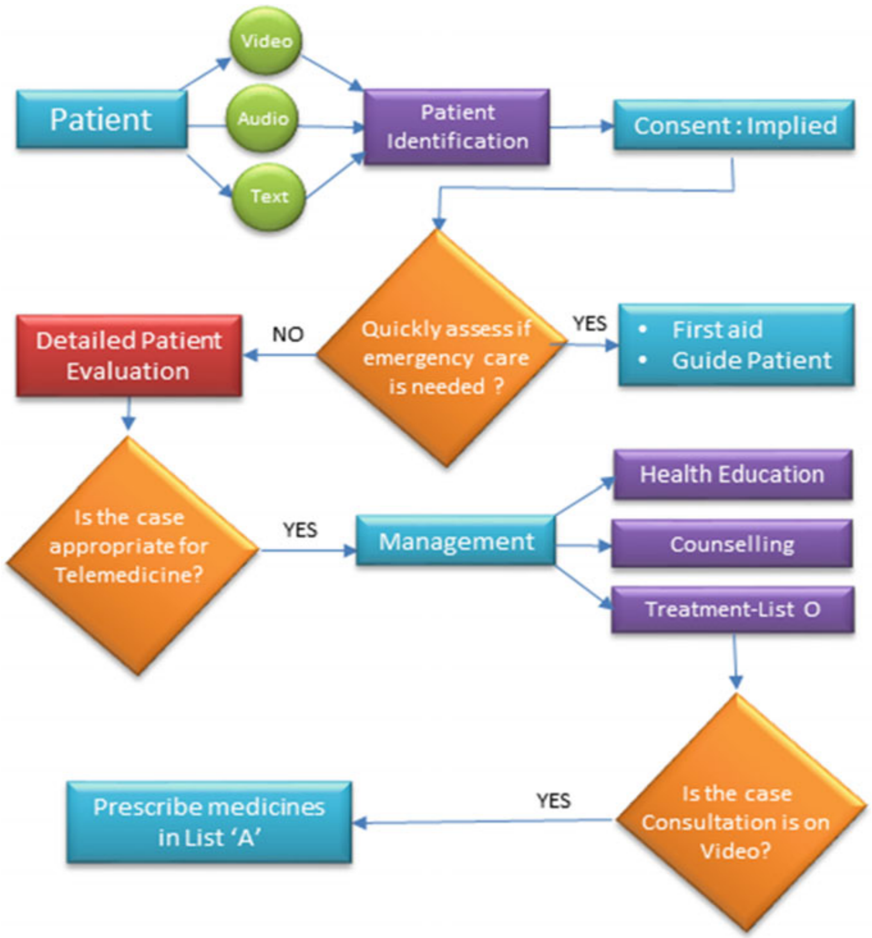


Fig. 8 Workflow showing first consult for telemedicine

RMP is not reminiscent of past therapy and guidance. The workflow showing the follow-up consult is presented in Fig. 9

5.7 *Management of Patients, Education in Health, Counseling, and Medicine*

If on the basis of the type of consultation, the ailment may be addressed appropriately using telemedicine, the RMP may take a professional judgement to

- Provide health education in the case and/or

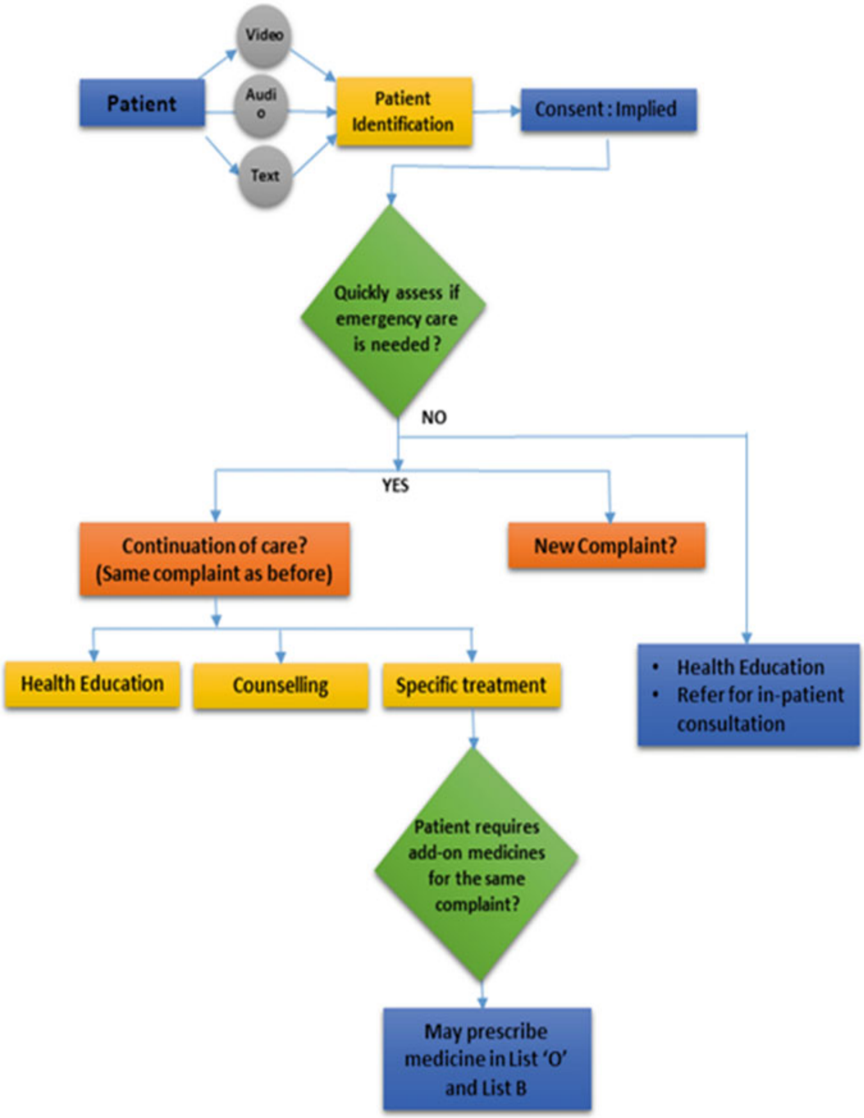


Fig. 9 Workflow showing follow-up consult for telemedicine

- Advice on specific clinical conditions and/or
- Prescribe medicines

Health Education: An RMP can prompt messages about health promotion and disease prevention. These could include nutrition, physical exercise, smoking cessation, infectious diseases, etc. He/she can also give recommendations on vaccinations, exercises, sanitation, mosquito control, etc.

Counseling: This is specialized guidance offered to patients and may include food restrictions, dos and don'ts for a patient, proper use of a hearing aid, and home physiotherapy, amongst other things, to alleviate the underlying disease. This may also contain recommendations for additional inquiries to be conducted prior to the next consultation.

Prescribing medicines: The prescription of medicines via telemedicine consultation and RMP professional description implies the same professional responsibility as in the usual in-person consultation. If a medical problem requires a specific diagnostic and prescription procedure, like a personal consultation, the same notion applies to a telemedicine consult. RMPs may only telemedically prescribe medicines if they are satisfied that they have received enough and relevant information on the state of the patient and that the drugs supplied are in the best interests of the patient.

5.8 Guidelines for Technology Platform Enabling Telemedicine

Technology platforms (mobile applications, websites) are required of suppliers of consumer telemedicine services to ensure that customers consult the national health counsel accredited with RMP and also that the relevant provisions are complied with. Before listing any RMP on its online portal, the technology platform will exercise due diligence. The name, qualification, and registration number must be provided for the platform and contact data for each RMP should be included on the platform.

In case of non-compliance, the technological platform shall report savings to BOG in supersession to MCI which may take necessary actions in the event of non-compliance. Artificial Intelligence/machine learning-based technology platforms are not permitted to do any medicine prescribed to patients. RMP alone has the right to advise and prescribe drugs and has to communicate directly with the patient. Whilst emerging technologies such as artificial intelligence, the Internet of Things, Advance Data Science-based decision-making systems etc. can aid and support an RMP on patient evaluation diagnostics or management, have to be directly provided by the RMP with the ultimate prescription or consultation. The technology platform must ensure to dealt with any issues and grievances regularly. In the event of a technological platform being found to be infringed, BOG may refer to the technology platform as a listed block and no RMP may utilize the platform to supply telehealth.

6 ICT Applications of Telemedicine Facilities

The ICT application is extensively used in the following Top Telemedicine facilities.

· Teleradiology	· Telepsychiatry	· Teledermatology
· Telepathalomology	· Teleoncology	· Telepathology
· Teledialysis	· Teleechocardiography	· Telesurgery
· Telediabetics	· Telecare in Geriatrics	· Tele ICU
· TeleObstreritics	· Telerehabilitation	· Teledentistry
· Teleneurology	· TeleEmergency services	

6.1 Tele-robotics in Health Care and Surgery

The conventional system of public health surveillance on manual and off-line analyses are slapped with low efficiency [2]. Sometimes tabular information overlooks some critical relationships and trends which are crucial for outbreak analysis and monitoring. Firstly, a static bedside robot providing drugs to patients with emotional support. The second wheel is attached for telecommunication, in particular for EB, OPD, and ICU. After a remote physical examination, cardiologists and neurologists can offer streptokinase and other relevant medications after diagnostic confidence in the golden time. The point of care (POC) robot was found to be extremely beneficial.

Automation can convert new issues when surgery is done even if fundamental and other talents are absorbed. If there are several reasons why the need arises, a surgeon may or may not feel fatigued. Tools and even research manipulation for lengthy durations are less ergonomic during endoscopy. Endoscopic manipulation is done in 3D, whereas viewing is done in 2D, and the camera is usually moved by someone else. Working with new assistants is difficult, and doing the same task day after day is monotonous.

Computers and robots will never get tired, they can configure multi-level hands and coordinate different visual differences. Robots are recommended for repetitive jobs that can be risky for users (radiation hazard) or have to be accessible to tough to reach places. The robotics score greater than human-beings comprises 360º vision, automotive zoom and unique sensors. For example, colour temperature filters can differentiate between malignant cells and normal. Multiple attachments between these sensors are most often coordinated. Even though robotics is expensive still it is used in many surgical fields especially in the endoscopic procedure that require remote manipulation. There are some limits in laparoscopic and thoracoscopic and robotics have attempted to cover these. Neurological operation is well-suited to robotic assistance implementation.

6.2 Blockchain Application in Telemedicine

In health and medical care, information regarding patients' health is shared between doctors/nurses/caregivers. Transactions must be documented and arranged in such a way that they remain untampered. The nodes in such transactions include patients, physicians/ nurses/ health care providers, and points of care. Each transaction is recorded as a block on the blockchain, which anyone interested in the information may access without the sender's consent. By utilizing blockchain, data from operations is securely saved and sensitive data is maintained in a state of secrecy.

A blockchain is a decentralized public ledger in which legitimate peer-to-peer transactions are recorded as blocks in a distribution chain [2]. The data are shared over the whole distributed structure when a block is added to the blockchain, enabling redundancy, transparency, and security. The components of blockchain technology include

- Nodes that contain the database of ledgers and current state of the transaction.
- Nodes that maintain the database of books and current transaction status.
- Smart Contracts are the consent that governs the Transaction Network.
- Contract-enabled Consensus Networks.
- Wallets manage the identity of network users.

Bitcoin (B7C) and Ethereum are examples of a public blockchain.

6.3 Geospatial Technology and Telemedicine

Recent worldwide IT developments have led to paradigm shifts in education, banking, governance, and healthcare. Global public health authorities should design a plan to modernize epidemiology with emerging ICT technology.

Geospatial, telemedicine, and internet technology are components of intelligence on public health that can help to tackle certain problems. The organization and management of geographical data is done via GIS and remote sensing and spatial modelling. Spatial data are usually in the form of layers which represent topography, health statistics, demography of healthcare, and environmental factors. Geospatial technologies are now a key tool for merging different map and satellite information sources in models simulating the interplay of complex natural systems.

The use of geospatial technologies can be made for applications such as disease surveillance systems, contingency planning systems, and the real-time reaction monitoring system. Remote sensing technology, which is a part of GIS, can help model diseases spread using satellite photos through isolating areas more sensitive to the spread of disease. Studies have also created a new paradigm that links metrology.

Climate change studies—GIS, remote sensing, and disease spread monitoring.

GIS supports the broad-based analysis of health-related events, telemedicine enables to rapidly capture information and provide health recommendations. ICT technologies are the platform for the efficient functioning of both systems. The main use of GIS and telemedicine for each of five public health activities (viz.) (a) monitoring of events (b) evaluation of events (c) verification of events (d) event information dissemination and (e) event response [14].

(a) Event surveillance

This allows health care administrators to acquire information that aids in the prevention or control of outbreaks, emerging illnesses and bioterrorism. Following is a list of data that was collected during this activity.

1. Where could be a possible event break?
2. Is a particular healthcare setup equipped to handle a potential disaster?
3. Which location is most susceptible to an outbreak of a certain type?
4. Do we have enough resources (infrastructure and personnel) to deal with the outbreak effectively?
5. What are the risks of an epidemic spreading?
6. Where should we focus our efforts on health?

Many health-related queries either ask for spatial intelligence or ask for basic health facts.

Public health surveillance systems rely on manual processes and offline analyses, limiting their effectiveness. Tabular data can miss essential dependencies and trends that are needed to assess and monitor an outbreak. However, geographical mapping and analysis tools promise to improve epidemiological surveillance quality in terms of (i) Sensitivity (ii) specificity (iii) representativeness (iv) timeliness (v) simplicity (vi) flexibility (vii) acceptability. Map overlay techniques allow GIS users to view data from several sources simultaneously. This gives the user a "Big Picture" view of the outbreak.

(b) Event Evaluation

Public health officials analyse an occurrence once it is identified by a local authority or a patient. It is used to plan an epidemic or strategy for disease eradication, calculate the risk associated with an outbreak, or visualize the impact of an event on society.

The healthcare administrators obtain answers to the following questions in order to assess a specific epidemic.

1. How an event would spread across geographic?
2. Which hospital is the closest to the centre for the specific, emergency?
3. What might be the ramifications of an outbreak?
4. If the virus spreads further, who would be at risk?
5. What impact does the outbreak have on the existing health care system?

Using GIS provides the capability to examine data by utilizing both statistics and the geographical element. As a result, a user-friendly output defining the entire problem is produced. Using geostatistical techniques the choropleth map and spatial patterns generate findings that enable the user to comprehend how the disease has spread historically and across different Geography. The outcome is extrapolated using an additional set of risk factors. One such geostatistical modelling technique "kriging" takes into account the existing underlying spatial structure of geo-referenced information. This technique is used for visualizing the spatial pattern of disease spread of the outbreak of severe acute respiratory syndrome. (SARS) was analysed using GIS techniques.

(c) Event verification

Following event assessment, event verification is used to demonstrate the event's potential significance based on available background information and facts about past outbreaks. The event verification mechanism aims to improve epidemic disease control by informing key public health personnel about confirmed and unconfirmed outbreaks of international public health significance. With the advent of ICT in the public health domain, the event verification mechanism converts large amounts of data into accurate information for appropriate action and sheds light on the following: (i) The outbreak's sensitivity/urgency of reaction (ii) populate areas that have been impacted by the epidemic event; and (iii) planning plan for public alarm and resource mobilization. WHO has developed an innovative epidemic verification system that utilizes a web-based telemedicine concept in which information is transmitted via email for the benefit of the vulnerable population.

(d) Dissemination of information

If the disease is suppressed as simply as possible, the impact of a potentially disastrous breakout can be minimized. Therefore, information on the disease and its extent should be exchanged amongst the medical institutions, healthcare authorities, NGOs, and the government, to provide a timely and efficient response. Epidemic dissemination of information solves questions such as.

(i) Where did the incident occur or did it spread?
(ii) Who or what is to blame for the occurrence?
(iii) What is the current state of resources available at the catastrophe site?
(iv) Where is the subject matter specialists located?

Geospatial intelligence incorporated in hospital information systems (HIS) provides a framework for managing, integrating, analysing, and transmitting massive amounts of data, allowing hospitals to respond rapidly to disease outbreaks.

(e) Reaction to an event

If the most crucial action plan for public health authorities because response at the wrong time sent to the wrong person, with incomplete or untrue information cost number of lives. Therefore, external expertise and help are required in order to mellow down the crisis. Each response activity answers the following queries.

