Data Science and Society

(DLMDSSDSS01)

A Research Essay on

Data Science and Analytics in Healthcare

and A Course of Study on

Data Science Use Cases in Healthcare

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Introduction

The health care system deals with disease prevention, early detection, diagnosis, investigation, and timely, affordable, and safe treatment. For better delivery of services in the health sector, communication is the key to linking the service provider and the patients. Mobile technologies have rendered various platforms of communication for the healthcare system. With advancements in mobile technologies and are growing number of mobile users, new opportunities, has opened for the use of mobile for patient care. Due to rise in mobile users and the help of the Internet of things (IoT) have been instrumental in the integration of different health sectors with mobile technology.

In this paper, a few factors (use cases) are described that make data science an imperative necessity for the healthcare sector in the current environment, with the competitive desire for quality information in the health market being the most important factor. Healthcare systems have become costly and increase in chronic disease cases, many efforts have been taken to improve access to and quality of health care. Every human body can generate up to 2TB data per day, these data can include all the activities of the brain, stress level, heart rate, and sugar level. With the help of Data Science, we can detect the symptoms at an early stage. With the advent of various innovative tools and technologies, doctors can monitor patients' conditions from remote locations. Also, with the help of wearable devices and machine learning applications, doctors can be notified about the health condition of patients through wearable devices. (Data Science in Healthcare – Applications, Roles, and Benefits, n.d.)

In this paper, I have highlighted the highlight of data science use cases with greater effects and future development potential in medicine and health care, different methodology, In this paper, a few factors (use cases) are described that make data science an imperative necessity for the healthcare sector in the current environment, with the competitive desire for quality information in the health market being the most important factor. Moreover, the following work highlights the data science use cases with the greatest effect and future development potential in medicine and healthcare.

The Data Scientist not only collects data from patients. It also analysis the need of the patient, and structures, and shortens the data for use. From the data collected, we can predict and develop a model for future prediction and providing better healthcare.

In this work, the reader can expect to find out about some of the most comprehensive data science use cases in healthcare and medicine, as well as the diverse techniques and methodologies that are considered when dealing with such use cases. In addition, the existing benefits and roles played by data science are described while addressing each use case.

1. Medical Image Analysis

Medicine and healthcare together form promising fields for utilizing technological advancement. The healthcare sector has acquired new heights due to the advancement in Data Science. Image analysis has been an interesting area of study. The medical image test includes X-ray, Sonography, Magnetic Resonance Imaging, CT Scan, Mammogram(scanning Breast cancer), Ultrasound, and PET Scan. Proper analysis of the image of these tests helps to gain valuable insights for the doctors to provide the patients with better treatment. It is applied for organ

delineation, lung tumor identification, spinal deformity diagnosis, artery stenosis detection, aneurysm detection, and soon. In a recent study published by Google AI, a Deep learning model has been created for diagnosing skin disease. With the help of Artificial intelligence, 26 diseases related to the skin can be diagnosed with an accuracy of 97%. All the diagnoses were based on deep neural networks, machine learning, and data science (Skin disease detection using artificial intelligence, Kuzhaloli Selvakumar, Vel Tech Rangarajan Dr Sagunthala R & D Institute of Science and Technology)

1.1 Types of Medical Image processing

I. Magnetic Resonance Imaging

MRI is one of the most standard strategies for the screening of the ligament. MRI does not use ionizing radiation, is non-intrusive and repeatable and image quality of image are high with high contrast and details.

With the help of Deep Learning, the reconstruction of images from under sampled raw data by learning the regularization parameter dynamically.

II. CAT Scan Computed Tomography Scan

A computerized tomography (CT) scan combines a series of X-ray images taken from different angles around your body and uses computer processing to create cross-sectional images (slices) of the bones, blood vessels, and soft tissues inside your body. (Mayo Clinic) We can identify Automated brain hemorrhage using CT scans and deep learning. The deep learning algorithm uses 3D context from neighboring slices to enhance predictions at each slice and then combines slice-level predictions to offer a CT-level diagnosis (Grewal et al., 2018).

The technique has been involved in creating to enhance the image quality to extract data from the image more rapidly, to give a more precise interpretation.

III. X-Ray

X-Ray is one of the oldest types of imaging used in the medical imaging process. X-rays are a type of radiation called electromagnetic waves. The image in the x-ray shows part of the body in different shades of black and white as different tissue absorb different amounts of radiation.