- Measuring accessibility to the deceased.
- Allocating resources according to geography scenarios.
- Visualizing damage progress.

- Timing event in many locations.
- Health information via Telemedicine.
- Assessing the aftermath of the outbreak event.

Resources allocation is the primary step that any government takes in care of an outbreak. As a result, geospatial technologies enable easy deployment of teams based on their experience, proximity to needy areas, and information on existing social infrastructure such as roads, administration buildings, and military camps. Once reaction teams arrive at the scene of the incident, mobile GIS enables the collection and transmission of real-time data. In the event of an emergency, hospital space management becomes a stumbling block to giving better care to the affected. Not only do geospatial technologies aid in the visual representation of hospitals down to the bed level, but they also provide information about hospital capacity, staff on call, and patient enrollment.

As previously stated, geospatial technologies combined with remote field data collection tools, connectivity to information highways, wireless applications, and satellite systems hold a new promise for rapidly and effectively responding to infectious disease threats at the local and global level, even in countries with limited infrastructure. Traditional public healthcare will be transformed into a sort of omnipresent healthcare in the not-too-distant future, thanks to technologies such as distributed geographical data portals, geospatial libraries, and so on. Bearing in mind the explosive ICT scene, establishing and integrating the complete and responsive field of information in public health despite shifting health needs is very clearly a tough but feasible deal.

6.4 Telemedicine and eHealth Technology is Being Used to Combat the Covid-19 Epidemic

Telemedicine and eHealth platforms provide healthcare services through the use of high-speed telecommunication systems and software application technologies, medical care service management and monitoring to prevent medical practitioners and outpatients from Covid-19 exposure. These applications enable patients and physicians to communicate 24 h a day, seven days a week, via webcam-enabled computers or smartphones. This helps to conserve resources such as personal protective equipment (PPE), improves access to healthcare, and lowers the chance of Covid-19 transfer from person to person [15].

6.4.1 Telemedicine and eHealth Software Platforms for Outpatients

Telemedicine and eHealth platforms use computer telecommunications, hardware, and software system to provide healthcare remotely or from a distance. It uses interactive visual, textural and data exchanges in real-time to provide medical attention, consultation, diagnosis, advice, medical data transmission, and treatment. Telemedicine can begin with telephone consultations, but additional computing technology can be used, like webcam-enabled personal computers, smartphones, and high-speed Internet. ICT platform is perfect for managing Covid-19, therefore limiting person-to-person infection by preserving social distance and quarantine [15, 16].

6.4.2 Synchronous and Asynchronous Telemedicine Application

Synchronous telemedicine technologies empower both patients and physicians to create an idea sitting in real-time whilst rapidly exchanging important data. Asynchronous consultation may be best suited to non-emergency and outpatient routine follow-up.

6.4.3 Artificial Intelligence (AI) and Decision-Making for Machine Learning

Telemedicine incorporates algorithms to help with the definitive disposition of the patient evaluated via remote analysis. The AI conversation boxes are used for the newest information about Covid-19, including suggestions on prevention and appropriate social guidance. It also supplies medical practitioners with real-time situational reports. AI is developing the Covid-19 screening tool that can be used for preliminary testing of patients with symptoms and, if necessary, prescribe further treatment.

AI bots can be deployed to lesser high volumes of traffic through hotlines during the pandemic. Machine learning models are used to predict the most likely location where Covid-19 might be high and with AI applications to minimize and expedite the process in diagnoses and monitoring of the infection. Importing Covid-19 infection scan data into machine learning can aid algorithms in learning and improving viral detection accuracy. Thus, the application of artificial intelligence and machine learning aids in reducing the burden associated with medical operations during the current Covid-19 outbreak.

6.4.4 Robotic Technologies

Robotic technologies are being used to give concurrent and direct help to incapacitated patients more quickly and to ensure the safety of medical practitioners and volunteers responding to patients impacted by Covid-19. Several robotic techniques used in medical care (e.g. rehabilitation assistance and medical robotics) provide diagnostic and patient-care advancement support in AI; robots now operate more quickly and serve patients at a quarantine-centre isolation facility as used in countries such as China for Covid-19 treatment. These robots are equipped with inbuilt mood interpreters to understand the facial phrases of patients and receive feedback, evaluate their voice recognition and administer drugs.

Social networking applications (Facebook, Skype, WhatsApp, Face time Etc.)

The programs for social networking are utilized in self-sufficiency and social isolation. Although the eHealth platform fully replaces face-to-face interaction, it offers cases that feel lonely and unhappy because they stay at home/lock. These applications can be used in windows phones, Android, Blackberry, and ios. It can be installed in Windows computers and Apple mac books as desktop applications.

6.4.5 Medical Applications

Medical applications encompass programs providing patients with both synchronous and asynchronous medical services. eHealth platform offers medical assistance to patients residing in for off undeveloped areas where medical access care is limited. In addition, eHealth platforms link patents to remote doctors during natural disasters or emergencies. Examples of the available software for medical applications such as primary care, KHealth, Teledoc, and Doctor on request can be downloaded from Google Play or the Apple Store [17].

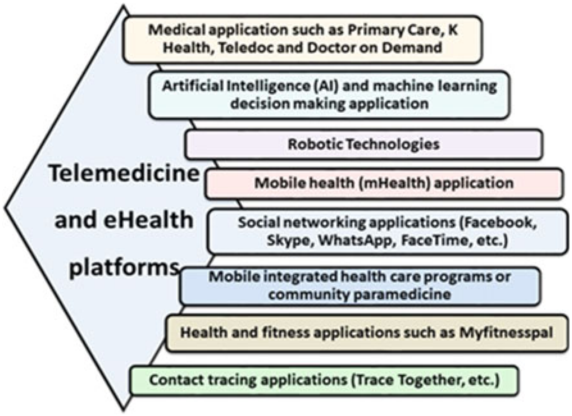
6.4.6 Health and Fitness

Applications for health and fitness are now being employed because of quarantine and social isolation leading to sedentary behaviour and reduced physical activity. This is a problem for the population spent most of the time engaged in sedentary actively. Thus, the usage of health and fitness applications may help mitigate the negative consequences of sedentary behaviour. Software such as my fitness companion, which includes a meal planner and calorie counter, is utilized to deliver health benefits.

Medical care delivery has been harmed by the Covid-19 epidemic. Fortunately, the time has come to implement technical tools like Telemedicine and eHealth platforms. Telemedicine enables secure patient communication and administration of medical care amid the Covid-19 pandemic. Telemedicine helps physicians and patients avoid the risks of infection associated with physical contact. Additionally, telemedicine and eHealth platforms can be used to deliver clinical services, and the article discusses eHealth software that can be used to deliver clinical services during the Covid-19 pandemic.

The application of telemedicine and eHealth platform is presented in Fig. 10

Fig. 10 Application of telemedicine and eHealth platform



7 Future Trends of Telemedicine Using ICT

The increase in demand for telemedicine applications is evolving day by day for online health care services. Due to the current pandemic, the majority of people are unable to see a doctor in person and are becoming increasingly receptive to telemedicine technology. The majority of physicians offer consultations via video conferencing. The telemedicine market during the year 2019 was US$ 45 billion whereas it is increased to $66 billion in 2021.

7.1 Telemedicine Market Trends

The telemedicine and the healthcare market are thriving due to COVID-19 restriction. Even those who were previously hesitant to embrace telemedicine have begun to utilize digital technologies to access medical care. According to industry forecasts, the market is estimated to reach US$178 billion in 2026.

7.2 Using of Healthcare Apps

Nowadays, the majority of healthcare organizations are establishing apps and utilizing ICT to give services to the general public. These apps are beneficial to both doctors and patients. One can easily access the apps from home with your smartphone. You do not have to go to the doctor or stand in the big queue for an appointment. Anybody can easily download the apps are available both for consultation as well as for preventive care.

7.3 Use of Electronic Health Record System

It is a computer system or software that is used by most major healthcare firms and the hospital. This system is used to efficiently manage all patients' medical records. It facilitates the online process, because the data is kept and handled automatically by the systems, and prevents duplication of data, data inaccuracies and time-saving. Doctors can easily access the data of the patient to provide the best treatment.

7.4 Use of Artificial Intelligence, Machine Learning, and Big Data

Today, the majority of industries use artificial intelligence technologies, machine learning, and big data to stimulate business. All these technologies are the driving force behind the telemedicine business. Most diagnostics and research centres in various countries use large amounts of data to predict the growth of COVID-19. Big data lets them manage enormous numbers of data in order to gain insight. In addition to this AI and ML-driven software, numerous medical processes can be automated.

7.5 IoMT and Wearable Technologies Use

Most people use intelligent wearable to track their overall health. It helps them monitor their heart rate, oxygen level, blood pressure, and much more. It is the current telemedicine trend. The wearable device data is updated instantly on the smartphone with IoMT technology in health apps.

7.6 Data Security and Blockchain

With the help of HIPAA, patient personal data are kept secure. It prevents data and medical records from being misused. Only a limited amount of information can be used. If data is to be transmitted from one node to another node safely, blockchain technology is used and the security of the data is maintained.

8 Conclusion

Telemedicine offers much in improving the health support system. Telemedicine is useful in situations where the patient is unable to attend the healthcare facility in person. The telemedicine system provides some advantages to the patients. The people who use telemedicine spends less and leads to saving in cost and makes it easier for people with disabilities can also access. It facilitates the access of people to long-term preventive care.

In order to use telemedicine effectively, ICT plays a dominant role. The various technologies viz. artificial intelligence, machine learning, large data, the Internet of things, and blockchain are extensively used. All these technology combinations are the driving force for the telemedicine business. Telemedicine also flourishes because of the spread of Covid-19. Even the people who are reluctant to use the service of telemedicine started to peer advantage of digital technology to avail medical treatment. The market is predicted to reach US$ 178 billion in 2026, according to a growing trend.

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Chapter 13
NSDI Based Innovative Approach for Development of Open Source SDI for Health Sector: A Way Forward

Rajan Dev Gupta, Sonam Agrawal, and Ashutosh Kumar Tripathi

1 Public Health and GIS

India has a rich heritage of health sciences since Vedic times (5000 BC) which has mention of Dhanvantari as God of medicine. Ayurveda emerged from Atharvaveda as a traditional form of holistic medicines. Indian medical principles were even taught in the University Nalanda in ancient times. The system of modern medicines keeps on growing slowly but steadily during seventeenth and eighteenth centuries in India. The 1st Medical College of India was established by Lord William Bentinck, Governor-General of India, in 1835 in Calcutta. This was followed by one in Mumbai in 1845 and another in Chennai in 1850 during British Raj. Since independence, successive Governments of India have achieved considerable progress in the promotion of health sector in India. Public and private are the two major pillars of delivery of health services in India. The elimination of Smallpox is commendable along with significant reduction in the mortality rate for Cholera and other serious diseases.

During last decade, health education, healthcare services, control of communicable diseases, preventive healthcare and public sanitation have improved. However, more public health centers, hospitals and other medical facilities are required keeping

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*, Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_13

in mind the growing requirements of public health for ever-increasing population. Further, quality medical service in rural areas need to be improved along with the improvement in health infrastructure to serve the rural population in a better way. In this direction, the Telemedicine Project of Indian Space Research Organization (ISRO) needs special mention which has the potential to provide specialist health services in remote areas. With a vision of reviving knowledge of ancient systems of medicine, Government of India formed Ministry of AYUSH (Ayurveda, Yoga and Naturopathy, Unani, Siddha and Homoeopathy) in 2014 for imparting education and conducting research for propagation of indigenous medicine systems.

The coronavirus disease (COVID-19), an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) novel virus, quickly turned from endemic to pandemic resulting in severe social and economic disruptions around the world. COVID-19 brought even the best health infrastructures and services of the developed nations across the globe to its knees. This is a wake-up call for the Governments of all nations for having a robust healthcare system that can handle the next pandemic as well as for greater cooperation among all the nations. Thus, there is a need of development of an efficient and scientific system for collection, storage, access, analysis and management of data related to public health in a decentralized manner necessitating the intervention of modern technological tools for improving health infrastructure and services.

In fact, about 80% of health information has spatial component that is used for assessment, planning, monitoring and decision making. Spatial data is heterogeneous and is collected from multiple organizations at different scales at varied accuracy level in different coordinate systems. There is a need for proper spatial data storage, analysis and management of spatial information which can be efficiently done using Geographic Information System (GIS). As per [3], "GIS is a system of computer hardware and software, designed to allow users to collect, manage, analyze and retrieve large volumes of spatially referenced data and associated attributes collected from a variety of sources". GIS can be used for modelling real world problems for their effective solution. World Health Organization (WHO) has also identified the value of public health mapping and GIS.

The integrated geographic database created under GIS environment consists of spatial database and non-spatial database which are properly linked together. The requirements of spatial elements of a GIS database would depend on the goals of a project. These elements are application specific, and consist of maps obtained from various sources, e.g., field surveys, published maps, photographs and remote sensing images. Non-spatial or attribute data elements are also application specific. The linkage between spatial and non-spatial data and their inter-relationship is an important part of GIS database organization. A properly designed integrated geographic database can improve the efficacy of the geospatial project work, and is vital for any planning and decision-making process.

Internet provides a convenient way for collecting and sharing information. During 1990s, the internet and web have gone through significant technological advancements. This has triggered a shift from stand-alone GIS to web GIS. Web GIS has provided GIS functionalities to the common public with the minimal requirement of internet and web browser. The initial applications were mostly developed for visualization and web mapping purposes like Xerox PARC Map Viewer, Canadian National Atlas Information Service, etc. Later on, advanced versions of web GIS were developed that offered spatial analysis functionalities. MapQuest, National Geospatial Data Clearinghouse, National Atlas of the United States and National statistics of the UK are examples of such developments. The availability of a high-speed broadband network helped in sophisticated 2.5D and 3D data rendering and visualization products like Google Earth, NASA WorldWind and Bhuvan.

With the increased usage of internet in society, web based GIS applications are becoming an important part of our daily life. Web GIS applications will provide users an easy access of GIS based information and processing tools related to public health. Web GIS applications provide a dynamic way to display the disease and health related information on the maps. For health sector, the disease information is associated with spatial and temporal factors but sharing of this information is required for awareness, preparedness, response, and recovery and control of any disease. This will prevent, prepare and respond to health needs and threats on the basis of prevailing local conditions and the population. Gupta et al. [10] developed a web GIS framework for surveillance of Malaria for Allahabad (now Prayagraj) district of India. In fact, the health services in various countries are being provided to their citizens through properly functional public health infrastructure. The creation of Spatial Data Infrastructure (SDI) for health sector is a step in the right direction for both the developed and developing countries.

2 Spatial Data Infrastructure (SDI)

For providing better spatial data accessibility and reducing the efforts involved in generation of data, various spatial agencies realized the need of SDI. As per [6], "SDI encompasses the policies, technologies, standards and human resources necessary for the effective collection, management, access, delivery and utilization of spatial data in a global community". SDI can be utilized to resolve problems related with arrangement, management and provenance of geographic information to the clients. The development of SDI has been initiated by various countries at local, regional, national and global levels. The SDI is visualized as spatial information infrastructure and can be used for design, development, implementation and monitoring the health data and policies at all levels. There is a need to develop and implement SDI using platform and vendor independent technological infrastructure and non-proprietary standards.

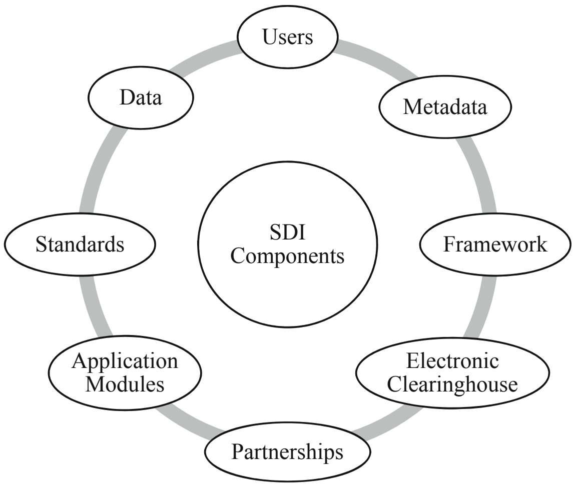
SDI development can be data or process or user centric [19]. In data centric or 1st generation SDI, its functionality is a point of concern to stakeholders because structure of data is established at a later stage after the collection and integration of data. In process centric or 2nd generation SDI, the focus is to develop the SDI using web 2.0 and latest web services. The needs of the users and data applications became the major point of focus. In user centric or 3rd generation SDI, the role of the users is shifted from passive to active. Users have now been given preference to build data infrastructure accordingly to their requirements and satisfaction. This has resulted in the design and development of SDI at local level for various sectors keeping in mind the local needs and available resources.

The backbone of SDI design and development is sharing and interoperability while discovery, access and the use of data being the purpose of SDI. The main goal of SDI is to ensure data availability to public, reduce duplication of data, improve quality of spatial data, reduce cost and promote partnership among stakeholders and users. SDIs can also be made available on the web in the form of geoportal for providing varied functionalities and facilities to the users.

The components of SDI are varied as per researchers which are primarily based on the requirements, objectives, work and spatial data vision of a particular country [8]. Based on review of the studies carried out by researchers in this field, the generic components of SDI can be conceptualized as having eight components, namely, Users, Data, Metadata, Standards, Framework, Electronic Clearinghouse, Partnerships and Application Modules (Fig. 13.1).

Users are the primary component of any SDI as SDI is created to provide data and services to the end-users. The role of users can be administrator, data producer, custodian and stakeholder. The other core component is Data because data sharing and minimization of data duplication are the major aims of any SDI. Metadata is data about the data and plays an important role in data discovery. Standards ensures interoperability of data, process, access mechanism and the technology adopted. Framework is data backbone for any SDI so that heterogeneous data collected from different sources are modified and integrated for same geographic area. This also ensures production, accessibility, maintainability and applicability of the data and standards. Electronic clearinghouse is visualized as a server whose prime function is

Fig. 13.1 Generic components of SDI



the search, discovery, access and transfer of data in SDI. This also includes various nodes from which geospatial data is accessed and shared.

Partnerships means collaborations between different agencies, institutions, corporates, public and private sectors and government so that responsibilities, costs of creation and maintenance of data, benefits and control can be shared. Application modules are value added services provided in the form of customized modules for use by end users, planners and decision makers because the goal of SDI is also the use of data for meeting their specific requirements. These application modules are based on region specific models to generate alternative scenarios for informed decision support. The access to these modules should be simple in the form of Graphical User Interface (GUI) that need to be user friendly.

3 NSDI of India

The concept of National Spatial Data Infrastructure (NSDI) came in the early 1990's when U.S. President, Bill Clinton signed an executive order number 12906 titled as 'Coordinating Geographic Data Acquisition and Access: The National Spatial Data Infrastructure' in 1994. This executive order was issued to ensure the development of 'National Information Infrastructure' so that duplication of efforts in data creation is avoided. Accordingly, "NSDI was conceptualized as the technology, policies, standards and human resources necessary to acquire, process, store, distribute and improve utilization of spatial data". This order resulted in the initiation of the process of NSDI development at national level by different countries around the globe. Tripathi et al. [20] carried out a review of SDI of various countries.

The process of developing NSDI of India commenced in year 2000 when Government of India set up a taskforce for accessing and sharing the geospatial data. NSDI taskforce was created involving ISRO and Department of Science and Technology (DST) for development of strategy and action plan for NSDI of India. The main vision was "the development of national infrastructure for the availability of and access to organized spatial data at the community, local, state, regional and national levels for use for achieving sustained economic growth [11]". Thus, there is a need for making geospatial data at local, state and the national level available and accessible to the users and stakeholders for sustained growth. In 2008, the NSDI portal was launched. However, the capabilities for data search and discovery were limited due to less spatial metadata information. The framework of Indian NSDI is shown in Fig. 13.2. The components of Indian NSDI framework consist of spatial data, metadata, standards, framework, electronic clearinghouse, communication network and application specific modules.

However, there are several issues that need to be addressed in Indian NSDI, e.g., geospatial database is maintained by National Natural Resources Management System (NNRMS), Natural Resources Data Management System (NRDMS) and Integrated Mission for Sustainable Development (IMSD) which works under ISRO, DST and Department of Space (DOS) respectively. These three organizations have

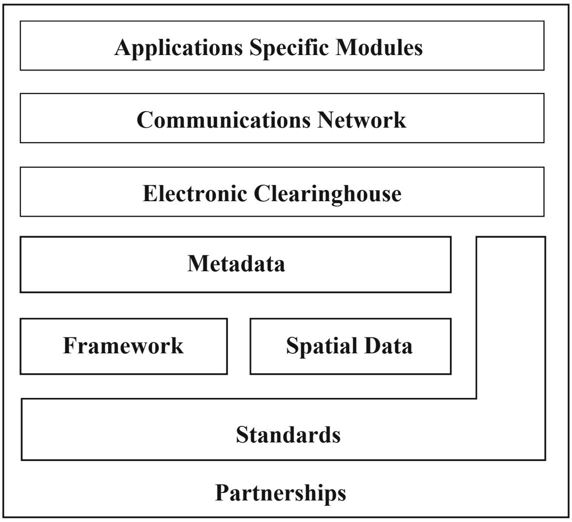


Fig. 13.2 Indian NSDI framework [11]

created duplicate geospatial data for same districts but data integration is difficult due to different standards and policies adopted [15]. The detailed analysis of Indian NSDI metadata standards reveals that the content and structure of Indian metadata profile is facing difficulties of elements and standard duplication. Further, lack of common catalogue repository, out-of-date datasets, non-accessibility of service metadata, duplication of effort during the generation of data are some common problems associated with the data, metadata and electronic clearinghouse of the Indian NSDI [7, 12, 14]. Therefore, there is a need to adopt Open Geospatial Consortium (OGC) standards for Indian NSDI for interoperability.

In developed countries, SDI has become a part of the basic infrastructural facilities that is efficiently coordinated and managed for development. Several countries have also taken initiative to establish a well organized GIS based disease mapping and surveillance system as well as public health information infrastructure. Tripathi et al. [21] proposed a framework of public health SDI. In India, there is a need for development of interoperable SDI for health sector at national level with its nodes being at State and district levels. The district level node will cover the information at micro level, i.e., village level. The development of interoperable SDI for public health can be taken up as the policy matter by Indian Government and can be implemented as one of sub-systems under Indian NSDI.

4 Open Source Geospatial Resources (OSGR)

OSGR refers to open source geospatial and other software and resources that are used for the development of web based open and interoperable SDI and GIS applications for solving real world problems. The distribution terms of Open Source Software (OSS) need to comply with ten stated criteria which primarily include free distribution of source code, software, derived work without any discrimination against any person and the license must be technology neutral. The mission of Open Source Geospatial Foundation (OSGeo) is to increase global adoption of open geospatial technology. OSS not only allow users to modify the source code according to their requirements but also provides better interoperability. Now-a-days, there is a shift toward open geospatial which includes open data and open standards. Open data refer to freely available geospatial data while open standards allow users to work together and promote interoperability between applications and systems without technology lock-in.

Open Geospatial Consortium (OGC) is working for making the geospatial information and services FAIR (Findable, Accessible, Interoperable and Reusable). OGC creates freely available open standards for interoperability so that map contents on web are published and the location information is exchanged among users and agencies as well as enabling fusion of information from diverse Internet of Things (IoT) devices. OpenGIS® is a registered trademark of the OGC to enable geoprocessing technologies interoperable or plug and play. OpenGIS® standards empower technology developers to design and develop interoperable solutions that 'geo-enable' the web. Interoperability enables the geospatial information and services accessible, modifiable and adoptable with different web based GIS applications.

OGC has empowered web GIS by providing protocols, technical specifications and data exchange standards to build interoperable solutions. The geospatial data is published, exchanged, processed and visualized over the web by the OGC standards like Web Map Service (WMS), Catalogue Service for the Web (CSW), Web Feature Service (WFS), Web Processing Service (WPS) and Web Coverage Service (WCS). The interoperability of web GIS has enabled the use of all kinds of geospatial data and software that adheres to the OGC protocols. The OGC compliant web services offer raster and vector data that helps in data sharing. The required web services can thus be integrated in web GIS applications. Agrawal and Gupta [1] developed OSS based Web GIS frameworks on WAMP and Apache Tomcat web servers and made a comparative study. The OSS available in geospatial domain for generation of integrated geographic database, geospatial analysis and web services were studied by Barik et al. [4]. Further, Gupta et al. [9] used OSS efficaciously for the development of non-proprietary framework for Health GIS. In fact, the capabilities of OSGR available now-a-days are comparable and in some cases are even better than proprietary software.

For web based GIS applications, one major issue faced is the capture of spatial data from heterogeneous sources and their integration for spatial analysis and modelling. With the advancements in the field of web technology, the access, visualization, management and analysis of geographic database has become easy. Now-a-days, the main focus is on the ease of use and support for open standards for enabling the varied users to share the spatial data in an interoperable way. OGC web services provide interoperable framework for discovery, access, integration, analysis and visualization of multiple web based geospatial data. The discovery of datasets is of utmost importance in SDI which is also managed by the OGC CSW services. Thus, OGC standards have supported the development of SDI by providing the specifications for the discovery, access, transportation and use of geospatial data. This laid the foundation for building the SDI and geoportal using OSGR.

5 Framework of Open SDI for Health Sector (OpenSDI*4*Health)

The main aim of this work is to develop an innovative approach based on Indian NSDI framework to design, develop and implement an OSGR based open and interoperable SDI for health sector (*acronym* OpenSDI*4*Health). Since Indian NSDI framework is adopted as the basis for the development of the framework for OpenSDI*4*Health, hence its framework is conceptualized and designed with six core components, namely, spatial data, metadata, standards, electronic clearinghouse, communication network and application specific module. The interoperable framework adopted for OpenSDI*4*Health is shown in Fig. 13.3.

The first component is spatial data which in the present case is integrated geographic database developed for the study area. The second component is metadata which is then gathered/generated and published on the web for searching and sharing of the spatial data. The third component is standards in which standardization of spatial data and metadata is performed to make it compliant with OGC services. WMS standards are used for the data distribution and access while CSW is used for data discovery. The electronic clearinghouse unit, i.e., the fourth component defines the availability of the spatial data and catalogue information. Metadata plays a crucial role here to check the availability of data. In other words, clearinghouse is a search and access protocol engine of the catalogue information.

The fifth component is the communication network unit which defines the medium of communication and network arrangement through network gateways and protocols. The authentication of users, i.e., authentication services and accessibility of spatial data is also done through this unit. Application specific module is the sixth component in which one selective user specific application is investigated and presented for users, planners and decision makers. The specific application in the form of hospital site selection is investigated by developing Spatial Decision Support System (SDSS) for this purpose and using Multi-Criteria Decision Making (MCDM) technique under GIS environment.

The building of web based GIS applications using OSGR makes the system interoperable and cost-effective. OSGR for analysis, processing, manipulating, storage and service delivery of geospatial data are available which suit the geospatial community. Various OSGR used in the present work for the development of OpenSDI*4*Health include the following:

- QGIS: GIS database creation and spatial analysis
- Apache Tomcat: Web server

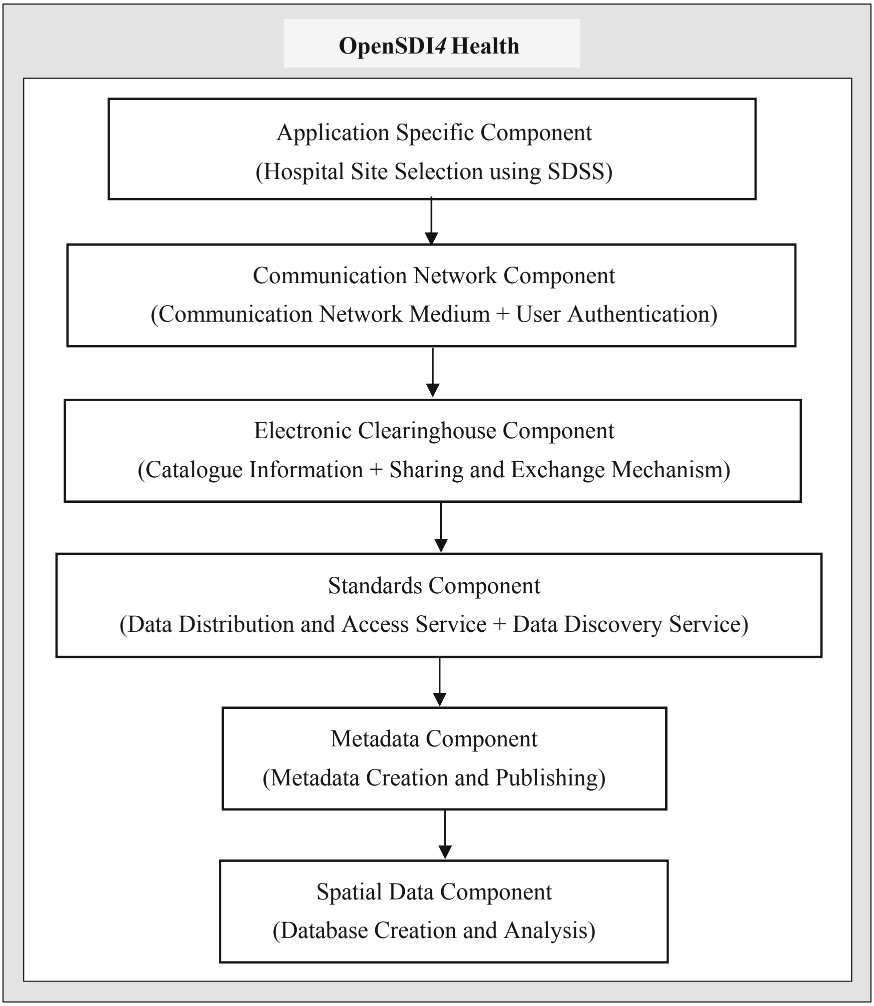


Fig. 13.3 Framework of OpenSDI*4*Health

- GeoServer: GIS server
- PostgreSQL with PostGIS spatial extension: Spatial Relational Data Base Management System (RDBMS)
- uDig: Styling of layers
- JSP, HTML, CSS: Web based GUI development
- OpenLayers: Generic web mapping components for applications

6 A Case Study: Prayagraj City (India)

Prayagraj city (*formerly* Allahabad city) of Uttar Pradesh State of India has rapidly developed and expanded in last two decades due to high urbanization. The city is located at Sangam (confluence) of three sacred rivers, i.e., Ganga, Yamuna and (invisible) Saraswati. Prayagraj is famous for Kumbh Mela religious gathering. Ministry of Housing and Urban Affairs (MoHUA), New Delhi has selected Prayagraj city as a Smart City in 2015 under the mission of 100 Smart Cities [13]. For improving the quality of life and driving economic growth, Government of India initiated an innovative mission, termed as Smart Cities Mission, throughout the country so that sufficient infrastructure facilities are provided for enabling local area development with smart outcomes for citizens. There is a need to adopt modern technological tools for scientific planning and sustainable development for the transformation of Prayagraj city as a Smart City. Therefore, Prayagraj city is selected as a case study for development of OpenSDI*4*Health.

Prayagraj district consists of 08 tehsils and 21 community development blocks. Prayagraj city lies between 25° 23′ 08" N and 25° 32′ 11" N latitudes and 81° 43′ 29" E and 81° 54′ 11" E longitudes having average altitude as 93.77 m. The total population is 1,112,544 [5]. The city is divided into 80 wards (Fig. 13.4).