2. Genomics

Genomics is one of the most interesting areas of study in medical science. Genomics is the study of sequencing and examination of genomes that consist of genes and DNAs of living beings. It integrates data storage, data sharing, data analysis, and data quality control. (Roukos, 2010) The main aim is to find characteristics and irregularities present in DNA. Data Science, Machine learning, and big data tools are used to analyze human genes. These tools not only help medical researchers to find the genes, and genetic issue but also helps in its diagnosis and help to find the correct drug that responds to it. people (Genomic Data Science Fact Sheet, n.d.).

The introduction of Data Science brings two laboratory activities together. That is Experimentation and Data Analysis. These experimental data are analyzed using statistics and

data are stored in a database, these databases are huge. Sequence from one single human can take up to 200 GB of space. AI tools help researchers to process vast quantities of Genome-sequence data in search of hidden patterns in DNA.

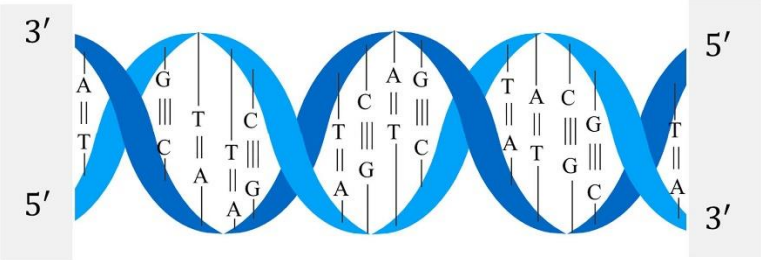
The basic tools used in Genome Sequence research are:

- **MapReduce**: MapReduce is a programming paradigm that enables massive scalability across hundreds or thousands of servers in a Hadoop cluster. The benefits of MapReduce programming are scalability, flexibility, speed, and simplicity. (Apache MapReduce, IBM). Therefore, with the help of MapReduce, the genetic sequence can be processed in lesser time
- **SQL**: With the help of SQL, we can retrieve and compute genomic data from various databases. The database can be a relational database or No-SQL
- **Bioconductor:** Bioconductor is used for analyzing genetic data.
- **Galaxy**: It is GUI based application used for biomedical research.

2.1 Data Structure of DNA Sequence

Biological sequences are not random and unordered strings, the structure consists of a linear arrangement of a smaller element. The DNA sequence is connected by four kinds of deoxyribonucleotides (bases). Base order contributes to the diversity of DNA molecules.

Figure 1 Double helix of DNA



Source: Front. Bioeng. Biotechnol., 2020

DNA Sequence data consist of non-numeric (A, T, C, G) characters. DNA sequence data contains its specific biological significance.

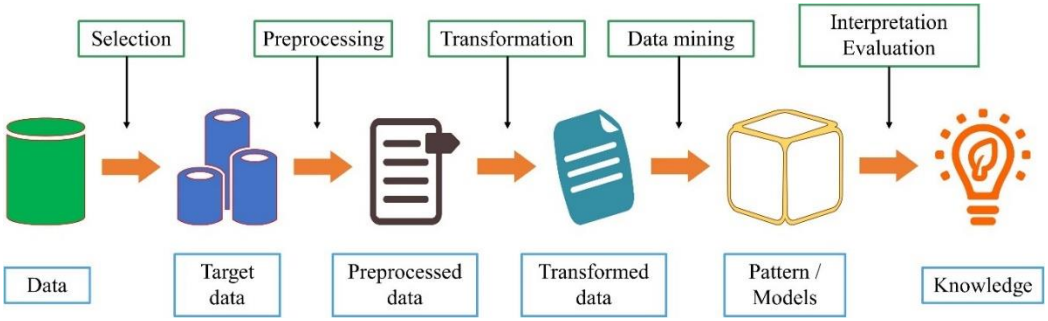
The machine Learning Algorithm used for the Geno sequence has faced revolutionary development in biological research and biotechnologies in the last few decades. The rapid development of biotechnology and biological data analysis methods has led to the emergence of a challenging new field: bioinformatics. Bioinformatics analyzes how to use data mining for effective biomedical data analysis and outlines some research questions that may stimulate the further development of powerful biological machine-learning algorithms. (Frontiers in Bioengineering and Biotechnology).

2.2 The basic process of Data Mining

Data mining is a combination of classic statistical tools with computer science algorithms. The main aim is to mine the knowledge from larger data. Once the data is gathered, the first process

is to clean the data. Data Cleaning is important because of the increasing amount of heterogeneous data, data sets often have missing data and inconsistent data. Low data quality will have a serious negative impact on the information extraction process. After cleaning the data, we follow Data integration in which we aggregate the data. After the aggregation of data, accurate data is selected for the model, called Data Selection. Once the data is selected, these data are transformed data into a form suitable for mining called Data Conversion. The next step is to select the appropriate model according to the problem and make subsequent improvements called Data Mining. After acquiring knowledge from the data, select appropriate indicators to evaluate the model. Each step of data mining is developed independently of other steps, and each step has a large number of machine learning algorithms. (Zhang et al., 2014)

Figure 2: The steps for data mining process.