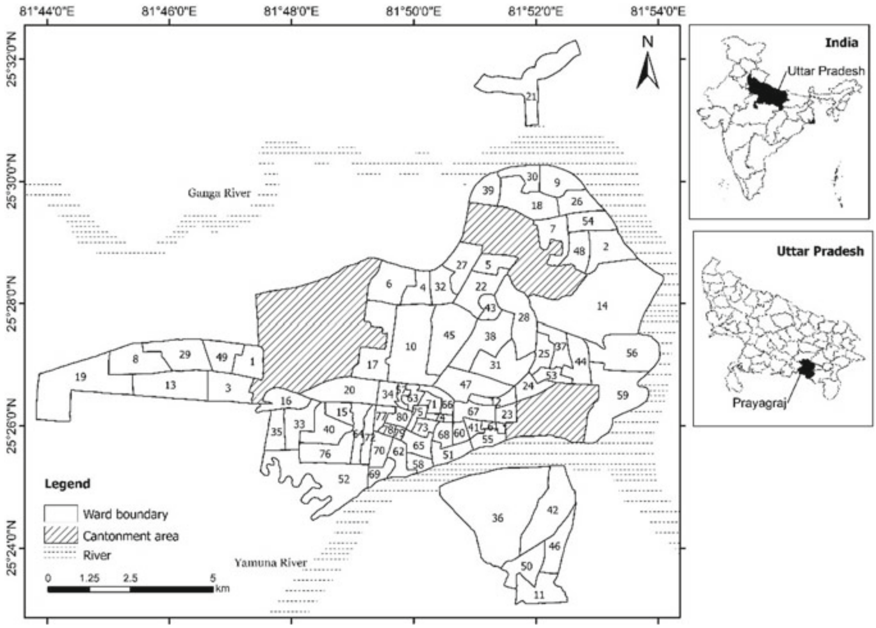


Fig. 13.4 Ward boundary map of Prayagraj City (India)

7 Development of Web GIS Based Architecture for OpenSDI*4*Health

In general, web GIS architecture has web browser as a client for sending the request and a web server for responding to the request along with an additional server called GIS server for providing geospatial functionalities. Three tier thin client server architecture is adopted in the present work for imparting geospatial web capabilities to OpenSDI*4*Health because it has minimal resource requirement on the client side as most of the processing is done at the server side [2, 16]. It uses OSGR to manage the database, publish the spatial data on the server and authorize the users. Figure 13.5 presents the layered architecture view of the proposed OpenSDI*4*Health, and consists of three main layers, namely, data layer, application layer and client layer.

7.1 Data Layer

This layer provides storage of spatial data and metadata in database. Metadata database is also known as catalogue. PostgreSQL with PostGIS is used for the creation of spatial database. GeoNetwork is by default installed with the McKoi SQL database. McKoi SQL database is an open source database written in Java. Apart from this, tabular file system format is also used for storing some additional metadata information at the time of creation or update. In the present framework, GeoNetwork CSW server is directly connected to this catalogue.

Users can store and maintain their metadata records through GeoNetwork CSW server. The synchronization between spatial database and metadata is necessary so that the changes made in published spatial data reflect in metadata automatically. Moreover, proper database creation also helps users to insert, delete and update spatial data and metadata as per their need. The multi-source data are uploaded on the spatial database and then published on GeoNetwork.

7.2 Application Layer

OSGR are used for creation of the application layer which include three independent servers viz., web server, GIS server and catalogue server. Apache Tomcat is deployed as web server through which other servers communicate. GeoServer acts as GIS server to publish different forms of data like raster, vector, etc. It directly publishes data that are stored in PostgreSQL/PostGIS database using OGC compliant services. GeoNetwork works as catalogue server, which stores metadata information related to the associated spatial data. It allows users to search, query, update and manage metadata information by implementing CSW services.

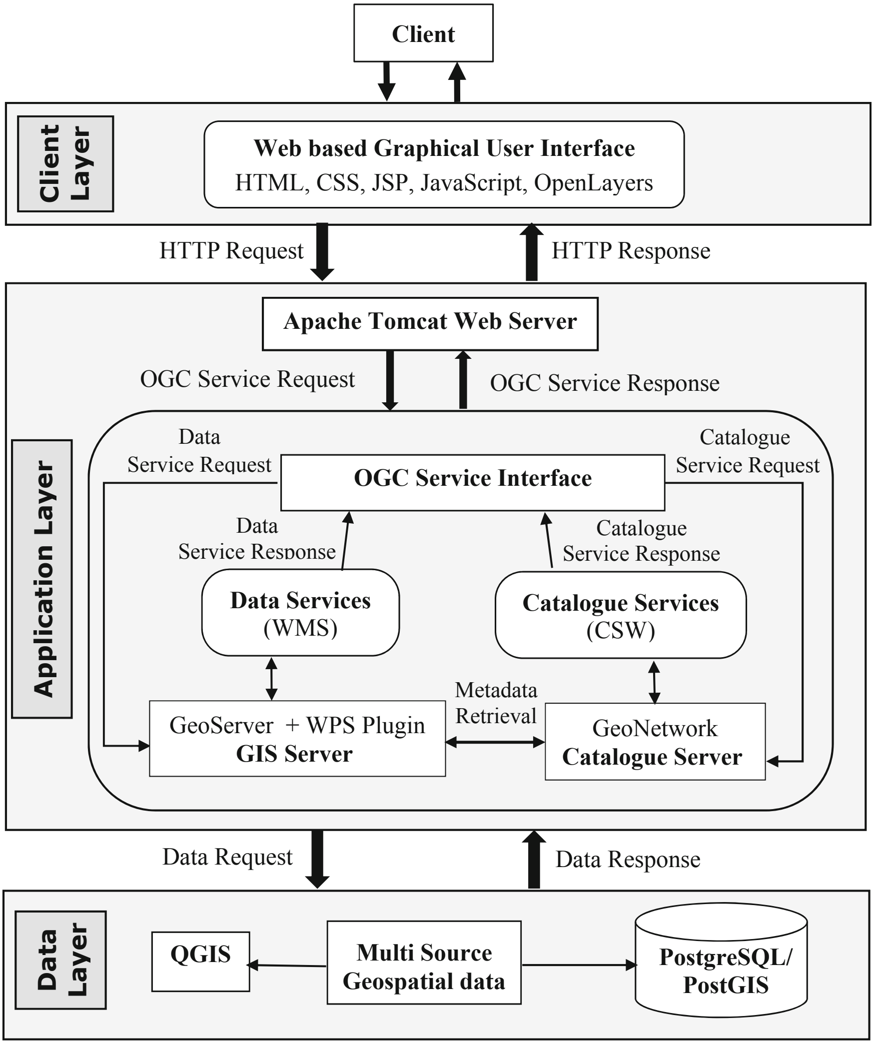


Fig. 13.5 Web GIS based architecture of OpenSDI*4*Health

In this layer, web server requests spatial services from OGC service interface. This interface divides requests into two parts. One is data service request which is handled by GIS server while other is metadata request which is catered by catalogue server. This layer configures a centralized environment where both servers are interconnected to each other to implement the synchronization between data and its metadata. Metadata catalogue is implemented by metadata retrieval operation. OGC service interface provides required metadata and data services by the response received from catalogue service and data service respectively.

This layer implements different OGC services, e.g., WMS, CSW, WFS and WPS to the application interface. OGC WMS specification helps users to render the processed data over the web in different image formats like png, tiff, or jpg. CSW specification helps to implement the discovery and retrieval platform for service metadata. WPS is used for performing geoprocessing tasks in web environment. WPS processes are flexible and remotely accessible; therefore, these can be easily reused for different applications. GeoServer with WPS plugin is used for providing geoprocessing functionalities to OpenSDI*4*Health.

7.3 Client Layer

The users interact through this layer and make data and service requests. When the user requests data or metadata services, it is sent as a HTTP request to the application layer where data and catalogue services are distributed and installed across different servers. Based upon the requested service, OGC service interface responds to the client. The response to the user can be either in XML, raster format, vector format or GML. Once the response is received, client renders the result on screen or uses it in some other application. For developing user friendly GUI for the client, programming languages and tools are used which include HTML, Cascading Style Sheet (CSS), JavaScript, JSP and OpenLayers.

HTML is a combination of HyperText and Markup Language. Hypertext is a text that links to other text or web page. This is one of the most powerful features of HTML as it helps in creating a web of pages and in performing an easy navigation through them. It is a markup language as it uses predefined tags to define layout and formatting of the document. CSS is an essential feature of the open web technology which standardizes web browser according to the W3C specifications. It is a stylesheet language used to add styles like font, colour, spacing, etc. to the web page. It describes how HTML elements will be rendered on the screen.

JavaScript is a multi-paradigm, dynamic and object based programming language. It allows to build standard objects and methods to create interactive webpages. It supports functional programming, i.e., objects and methods are stored in a variable that passes as an object to other parameters. In other words, the user can add working functions to the clickable buttons, popup menus, inboxes, etc. JSP is a server side programming language that is used to create the dynamic and platform independent method for creating web application based on HTML, XML and other document types. It is an extension of servlet technology and thus uses all Java Application Programming Interfaces (APIs), especially the Java Database Connectivity (JDBC) API to enable the database read/write operation over the servers.

OpenLayers is used to display the map data in web browsers, and is basically an open source JavaScript library. OpenLayers provides APIs for developing rich web based GIS applications. The core components of OpenLayers are map, view, source and layer. Map is a target container that is used to render the spatial layer. View describes the position, zoom level and projection of the map. Source is used to get

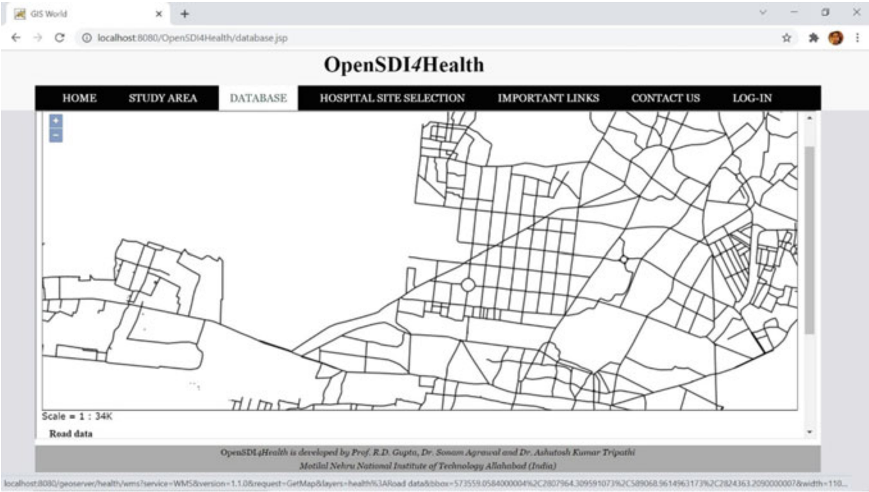


Fig. 13.6 'Database' page of OpenSDI4Health

the remote data for a layer. The layer feature describes the visual representation of data from the source.

All the vector and raster data are first uploaded on GeoServer GIS server. For this purpose, a workspace is created in GeoServer followed by the creation of stores. The publication of layers is then carried out. The Style Layer Descriptor (SLD) files are generated with the help of uDig software which are XML files used for styling of layers. The user can access OpenSDI4Health by typing the URL 'localhost:8080/OpenSDI4Health' in any web browser. This will open the index page of developed OpenSDI4Health. Then, users can navigate to desired web pages/data/information using hyperlinks provided in GUI. The 'Database' interface of developed OpenSDI4Health is shown in Fig. 13.6.

8 Hospital Site Selection Application Module for OpenSDI4Health

One of the main aims of OpenSDI4Health is to improve the availability and applicability of spatial data in decision making so that users are able to make informed decisions. This can be fulfilled by application specific module which is also one of the core components of the Indian NSDI. The application specific module involves the access of spatial data directory and the development of spatial decision support tools along with user friendly GUI. Therefore, an application specific module for OpenSDI4Health in the form of hospital site selection is designed, developed and implemented. The user friendly GUI will ensure that planners and administrators with basic knowledge of computers can use this for decision making.

8.1 System Architecture of SDSS Developed for Hospital Site Selection

In general, selection of suitable sites for establishing infrastructural facilities like new hospitals requires consideration of multiple criteria for evaluating different alternatives and taking the final decision. These are typically ill-structured decision-making problem that involves several stakeholders with varied interests. Therefore, for development of hospital site selection module, system architecture based on the concept of web enabled Spatial Decision Support System (SDSS) is conceptualized and developed. The SDSS includes DSS module with a spatial component and supports the planners in decision making rather than replacing the user's decision-making process. Further, Multiple Criteria Decision Making (MCDM) techniques are best suited for solving real world problems in which multiple criteria need to be considered for making the final decision. Analytic Hierarchy Process (AHP), a commonly used MCDM method, is used. The architecture of the web enabled SDSS for hospital site selection includes three core components, namely, Database, Model Base and User Interface (Fig. 13.7).

The database and model base components are managed by two servers, namely, Apache Tomcat (web server) and GeoServer (GIS server). Database refers to integrated geographic database created for this purpose. It accesses the spatially referenced multi source data uploaded on PostgreSQL/PostGIS. The data is used according to the choice of the facility because each such application is impacted by different criteria. This component is used to manage the data participating in decision making.

The model base is the heart of any SDSS and consists of problem specific spatial models for planning process, and accordingly, a rule based spatial model is developed for hospital site selection. The spatial model developed for site selection is composed of four components, i.e., Selection of Suitable Criteria, Creation of Criteria Maps, Criteria Weighting using GIS-MCDM Technique and Spatial Analysis for Generation of Hospital Site Suitability Map.

In web enabled SDSS, an interface is provided through which users can access and interact with functionalities of the application. This component is also used to handle user specific queries. This allows users to visualize the criteria maps used in site selection and also the hospital site suitability results. For the visualization and mapping of application components, a WMS request is sent to the GIS server through web server. GIS server responses with the corresponding data to the client.

8.2 Database

The database component is of central importance in the construction of an SDSS. The database in present case is contained in the integrated geographic database created for OpenSDI4Health. The system accesses and uses the same as and when this is

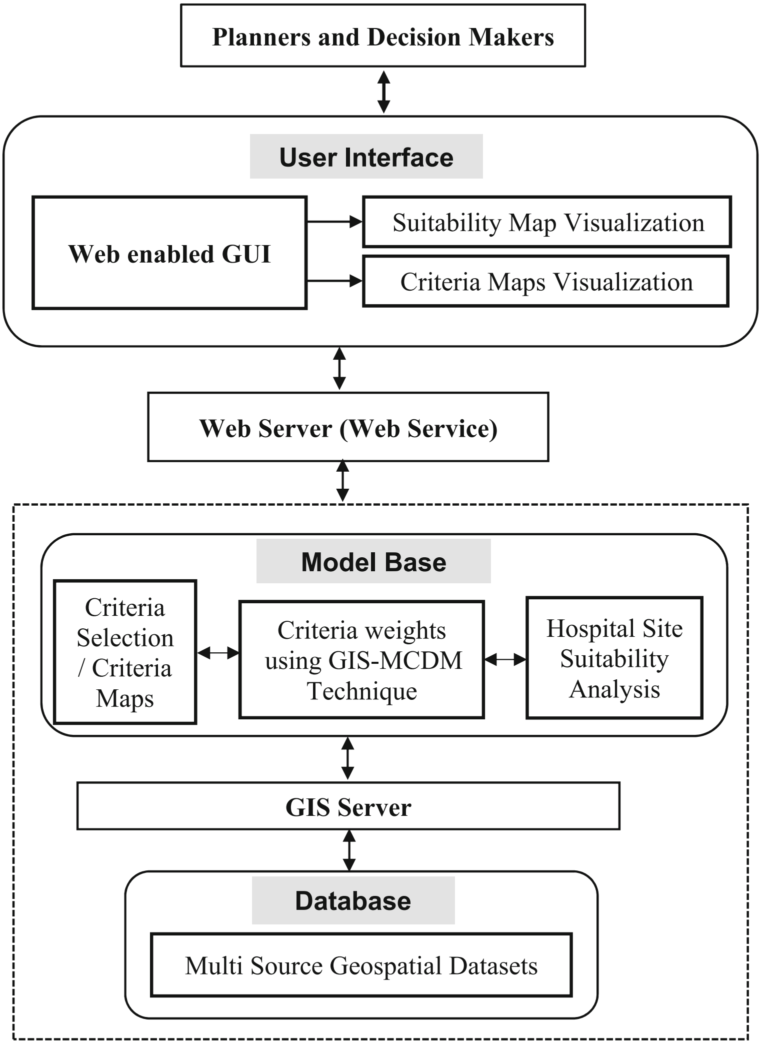


Fig. 13.7 Architecture of web enabled SDSS for hospital site selection

required to be used in the model base or accessed/visualized through user interface. For this purpose, the location of 127 hospitals of Prayagraj city is collected through GPS field survey.

8.2.1 GPS Based Field Survey

The location of hospitals of Prayagraj city is collected through GPS survey. Handheld GPS receiver is used for collecting the location of each hospital in latitude and longitude. These geographic locations in the field are collected in World Geodetic System-1984 (WGS-84) datum and Geographic Coordinate System (GCS) which is later projected into Universal Transverse Mercator (UTM) Zone 44 N for Prayagraj city.

The field survey is carried out using Trimble Juno 3B handheld GPS having 2–5 m accuracy which is acceptable for GIS mapping. The data dictionary is first created in TerraSync software which describes the features collected in the field. It includes a set of fields associated to a feature such as feature ID, name, data type, attribute type, GPS date, GPS time, among others. The location of facility is then captured by the GPS receiver. For collecting the location with high level of accuracy, clear view of the sky is ensured. The places secluded by the building or tree canopy are avoided to minimize the multipath error. The satellite signal strength is checked in the Skyplot section to ensure the availability of more than four satellites for position computation, and minimum PDOP of less than 4 is ensured.

The list of hospitals in Prayagraj city is downloaded from Prayagraj district official website (https://prayagraj.nic.in). It is found that 127 healthcare facilities are available in Prayagraj city. These include 10 medical clinics, 13 diagnostic centres, 6 government hospitals and 98 private hospitals. Their location is collected from the GPS based field survey. The attributes selected in the present work are name of the hospital, type of hospital, address and treatment specialisation. Geotagged image of each feature is also collected at the time of field survey with resolution of the images being set as 5 MP (2592 $\times$ 1944). These geotagged images have the photograph of the facility along with its latitude and longitude position.

The collected hospital location field data file is then exported into 'shapefile' format that is compatible with GIS. PathFinder Office, land surveying software, is used to convert field survey GPS data in the form of shapefile. In addition, a unique ID is also assigned to each hospital data. Then, hospital location thematic map is created by linking the hospital location with the attributes of that hospital. The location of all the hospitals is shown in Fig. 13.8.

8.3 Model Base

The spatial model for hospital site selection is developed through following major steps:

(i) Selection of Suitable Criteria
(ii) Creation of Criteria Maps
(iii) Criteria Weighting using GIS-MCDM Technique
(iv) Spatial Analysis for Generation of Hospital Site Suitability Map

These are discussed under subsequent heads.

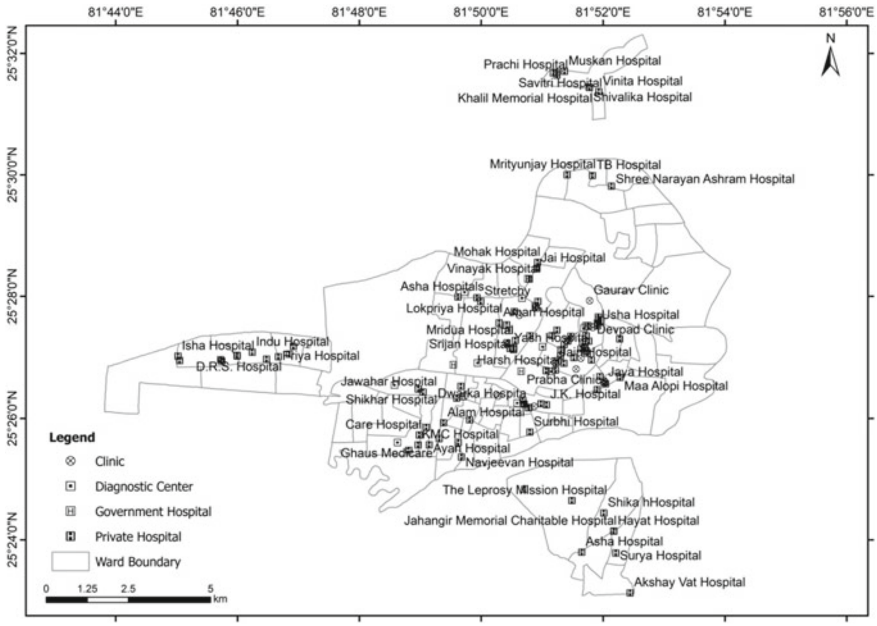


Fig. 13.8 Thematic map showing hospital location collected by GPS survey

8.3.1 Selection of Suitable Criteria

The first step is the selection of criteria that must be taken into consideration for developing the spatial model for hospital site selection. The suitable criteria are selected based on literature review and the opinion of the academicians and health experts. Based on literature review [22], it is observed that several researchers have selected population density, accessibility (proximity to road and railway), cost of land and possibility of extension as the criteria. Some researchers also discussed the need to take green area, air pollution and industry as important criteria. Few researchers have also taken urban slum population and slope as criteria for hospital site selection. Thus, as per literature review, 11 criteria are identified as possible criteria. Then, academicians and experts of health service domain in Prayagraj city were consulted to seek their opinion for making a final decision for criteria selection. Their opinion was slightly different about the number and priority of each criterion but none of them opined strongly to drop any of the aforesaid parameters.

Therefore, all the 11 parameters are selected as suitable criteria for consideration and further investigations. All these criteria are then grouped under three main criteria which are (a) socioeconomic, (b) geographical and (c) environmental criteria. The socioeconomic criteria consider the social and economic aspects related to public health. Geographical criteria examine the access to health infrastructure and available facilities. Environmental criteria determine the locations in green region with less pollution. All the criteria falling under these three main criteria are termed as sub

Table 13.1 Hierarchy of main criteria and sub criteria

Main Criteria	Code	Sub Criteria	Code
Socioeconomic	C1	Population density	C1-1
		Proximity to slum	C1-2
		Land cost	C1-3
Geographical	C2	Proximity to road	C2-1
		Distance to other hospital	C2-2
		Proximity to railway	C2-3
		Possibility of extension	C2-4
		Slope	C2-5
Environmental	C3	Air pollution	C3-1
		Green area	C3-2
		Industry	C3-3

criteria. Table 13.1 compiles the main criteria along with sub criteria in hierarchical structure with assigned code.

8.3.2 Creation of Criteria Maps

Thematic map for each criterion is created for detailed and better information to planners. Thus, the spatial extent of each criterion is expressed in the form of a thematic layer in GIS and the same is termed as criterion map. The possibility of extension and green area are extracted from Land Use and Land Cover (LULC) map prepared using freely available Sentinel-2A earth observation satellite image of Multispectral Imager (MSI) sensor [band 2 (Blue), band 3 (Green), band 4 (Red) and band 8 (Near IR)] of 04th April 2019 with 10 m spatial resolution. Free space is calculated from all LULC classes and the same is then used for the creation of possibility of extension. For creation of green area, vegetation class is considered. The vector layer is transformed into raster model in GIS. Further, Euclidean distance analysis is used to produce the distance maps like proximity to road, slum, other hospital, etc.

The ranges in all thematic layers are normalized on a scale from 0 to 1 with value 1 (white colour on map) denoting the most suitable while value 0 (black colour on map) being unsuitable for hospital site selection. This is required so that alternative sites for establishing new hospitals can be ranked and prioritized. Since normalization is used for the generation of criteria maps, the quantitative value corresponding to each criterion ranges from 0 to 1. Thematic maps of sub criteria of socioeconomic criterion are shown in Fig. 13.9. All the sub criteria thematic maps of geographical criterion are shown in Fig. 13.10. For environmental criterion, Fig. 13.11 shows thematic maps of all the sub criteria selected for hospital site selection.

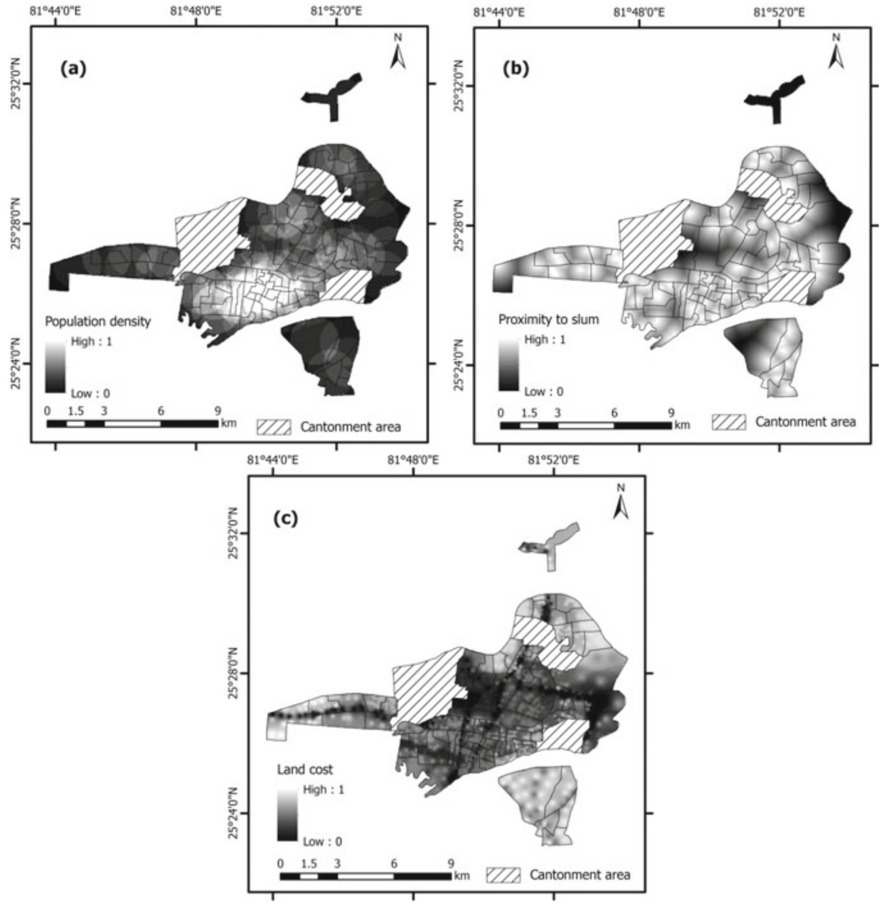


Fig. 13.9 Thematic maps of sub criteria of socioeconomic criterion: **a** Population density, **b** Proximity to slum, and **c** Land cost

8.3.3 Criteria Weighting Using GIS-MCDM Technique

Different schools of thought have been developed for the solution of problems involving multiple criteria. MCDM is a decision tool that involves structuring and solving the real world problems associated with qualitative and quantitative multiple criteria. MCDM deals with techniques that are used for making decisions when multiple criteria or attributes are considered for ranking, and thereby choosing between various alternatives being evaluated. GIS-MCDM technique refers to the application of MCDM methods under GIS environment for solving real world problems involving multiple criteria in geospatial domain, and is used in the present study.

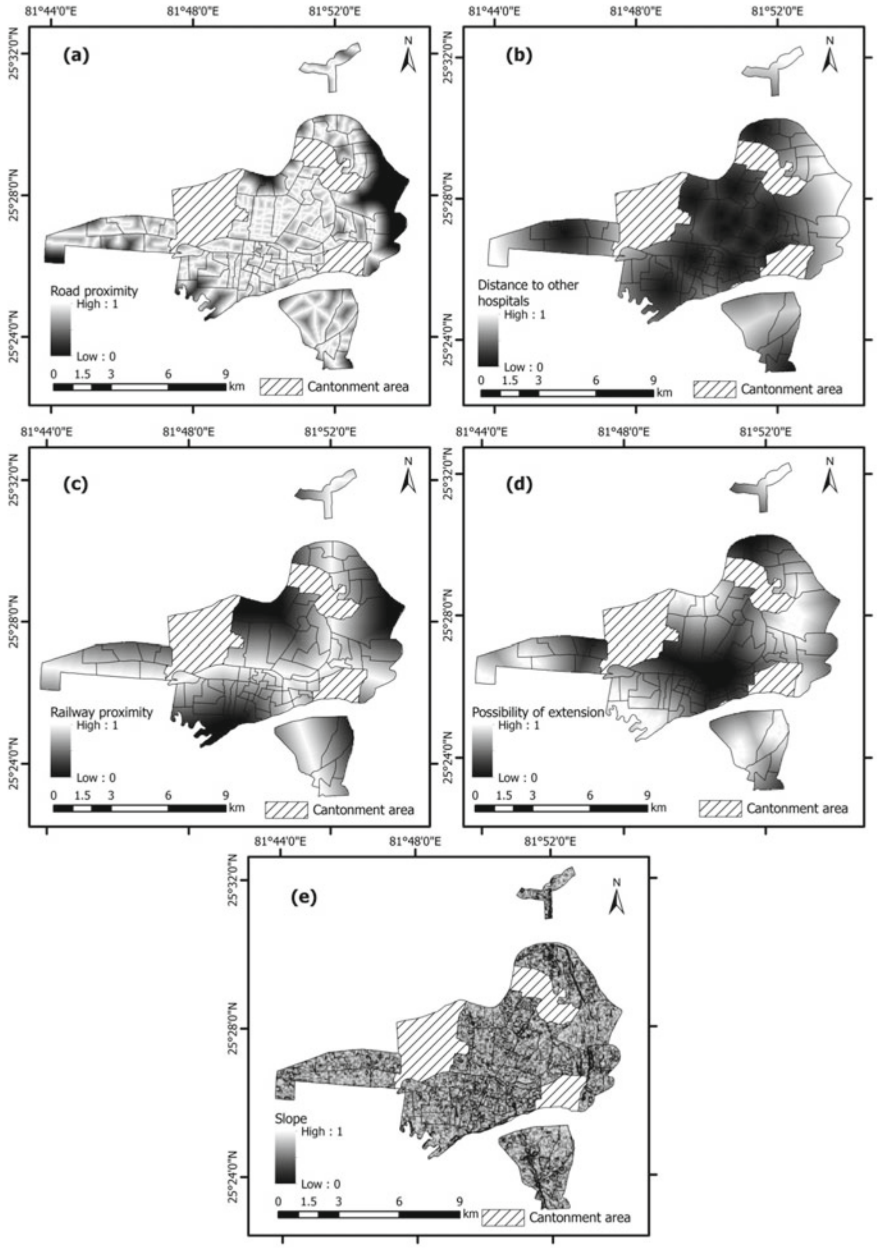


Fig. 13.10 Thematic maps of sub criteria of geographical criterion: **a** Proximity to road, **b** Distance to other hospital, **c** Proximity to Railway, **d** Possibility of extension, **e** Slope

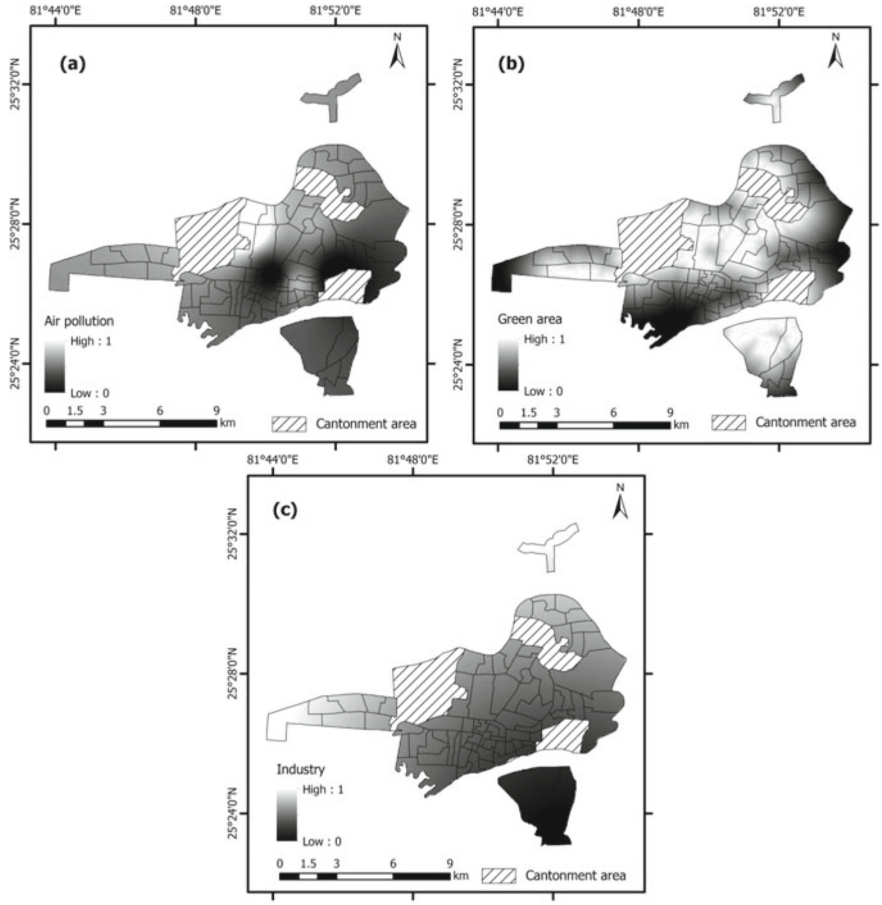


Fig. 13.11 Thematic maps of sub criteria of environmental criterion: **a** Air pollution, **b** Green area, and **c** Industry

Hospital site selection is a multiple criteria analysis problem in which one has to consider multiple criteria for finding alternative solutions. This cannot be solved by traditional single criteria approach of making decisions. The MCDM techniques provide a better and flexible tool for decision making. AHP is commonly used MCDM technique among researchers, planners and decision makers in a wide variety of decision situations including healthcare and education. Therefore, AHP is used and accordingly decision problem is first broken up in to various elements. In AHP, relative importance of a criterion is considered based on Saaty's scale of relative importance on 1–9 in which score 1 indicating equal importance among two criteria and score 9 indicating absolute importance of a criterion over the other [17]. The relative importance of these elements is then evaluated by pairwise comparison through Pairwise Comparison Matrix (PCM). After formation of PCM, Consistency Ratio (CR) is computed to ensure whether PCM formed is consistent. The normalized matrix is then formed. These PCM evaluations are then converted to numerical values in terms of weights. These weights are then used to compute final score for various alternatives [18].