Source: Front. Bioeng. Biotechnol., 2020

2.3 Machine Learning Algorithm used:

- **Apriori Algorithm**:

The Apriori algorithm is a typical association rule-based mining algorithm, which has applications in sequence pattern mining and protein structure prediction. The majority of machine learning algorithms are based on or derived from the Apriori algorithm. (Apriori Algorithm, geeksforgeeks.org). It follows the basic rules for data mining use of metrics to analyze the strong associations in the database. (Srikant and Agrawal (1996))

- **Classification Algorithm**:

Classification is one of the most used algorithms used in building a Machine Learning Model. It is based on predicted attributes to predict the class of target attribute specified. The key issues are genome classification and sequence annotation. In mining Geno- sequencing, the major classification algorithm we use are fuzzy sets, neural networks, genetic algorithms, rough sets Bayesian networks, decision trees, neural networks, and rule learning using evolutionary algorithms. (Apply Machine Learning Algorithms for Genomics Data Classification, Ernest Bonat, Ph.D., Bishes Rayamajhi, M.S)

- **Clustering Algorithm**

Using the clustering Algorithm, we can cluster together sequences with the same characteristics to explore more effective information about unknown sequences from function and structure.

The purpose of cluster analysis is to divide the data with common characteristics into one category and then use other methods to analyze the data. (Gerhardt et al. (2006)) Clustering does not implement a set category which is an advantage of using Cluster over classification. (Krause et al. (2000))

- **Genetic Risk and Gene Expression Use Case Models**

Genetic Risk Prediction uses genetic data for individualized prediction of outcomes. It helps in the prediction of the result or impact of exposure to a known dangerous toxin. Genetic polymorphisms are associated with a multitude of cardiovascular traits and raise the possibility that these variants can be used in clinical risk prediction. This prediction can be calculated using ROC, the Reclassification method, and risk score (Methods to Assess Genetic Risk Prediction). Gene expression prediction research has traditionally used convolutional layers as its primary architecture. Convolutional layers can be good at finding patterns, but they cannot always simulate how far apart parts of the input sequence are connected.

Therefore, it is necessary to gather accurate personal genetic data to understand deeply human DNA. Also, it helps to predict genetic risk and diagnose diseases related to genetics.

3. Drug Design

Big Data is used to defining huge volumes of data and sizes beyond the handling capabilities of common software. The advent of faster and cheaper technology combined with the development of computing power has led to the generation of big data in the pharmaceutical world. Artificial intelligence (AI) is defined as intelligence demonstrated by machines, particularly computer systems (The role of artificial intelligence (AI) and big data in drug discovery, Immy Mobley,2021)

The use of Artificial intelligence has proven, how it can manage big data and deliver cost-effective solutions at every step. The pharma industry is growing by more than 40% per year and it is estimated that by 2024 market will become 1.43 billion dollars.

3.1 Big Data Resource in Drug Design

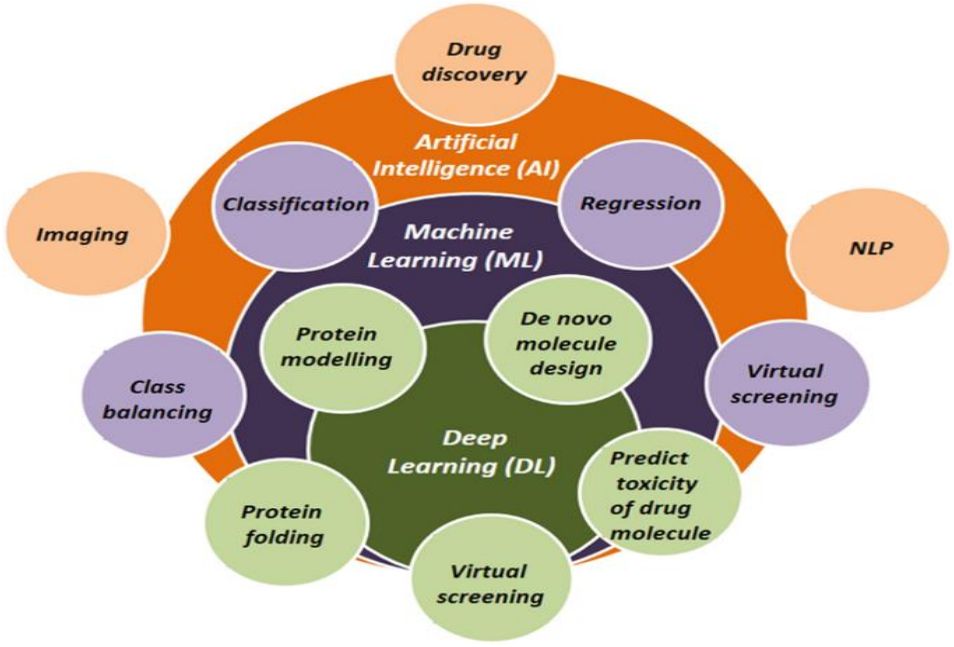
The Pharma industry has huge ever-expanding data libraries which contain multiple properties like chemical structure, chemical assay, target structure, and clinical data. The complexity of big data is resolved using AI. With the help of Cloud computing, Graphical processing units, and high-performance computer are very useful for data-driven approaches.