In this study, three experts (E1, E2 and E3) in the domain of hospital planning are consulted for seeking their views related to various parameters used for site selection for a new hospital. The Experts' opinion regarding relative importance of each criterion is in linguistic terms. This is converted and evaluated on nine-point scale of AHP. Tables 13.2, 13.3, 13.4 and 13.5 show the PCMs thus formed for all criteria and sub-criteria.

Table 13.6 shows the weight and ranking of each sub criterion obtained using AHP. The local weight is a term used for the weights computed in accordance with PCM. For obtaining the overall impact of all criteria to the site selection, global

Table 13.2 PCM of main criteria

	Experts	Socioeconomic (C1)	Geographical (C2)	Environmental (C3)
Socioeconomic (C1)	E1	1.00	0.33	0.33
	E2	1.00	0.33	2.00
	E3	1.00	3.00	2.00
Geographical (C2)	E1	3.00	1.00	1.00
	E2	3.00	1.00	1.00
	E3	0.33	1.00	3.00
Environmental (C3)	E1	3.00	1.00	1.00
	E2	0.50	1.00	1.00
	E3	0.50	0.33	1.00

Table 13.3 PCM of socioeconomic sub criteria

	Experts	Population density (C1–1)	Proximity to slum (C1–2)	Land cost (C1-3)
Population density (C1−1)	E1	1.00	2.00	4.00
	E2	1.00	3.00	2.00
	E3	1.00	2.00	2.00
Proximity to Slum (C1−2)	E1	0.50	1.00	2.00
	E2	0.33	1.00	2.00
	E3	0.50	1.00	2.00
Land cost (C1−3)	E1	0.25	0.50	1.00
	E2	0.50	0.50	1.00
	E3	0.50	0.50	1.00

Table 13.4 PCM of geographical sub criteria

	Experts	Slope (C2−1)	Possibility of extension (C2−2)	Proximity to road (C2−3)	Proximity to railway (C2−4)	Distance to other hospital (C2−5)
Slope (C2−1)	E1	1.00	1.00	0.33	0.33	0.25
	E2	1.00	2.00	0.33	0.33	0.50
	E3	1.00	2.00	0.33	0.25	0.20
Possibility of extension (C2−2)	E1	1.00	1.00	0.25	3.00	0.33
	E2	0.50	1.00	0.50	0.33	0.33
	E3	0.50	1.00	0.50	0.33	0.50
Proximity to road (C2−3)	E1	3.00	4.00	1.00	3.00	3.00
	E2	3.00	2.00	1.00	3.00	0.50
	E3	3.00	2.00	1.00	3.00	0.50
Proximity to railway (C2−4)	E1	3.00	0.33	0.33	1.00	0.25
	E2	3.00	3.00	0.33	1.00	0.33
	E3	4.00	3.00	0.33	1.00	0.33
Distance to other hospital (C2−5)	E1	4.00	3.00	0.33	4.00	1.00
	E2	2.00	3.00	2.00	3.00	1.00
	E3	5.00	2.00	2.00	3.00	1.00

Table 13.5 PCM of environmental sub criteria

	Experts	Air pollution (C3−1)	Green area (C3−2)	Industry (C3−3)
Air pollution (C3−1)	E1	1.00	1.00	2.00
	E2	1.00	3.00	3.00
	E3	1.00	0.33	3.00
Green area (C3−2)	E1	1.00	1.00	3.00
	E2	0.33	1.00	3.00
	E3	3.00	1.00	0.25
Industry (C3−3)	E1	0.50	0.33	1.00
	E2	0.33	0.33	1.00
	E3	0.33	4.00	1.00

weight for each sub criterion is computed which is based on the weight of main criterion and the weight of its sub criterion.

Table 13.6 Final weights of main criteria and sub criteria

Main Criteria			
	Local weight	Global weight	Ranking
C1	0.300		
C2	0.419		
C3	0.281		
Sub Criteria			
C1-1	0.535	0.161	1
C1-2	0.288	0.087	6
C1-3	0.177	0.053	9
C2-1	0.306	0.128	3
C2-2	0.336	0.141	2
C2-3	0.156	0.065	7
C2-4	0.101	0.042	10
C2-5	0.101	0.042	11
C3-1	0.438	0.123	4
C3-2	0.349	0.098	5
C3-3	0.213	0.060	8

8.3.4 Spatial Analysis for Generation of Hospital Site Suitability Map

For obtaining the hospital site suitability map, weighted Linear Combination (WLC) spatial analysis technique is used. In this, multiple criteria along with their weights are considered. Each criterion is represented as thematic layer. The suitability of each pixel is evaluated based on normalized weight and standardized score for hospital site suitability. The normalized suitability maps is then classified in to five suitability classes, namely, Highly Suitable, Suitable, Moderately Suitable, Marginally Suitable and Unsuitable for obtaining the classified hospital site suitability map. For this purpose, Jenks natural breaks classification method is applied to the normalized map. The classified suitability map will help planners in analysing spatial pattern and distribution of suitable locations for setting up a new hospital in Prayagraj city as compared to normalized suitability map. The classified hospital site suitability map is shown in Fig. 13.12.

The area covered by each site suitability class is obtained and compiled in Table 13.7. It can be observed that 13.83 km^2 area is classified as highly suitable while 21.10 km^2 area is classified as suitable class. These two classes together constitute 47.45% of total area of the city. The marginally suitable and unsuitable classes constitute 10.50 km^2 and 3.81 km^2 area respectively which together constitute 19.44% of total area. This signifies that there is a need for more hospitals in Prayagraj city for serving the population in a better way.

The highly suitable class is further investigated for selection and prioritization of 07 sites based on combined pixel values by applying additional conditions. The high

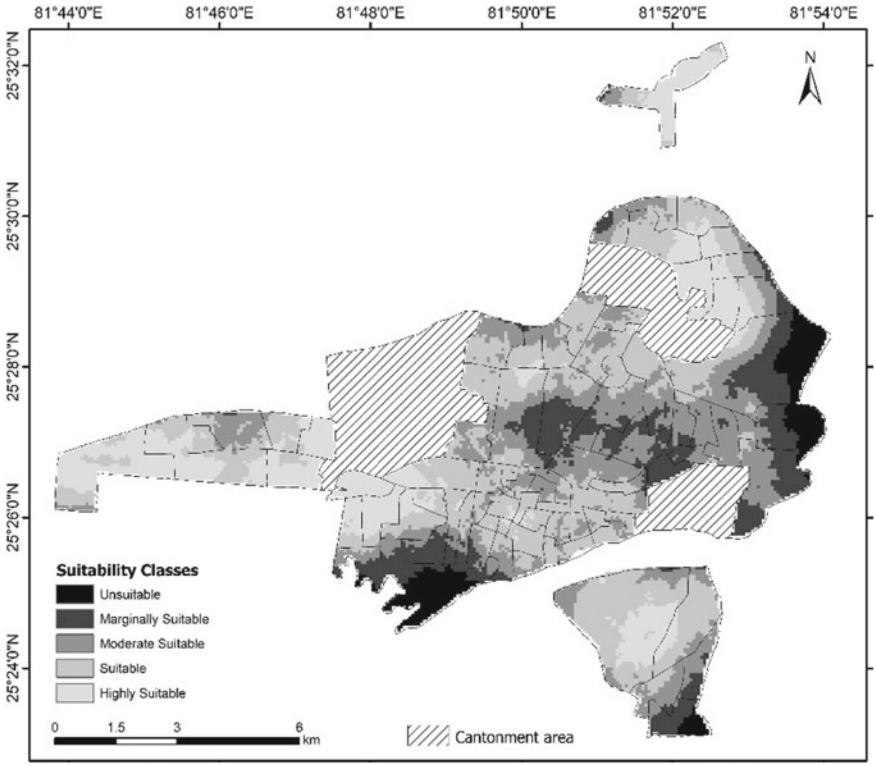


Fig. 13.12 Classified hospital site suitability map

Table 13.7 Area of each suitability class

Suitability Class	Area (km^2)	Area (%)
Highly Suitable	13.83	18.79
Suitable	21.10	28.66
Moderately Suitable	24.37	33.11
Marginally Suitable	10.50	14.26
Unsuitable	3.81	5.18

pixel value shows that all the criteria are satisfied to a higher level as compared to a lower pixel value. The additional conditions imposed include that the new hospital site should be only in the wards which do not have any other hospital. These 07 sites for establishing a new hospital are shown in Fig. 13.13. The analysis for spatial distribution and ranking of identified 07 sites is then carried out. For this purpose, weight of each site with respect to each criterion is obtained. The weight of each criterion and ranking of all these 07 sites is compiled in Table 13.8.

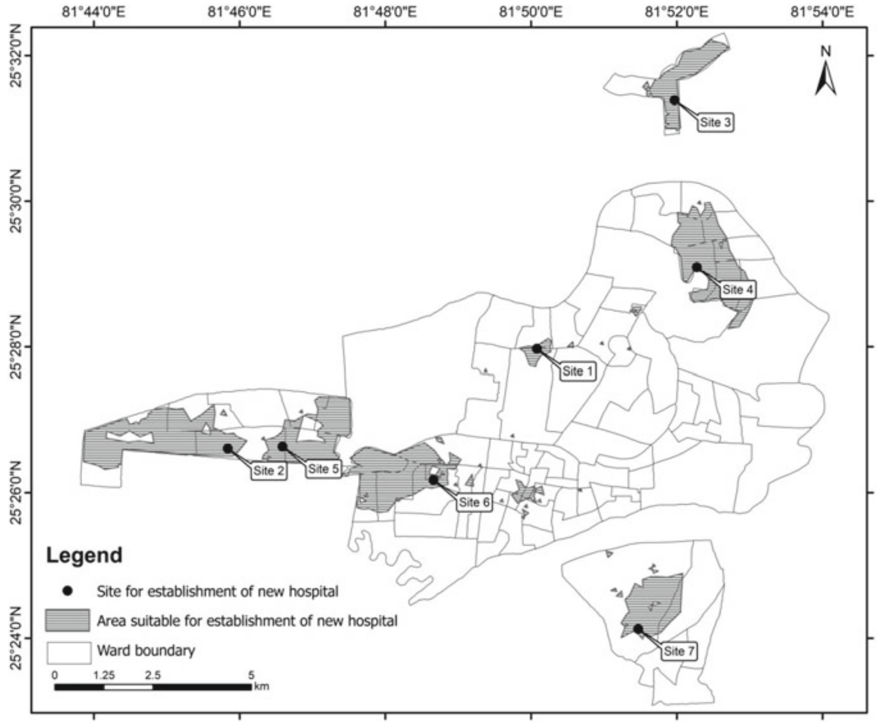


Fig. 13.13 Prioritized hospital sites in highly suitable class

8.4 User Interface

The developed user interactive menu driven GUI for OpenSDI*4*Health incorporates the functionality of application specific module through which user can perform various operations for hospital site selection. By clicking 'Hospital Site Selection' menu, users can access its various components. The criteria maps can be accessed through this module. Figure 13.14 shows one such functionality of this interface. On clicking a button, user query is sent to GeoServer as WMS request and the correct map is returned and displayed on the panel of the interface. Planners can visualize the suitable sites by clicking 'Suitability Map' for making informed decisions for setting up new hospitals in Prayagraj city.

9 Concluding Remarks

Health information plays an important role in planning so that goal of universalization of public health is achieved. This research includes the design, development

Table 13.8 Ranking of suitable sites

	Rank	C1−1	C1−2	C1−3	C2−1	C2−2	C2−3	C2−4	C2−5	C3−1	C3−2	C3−3	Weight
Site 1	1	0.250	0.167	0.051	0.187	0.080	0.066	0.157	0.070	0.305	0.240	0.082	0.172
Site 2	2	0.082	0.167	0.120	0.187	0.076	0.106	0.235	0.198	0.186	0.132	0.256	0.145
Site 3	3	0.050	0.083	0.215	0.187	0.221	0.163	0.108	0.118	0.108	0.132	0.256	0.143
Site 4	4	0.144	0.167	0.215	0.098	0.134	0.297	0.043	0.198	0.108	0.132	0.114	0.143
Site 5	5	0.144	0.167	0.064	0.187	0.080	0.071	0.043	0.070	0.186	0.240	0.167	0.142
Site 6	6	0.250	0.167	0.120	0.098	0.134	0.071	0.069	0.286	0.065	0.048	0.051	0.127
Site 7	7	0.082	0.083	0.215	0.058	0.276	0.226	0.346	0.060	0.043	0.076	0.075	0.127

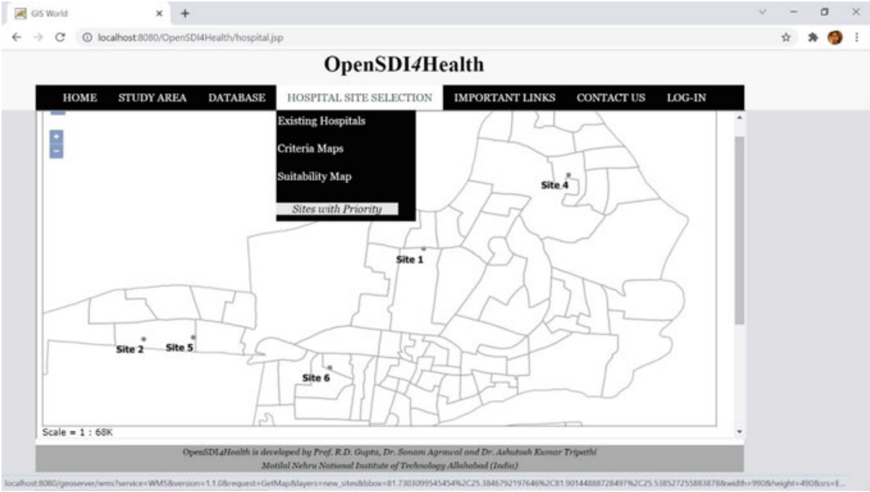


Fig. 13.14 Application specific module interface of OpenSDI4Health

and implementation of OSGR based interoperable SDI for health sector using NSDI of India framework based innovative approach (*acronym* OpenSDI4Health). OGC compliant open standards and web services are embedded for providing interoperability of data and services which is the core of open SDI development. The framework of OpenSDI4Health is designed with six core components, namely, spatial data, metadata, standards, electronic clearinghouse, communication network and application specific module. The three tier thin client server web GIS architecture is implemented using QGIS, GeoServer, Apache Tomcat, PostgreSQL/PostGIS, uDig Java Script, CSS and HTML. The developed OpenSDI4Health will provide a web GIS based mechanism to publish, search, visualize, query, analyze and report the geospatial information related to health sector in an easy, efficient and cost effective manner. The architecture designed and developed for OpenSDI4Health is open, interoperable, secure and modular and can be adopted for different districts of India as well as for other fields of applications like education sector.

Hospital Site Selection is selected as an application module for OpenSDI4Health, in accordance with Indian NSDI core components, for improving the availability and applicability of spatial data in decision making in the field of health, in particular, for selection of appropriate sites for establishing new hospitals. GPS based field survey of 127 hospitals for obtaining their locations is then carried out using handheld GPS. The hospital site selection is achieved by developing SDSS with three core components, namely, database, model base and user interface. AHP, one of the MCDM technique, is used to develop rule based spatial model for criteria selection, criteria weighting and spatial modelling under GIS environment.

OpenSDI4Health will empower the policy makers to make informed and effective decisions for developmental planning. The use of OSGR makes OpenSDI4Health interoperable for sharing across different technologies, data, platforms and organizations as well as economical by reducing the licensing costs thereby enabling broader societal applications along with promoting indigenous technological development. The development of OpenSDI*4*Health can therefore be taken up as a policy matter by Government of India for its implementation as an essential component under Indian NSDI.

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Chapter 14
The Future Healthcare Technologies: A Roadmap to Society 5.0

P. K. Garg

1 Introduction

The UN has developed "The 2030 Agenda for Sustainable Development", which has been adopted by all its members in 2015. The agenda includes 17 Sustainable Development Goals (SDGs) which built on decades of work and with a serious call for action by all the countries. For instance, the SDGs aim to end poverty, improve health and education, reduce inequality, drive economic growth, and tackle climate change [1]. In anticipation of global trends, the 5th Science and Technology Basic Plan, adopted by the Japanese Cabinet in January 2016, presented a core concept, called "*Society 5.0*". They outlined a plan for a "Super smart society" or "Imagination Society" or "Society 5.0" to tackle various socio-economic challenges, and other aspects of society, like healthcare, mobility, infrastructure, politics, government, economy, and industry. Society 5.0 is a "*human-centered society that balances economic advancement with the resolution of social problems by a system that highly integrates cyberspace and physical space*". The Society 5.0 will contribute to delivering on United Nations SDGs.

In order to achieve this, Keidanren [2], Japan Business Federation, published a vision paper which describes that tackling the challenges will require the breaking down of five walls in Society 5.0. The Society 5.0 is also depicted as an evolution in five societal stages in the paper, as: (i) the hunting society, (ii) the agrarian society, (iii) the industrial society, (iv) the information society, and (v) the super-smart society (Society 5.0), as shown in Fig. 1. Historically, we can define Society 1.0 as groups of people hunting and gathering in harmonious coexistence with nature, Society 2.0 as forming groups based on agricultural cultivation, increasing organization and nation-building, Society 3.0 is a society that promotes industrialization

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P. K. Garg et al. (eds.), *Geospatial Data Science in Healthcare for Society 5.0*,
Disruptive Technologies and Digital Transformations for Society 5.0,
https://doi.org/10.1007/978-981-16-9476-9_14

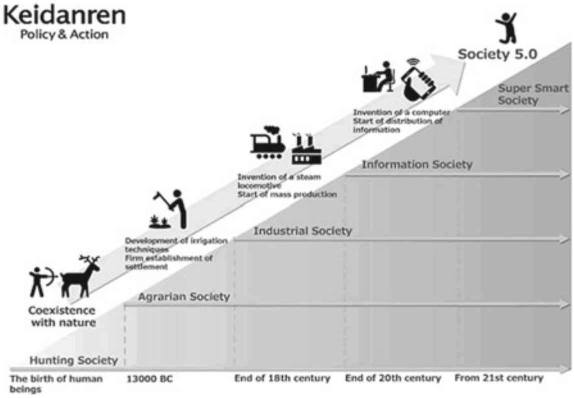

Fig. 1 The evolutionary aspect of the Society 5.0 concept [2]

through the Industrial Revolution, making mass production possible, and Society 4.0 as an information society that realizes increasing added value by connecting intangible assets as information networks. Society 5.0 is an information society built upon Society 4.0, aiming for a prosperous human-centered society. In Society 5.0, the new values created through Social Innovations would eliminate, regional, age, gender, and language gaps and enable the provision of products and services customized to various individual requirements and needs. It has the potential to resolve a variety of challenges in various fields, such as Mobility, Healthcare, Agriculture, Food, Manufacturing, Disaster Control, Energy, and many more. It will transform lives and industries which enable all people to pursue their own happiness and lifestyles (https://www.keidanren.or.jp/en/policy/2018/095_booklet.pdf). Society 5.0 concept fully integrates the vision of a *"Sustainable Society"* where everyone can live a safe and fulfilling life.

The "break through" of 5 walls in moving to Society 5.0 is given below [2]:

1. **The Wall of the Ministries and Agencies**: It means formulating a national strategy and to promote a thinktank environment of public and private sectors through multi-stakeholder collaboration.
2. **The wall of the legal system**: Whereby advanced techniques need to be developed to implement the law. In practice, this would also mean regulatory reforms and a push of administrative digitization.
3. **The wall of technologies**: It is the quest for the formation of the "knowledge foundation". As the actionable data plays a foundational role, similarly all modern technologies will protect and leverage the data. It also mentions a serious R&D commitment on various levels. It is necessary to promote technologies such as cyber security, AI technologies, robotics, nano, bio and systems science and technology.
4. **The wall of human resources**: It provides education to foster creativity, to improve digital literacy and to encourage dynamic engagement and value creation of all citizens.

5. **The wall of social acceptance**: It integrates advanced technologies in society and builds social consensus among all stakeholders including citizens. Furthermore, it examines social implications and ethical issues from a philosophical perspective about the relationship between humans and machines, happiness, and humanity.

Japan, like other countries, is facing an aging society ahead of other countries. According to the UN Statistics Division, as cited by Fukuda [3], the population of Japan is expected to decline by 22.1 million people in 2050. Thus, the current Japanese labor force, which comprises of around 77 million people, being 15–64 years old, is forecasted to shrink by 30% to 53 million people in 2050 [4, 5]. It is expected that across the globe over 20% of population will be over 60 years of age by year 2050. Japan has one of the world's longest life expectancies of 85.5 years. About 53% of the Japanese population is expected to be over the age of 65 by 2030, as compared to 43% of Western Europe and 33% of North America. In Japan, the most pressing social challenge is an aging population, resulting in a shrinking of labor force and lowering the productivity, as compared to similar major advanced economies [5]. The country is suffering from increasing medical and social security expenses and demands for caring for the elderly. Society 5.0 would promote healthy longevity and reduce the total medical expenditure which has also become part of a major national agenda in Japan [6].

Healthcare does not just deal with the health aspect with more chronic diseases mostly affecting old age people, but it mainly focuses on reorganizing the healthcare in relation to this ageing population using digital technologies. The IT is playing a lead role in the business in considering the digital transformation in healthcare. Figure 2 shows main growing concerns and their possible solutions to be achieved through implementation of Society 5.0 concept. The model proposed by Society 5.0

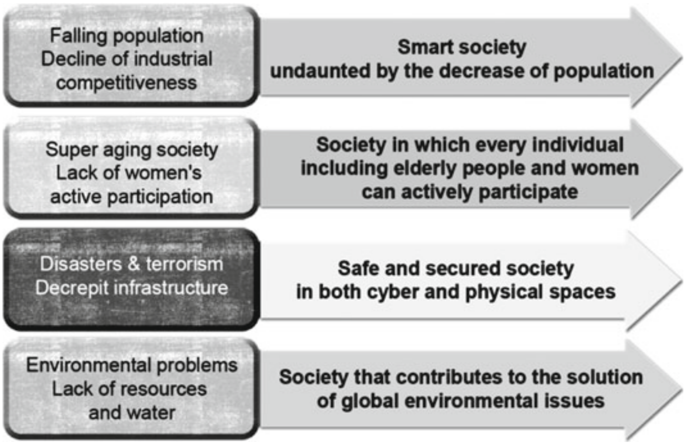

Fig. 2 Main growing concerns and their possible solutions in Society 5.0

has a number of challenges (i.e., technological, economic, geopolitical, and mental changes) that offer opportunities to create new systems and processes. Those are.

2 Innovative Technologies

We are now in an era, where innovations driven by the technologies, such as Internet of Things (IoT), Artificial Intelligence (AI), Augmented Reality (AR), Virtual Reality (VR), Wireless sensors, and robotics, are bringing fast changes to the society and its economic activities [7]. Just as Industry 4.0 is the digital transformation of manufacturing, Society 5.0 aims at digital transformation by tackling several challenges toward the digitalization across all levels of the society. In digital transformation, the advances in digital technology and data utilization significantly change various aspects of society, including quality of life, public administration, industrial structure, individual health, and employment. Digital technologies and data can be utilized to create a society where people can lead diverse lifestyles and pursue happiness in their own ways.

For continuous growth, it is important to bring about a digital transformation/revolution that extends across all areas of society, such as social infrastructure, public services, energy, and railways, as well as services ranging from commerce to healthcare [8]. The IoT supported with AI can overcome the large challenges for such applications for growing population. Thus, a human-centric smart society can be created where people can live and work in total safety and comfort regardless of wherever they are. In addition, everyone can play an important role regardless of age or gender, not only by the laws of the land but also by using the modern technology. Traditionally, innovation driven by technology has been responsible for social development (Fig. 3), but in the future, individual way of thinking has to be

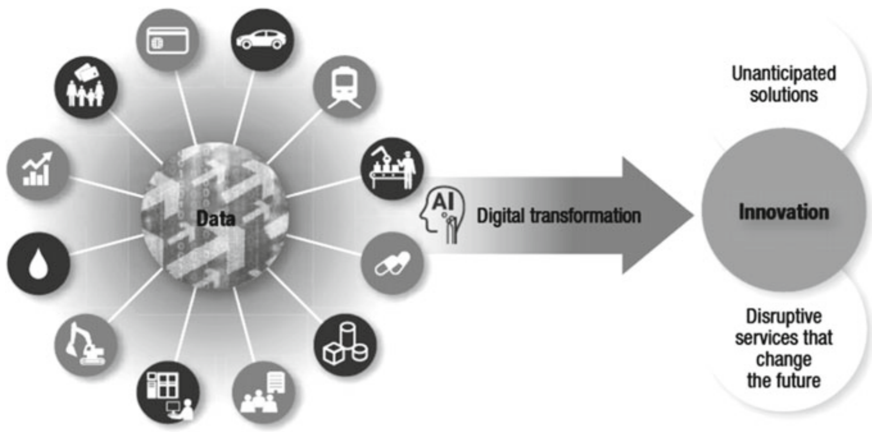

Fig. 3 Digital transformations leading to more rapid innovations

reversed, focusing on how to build a society that makes us happy, healthy, and safe.

Digital transformation will drastically alter many aspects of society, including life, public administration, industrial structure, and employment, through the use of cyber spaces and their integration into physical spaces. The modern technologies, such as AI, IoT, cyber-physical systems, VR/AR, Big Data analytics, Blockchain etc., play an important role for achieving the goals of super-smart society [9]. The Society 5.0 offers a high degree of convergence between cyber space (virtual space) and physical space (real space). In Society 5.0, huge amount of information is required to be collected from sensors in physical space, which is often linked to the IoT, and subsequently stored and analyzed in cyber space using the AI. It therefore encompasses a technology-driven socio-economic societal system powered by AI, IoT, robotics, Big Data analytics, and many more modern technologies. In the reform age, IoT, AI, robots, and life science will drastically change industrial and social structures. The foundation to underpin the reform is the creation of new values by integration of cyber space and physical space with rapid evolution of ICT. The value creation is also accelerated by AI and robots based on cyber space and physical space, as shown in Fig. 4. These technologies are to be used in an integrated way into every aspect of societal life so as to support individual well-being, resolve social problems, and increase the productivity.

The cyber-physical systems, IoT, Cloud computing, Big Data, AI, Robotics and Blockchain are the signature elements of the next industrial revolution commonly termed as Industry 4.0 [10]. These technologies have made remarkable progress in recent years, and are bringing about the 4th Industrial Revolution, that would make dramatic improvements in productivity as well as the creation of new business and service models. The IoT aims at providing a seamless integration of various smart devices, different sensors, computing resources, and actuators. Sensors allow perception of external environment, whereas actuators allow such system to provide utility in different applications, like healthcare, transportation, surveillance, among others. Cloud computing provides the computational resources to remotely execute various tasks, and derives results to several applications. The new paradigm of AI

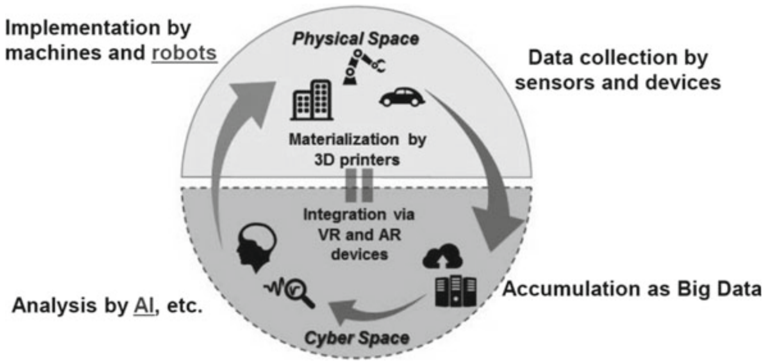

Fig. 4 Integration of physical space into cyberspace [2]

and Machine Learning (ML) provides users with high quality services, low response times, scalability, and robustness to different users' needs [9].

Society 5.0 was a symbolic term which showed that Japan is focusing on social level innovations [6]. The idea is to resolve broad social challenges by making best use of emerging technologies, with an emphasis on connecting systems, equipment, services, people, and data. This way, it would be possible to develop smarter solutions and services more tailored to individual needs with open innovation approach. According to a recent study conducted in the Asia–Pacific region by Accenture Research [11], the right combination of digital technologies, such as autonomous driving, robotics, AR and VR, Big Data, Machine Learning (ML) and AI, Blockchain, and 3D printing, could decrease corporate costs by up to 27% per employee and increase market value by an average of 28% across various industries. The report also reveals a correlation between digitization and corporate productivity by building up a digital-ready workforce [12]. So the use of these advanced technologies will contribute to significantly improving labor productivity as well as increase the technology expenditure, adoption, and thus increase its disruptive innovation potential.

The aim of Society 5.0 is to bring about a society where anyone can create value any-time, any-where, in security and harmony with nature, and free from various existing constraints. It is not about the ageing alone, but health and other aspects of society that are impacted by ageing populations, such as mobility, housing etc., will also be tackled. In Society 5.0, new approaches will provide care which are tailored to individual health at the preventive stage.

3 Healthcare Perspective

The demands of healthcare applications have been ever increasing due to modern AI application which is data intensive. Moreover, number of patients, types of analysis, and response time requirements are becoming more vigorous. New diseases are being discovered frequently, new treatments need to be tested via simulations, and most importantly, healthcare applications need to be deployed using robust and scalable frameworks that provide high quality results in shortest possible time. People, things, and systems all will remain connected in the evolution of Society 5.0, integrating cyber space, and physical space through Big Data collected from various sensors and devices. Big Data is analyzed using the capabilities of AI generating new values for people and industries to achieve both economic development and solutions to social issues which are then ploughed back into the physical space. Furthermore, these solutions will help reduce the social costs associated with healthcare and care providers as well as labor-shortage problems at healthcare locations.

The AI is a key pillar of Society 5.0, as it characterizes the AI as a service in three priority areas (i.e., health, mobility, and productivity) by: (a) expanding use of data-driven AI in each service domain, (b) general use of AI and data across services, and (c) the formation of ecosystems through a complex merger of these services. In

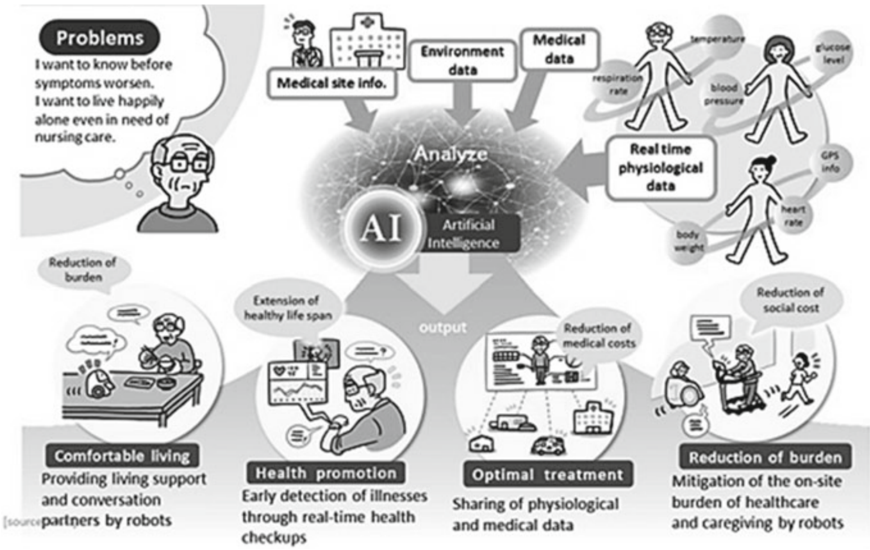

Fig. 5 New values genearted in healthcare

Society 5.0, new values can be generated through (i) AI-based analysis of Big Data with several types of information, including personal real-time physiological data, (ii) healthcare information, (iii) treatment/diagnosis information, and (iv) environmental information, as shown in Fig. 5.

It will realize the following

(a) Enable a comfortable living.
(b) Promote healthy living and early detection of illnesses through real-time automatic health check-ups.
(c) Provide optimal treatment by sharing the physiological and medical data.
(d) Provide ease of on-site burden of healthcare and care by using robots.

Deep Learning and AI can provide high performance systems, while Fog computing improves the response time, allows more scalable environments, and makes deployments more energy efficient and affordable. Blockchain and encryption with public–private signature management are the key elements for providing secure communication among patients and computational machines with high data integrity. However, the main challenge lies to integrate all these technologies to provide a single solution that meets to the needs and requirements of the healthcare industry. It requires a conceptual model of providing a holistic solution of the problem, and the expertise of different domains to be brought together, as proposed by Tuli et al. [10], and shown in Fig. 6.

The impact of 5G on healthcare is likely to be multiple (as shown in Fig. 7), such as faster internet, reliable connectivity for massive objects and medical devices, with greater bandwidth and super coverage [13]. The areas of VR and AR are also

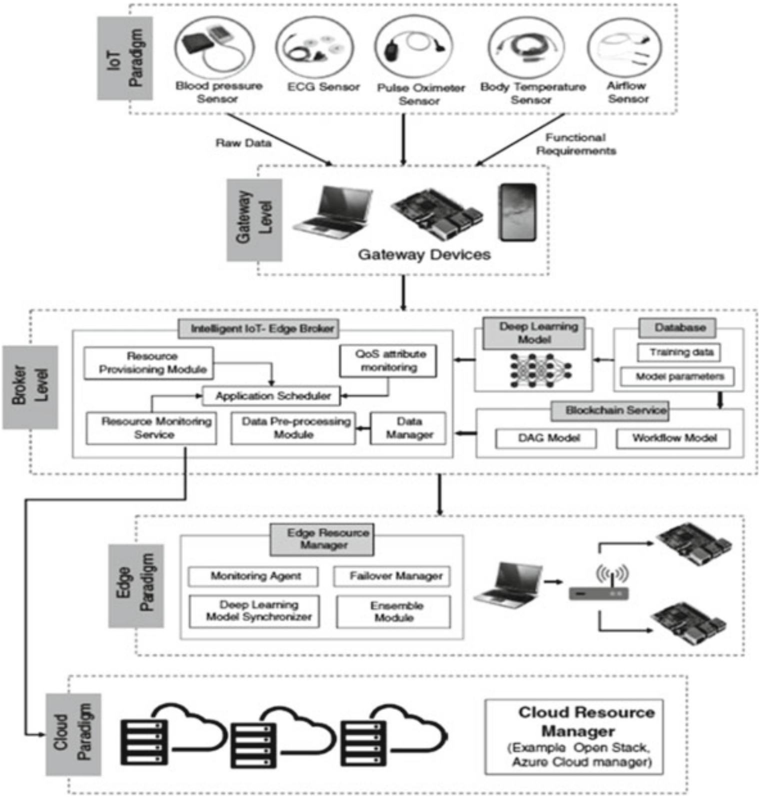

Fig. 6 Proposed model leveraging advanced technologies of Artificial Intelligence and Blockchain for enhanced performance and seamless task execution on Fog computing Environments [10]

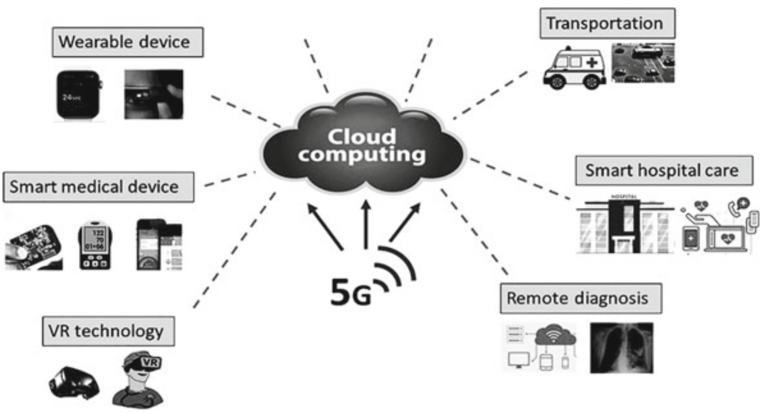

Fig. 7 Schematic drawing illustrating applications of 5G technology in healthcare. VR, virtual reality [13]

benefitted directly from 5G, with potential contributions to intelligent medicine. The integration of VR and AR is critical for comprehensive rehabilitation training as well as concise extremity rehabilitation and telemedicine.

The technologies envisage to provide solution by (i) connecting and sharing information between medical data users including medical checkup records, as well as treatment and nursing care records, (ii) putting remote medical care services into practice, and (iii) Using AI and robots at nursing-care facilities to support people's independence. Robots could take over specific routine tasks from staff in hospitals, deliver medications, supply food throughout the hospital. By connecting and sharing the medical data through various technologies, that is now dispersed in various hospitals, effective medical treatment based on data can be provided. Remote medical care makes it possible so that elderly people will no longer have to visit hospitals frequently. The health data, such as heart rate can be managed well while at home, to make it possible to extend people's healthy life expectancy. People in rural or remote areas find it difficult to visit hospitals because of a lack of public transportation. However, autonomous vehicles will enable them to travel more easily, while delivery drones will make it possible to supply their medical needs. By employing new technologies of ICT, robots, and sensors, detection of infrastructure systems that need repair and maintenance can also be made at an early stage [9]. By doing so, many unexpected and fatal accidents can be avoided during travel, and the time spent in maintenance work will be reduced, ensuring increased safety and productivity.

With mobile access becoming increasingly prevalent world-wide, mobile technology is well placed to support in the delivery of healthcare [14]. At any time, healthcare providers are able to see whether patients are taking their medication timely, and also can keep an eye on the condition of medical equipment to avoid any breakdown. These devices send real-time alerts in the event of an accident or sudden fall, meaning those who are less mobile or suffer from degenerative diseases, such as dementia, are able to stay at home and maintain a level of personal freedom, while receiving continuous care and protection. The increasing collaboration between the doctors and patients, facilitated by mobile communications, is changing the scenario of healthcare delivery system. While clinical trials support investment in new treatments and drugs, they can be time-consuming and costly. Vital sign monitors enable administrators to capture real-time patient data during clinical trials, speeding up regulatory evaluations, removing the need for manual, paper-based methods, and facilitating faster decision-making.

Remote health monitoring is also an important part toward home and remote care, and mobility. Rising hospitalization and treatment costs along with developments in remote monitoring and wireless communications are gaining popularity in home-based monitoring, diagnosis and treatment. Moreover, in regions where access to healthcare is less, mobile healthcare offers an alternative as the penetration of mobile devices is growing and healthcare workers are increasingly mobile. Mobile access to the patient's information, regardless of place and time, changes the patient expectations and this would increase the needs of mobile workforce.

The usage of wearables and personal healthcare devices is increasing. Data from wearable devices will also be used for health insurance and plans. The people will be

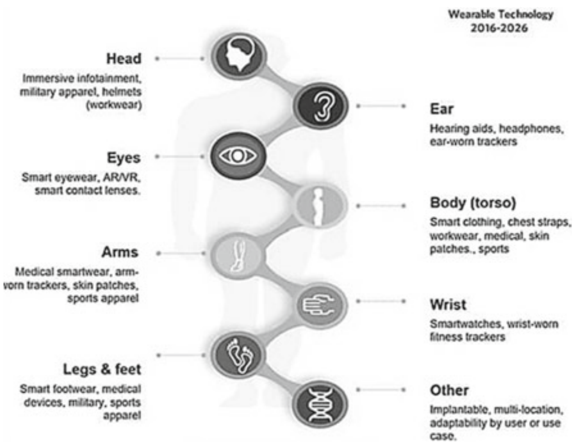

Fig. 8 Wearable technolgies [7]

engaged in their health because of real-time care plan adjustments with cognitive/AI and continuous data available from wearable devices. The patients will be engaged from passive to active mode for an increased care plans that are adjusted in real-time with the usage of AI/cognitive, in combination with the wearables. The Firms will offer personalized benefits with options to dynamically adapt the premiums with personal health data. The IDC expects that as a consequence, 20% more patients will be actively engaged in their health by 2021 [15]. Moreover, new models will continue to emerge whereby the disclosure of personal health data will be encouraged with all sorts of benefits. The patients are more “engaged”, “responsible”, “motivated” and “empowered” to take better care of their health. The wearable technologies are shown in Fig. 8.

All the stakeholders in healthcare ecosystem are adopting digitization and digital transformation in the healthcare and also investing more in digital health. Healthcare providers adopt EHR (Electronically Health Record) systems not only for digital transformation purposes in healthcare but also for enhanced patient care, efficiency improvement, saving time, minimizing the risk, and improving the productivity of medical staff. Digital transformation in healthcare isn’t just about the use of technologies, but also it is about the challenges to be addressed in healthcare across the entire ecosystem, innovation and building a viable healthcare future, leveraging all those technologies with unstructured data and information. The management of healthcare is different across the globe, depending on country, legal framework, political agenda, individual organization, role in the healthcare ecosystem and the goals of digital transformation, for instance, remote health monitoring by leveraging cloud computing and the IoT. Given the sensitive nature of patients’ records, government mandates, privacy concerns and security requirements, the healthcare industry has been relatively slow to adopt modern technologies with a higher perceived risk, such as the cloud. Data management, data governance, and data quality are important challenges in the context of EHR and healthcare information management. While data governance is about creating frameworks enabling IT and business work together in a credible and relevant way, data quality looks at the reliability and accuracy of the data. Data governance involves rules for managing data in order to ensure data quality but also data integrity (whether the data is used in the correct context) and data usability (whether data and associated metadata are accessible). The digital transformation of healthcare data can be used to enhance specific aspects of healthcare, solve challenges or come up with new healthcare models. The increasing adoption rate of EHR also showed the benefits, especially when the next goals are set (sharing of health data between providers): cost-saving by having a better patient view (e.g., avoiding duplicate tests), increased patient safety, etc.

4 Challenges and Opportunities

There are a few healthcare challenges as they drive digital transformation technology. One of the biggest challenges is regarding security and privacy of personal data, and compliance in an industry. The cybersecurity is a key priority area to create a sustainable and secure digital healthcare ecosystem. Next to cybersecurity, privacy is another major issue. Most of the attacks that Japan is experiencing is on the Internet of Things (IoT). Another challenge is how to make healthcare better from the perspective of patients and other stakeholders [7]. For example, people who have lost (parts of) their arms and legs already dispose of newer brain-controlled bionic limbs that can make their lives easier. In reality, these bionic limbs require a lot of data from patients. Among the other challenges, many countries have to deal with natural disasters and pollution, and Society 5.0 must be able to deal with these challenges. Digital technologies can be used to share disaster information across organizations for quick response and disaster mitigation as well as maintaining efficient medical services in case of disasters.

The aging population is another big challenge, as aging population means less people are "active" and are able to contribute to healthcare systems. It may lead to more healthcare costs and at the same time drive new solutions for the less mobile people, saving costs. Remote healthcare monitoring through IoT continues to be the major area in healthcare world-wide. Although in many countries people are living longer, but they may not be necessarily living healthier. The increase in aging population presents many opportunities and also several public health challenges that we need to prepare. It is believed that the chronic diseases increase with aging populations. These chronic diseases, so-called *non-communicable diseases*, already account for three quarters of deaths across the globe. According to the World Economic Forum, only five of these chronic diseases are expected to cost 47 trillion USD by 2030 [16]. America's population (65 years and more) is projected to nearly double over the next three decades from 48 to 88 million by 2050 (https://www.nih.gov/about-nih/what-we-do/nih-almanac/national-institute-aging-nia). It is expected that by 2050 over 1 in 5 people globally will be older and that the number of people aged 60 and over will be doubled in comparison to year 2000. In fact, in some countries, there are already more than 25% people aged 60 or older. In Japan, 26.3% of the population is even over 65 years old, in Italy that's 22.4%, in Greece 21.4%, and in Germany 21.2%. It is expected to further grow by year 2050.

Digital literacy and digital access go hand in hand. Although, it is debateable whether Society 5.0 would increase or decrease the digital divide. The digital divide is a true challenge for Society 5.0. It is understood that a too fast realization of Society 5.0 would increase the digital divide and too much digital contact will lead to digital fatigue, whereas a gradual step by step process would decrease it as it gives people more time to adapt. It is therefore important that a good balance between digital illiteracy and digital fatigue is maintained in Society 5.0. However, some countries might struggle more with the digital divide than Japan. Depending on how Society 5.0 is implemented, it is believed that the AI and IoT would increase the digital divide in Society 5.0. The COVID-19 pandemic has magnified the visibility of digital divide, and the lack of digitalization in certain sectors (e.g., Health) and regions is amplified. Thus, the crisis is expected to accelerate the digital transformation. The technological change might bring more positive changes toward the opportunities instead of the risks. Society 5.0 provides an opportunity to facilitate social acceptance of technology and reduce the digital divide which might bring humans closer.

5 The Last Word

Digital technologies can be used to improve health and make healthcare sysytem more affordable and cost-effective. It can be used to generate new revenue sources because healthcare tourism is seen as an importance source of revenue in some countries. The EHR and Big Data can be collected and used for better healthcare and enhancing patient-centricity. The IoT and other technologies, such as AI, robotics, and sensors provide patients with new or improved tools that enable individuals to improve their health, using either the personal healthcare wearable devices or through remote healthcare monitoring. Digital transformation in healthcare and the increasing deployment of IoT, Big Data, AI/cognitive, robotics, and EHR data and information, will move us toward an information-driven healthcare. These interconnected technologies with real-time location data are expected to detect the patterns that will free up to 30% of clinician's time.

The chronic diseases and mental issues are among the fastest growing illness that requires efficient use of wearables, Big Data, IoT, and fast technology. Physicians are now able to monitor the information about patients with chronic illnesses remotely. They are able to provide cost-effective home-based care to patients undergoing long-term treatment, and can help elderly patients maintain independence by creating safe and secure living environments. With time, an increase in wearables devices along with other connected devices is expected in the context of care plans, monitoring and Big Data pattern detection. Technologies can offer opportunities for patients to have interactions via video with the healthcare workers that would enable them to improve health or connect with the right healthcare system. In the current economy of efficiency, often efficiency and productivity of medical staff are mainly seen as cost saving which is possible through the use of enabling technologies. In the world of digitalization, drones and robots are an important part, but it cannot overlook the importance of human beings because it is the people who will come up with innovative ideas and generate value. Rapidly advancing digital technology enables the creation of new values through sophisticated use of data on realizing Society 5.0, a human-centric "super smart society".

Diseases place a greater demand on the healthcare industry, however the mobile technology is reducing the impact on health resources. Mobile devices provide readings remotely and maintain up-to-date records of patients, resulting in less hospital visits and more hinformation collection for doctors [14]. The automation is increasing the passive role of patients in taking care of their own treatment programmes. However, many-times it is the combination of data collected from devices and data entered manually by the patients that improves the patient's outcomes. Greater access to smart mobile technologies, combined with more readily-available health information online, and interactive social media and mobile health services, would enable patients and doctors to have a more engaged relationship.

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