3.2 AI Methods in Drug Design

The data are collected and analyzed, using several machine learning and artificial intelligence algorithms to recognize and learn from the pattern for better results. Machine learning algorithms are used that do not need any human intervention such as developing a model mine interesting pattern to predict d drug side effects. (Machine learning in drug discovery, Konrad Budek,2019) Deep Learning To build a successful training model of deep learning neural network, huge data is required. The De novo study designs approach has been proven highly effective approach to analyze the Big data. This approach consists of a Support vector machine

(SVM), neural network, and random forest techniques. DL has taken advantage of the increased amounts of data and the continuous increase of available computer power. (The rise of deep learning in drug discovery). A generative adversarial network is a combination of generative and decimator networks, which is used for distinguishing between real and fake data for novel molecule design and its optimization. For treating diseases like cancer researchers widely use Convolutional neural networks as its use for image classification for the diagnosis of disease. (Generative Adversarial Networks, Jason Brownlee,2019). With the Autoencoder, we can predict features for drug target interaction and assess drug similarities. Generative graphical models that can be trained in a supervised or unsupervised manner. They have applications in virtual screening, classification of multi-target drugs and classification of small molecules into drugs or non-drugs. (Autoencoder Based Feature Selection Method for Classification of Anticancer Drug Response, Pan Qin, 2019)

Figure 3: The role of AI technology in different phases of drug discovery



Source: Immy Mobley,2021

4. Virtual Assistance for the patients

Virtual Assistance for patients has seen rapid growth over a couple of years. During the global Pandemic of Covid-19, due to the lockdown imposed by the government, many hospitals and doctors come forward to help patients virtually using Video conferencing, and chat-bots. These not only help in collecting data regarding fever and Covid 19 symptoms. These data were then analyzed using ROC Curve.

For virtual assistance industry had developed Intelligent Virtual Assistance (IVA) of Medical Virtual Assistance (MVA).

MVA helps the healthcare industry to collect demographic information, insurance information, patient health history, finance, costing, procurement details, data mining, and analysis of all records. It is a combination of machine learning and artificial intelligence decision support

systems and leverages big data, natural language processing, and voice recognition. (Mvas and real-time, real-world data in healthcare).

With technological innovation, a voice enables virtual assistance has been introduced. Voice assistance has delivered many benefits. A few benefits are:

- Navigation of electronic health records.
- Navigation of diagnosis option.
- Improve access to data health records.
- Improvement in patient discharge and follow of treatments for the betterment of patients.
- Improvement of communication between the hospital and patients.

The VA technologies have brought a revolution in the healthcare sector. Introduction of an Automated calling system and interactive voice response system(IVRS), Mental health app MHealth app, Patient Portal, health Kiosks, and Anytime access from anywhere are a few features.

- **Automated calling system and interactive voice response system (IVRS)**: It is a virtual assistant which helps to track patients' pre-and post-treatment. It uses text and voicemail confirmation before an appointment. Using Voice over Internet Protocol (VoIP) implementation for clinical settings, healthcare organizations are using MVA due to the rising popularity of AI, Deep Learning, Natural Language Processing, and speech recognition applications in smartphones.
- **MHealth App**: Healthcare providers are encouraging patients to use their smart devices to track fitness progress, do their payments, and schedule many of their day-to-day activities. Fitness devices track health parameters which are sugar level, heart rate, blood pressure, and oxygen level, which can be uploaded to the portal where patients and doctors can access these data.
- **Patient portals and Health Kiosks**: It helps patients to book appointments. By filling in the medical and social details, patients can view their lab records and help make outstanding balances. Kiosks collect patient information through an integrated VoIP System (Voice over IP).

Figure 4: Virtual Assistance Model

Source: real-world data in healthcare

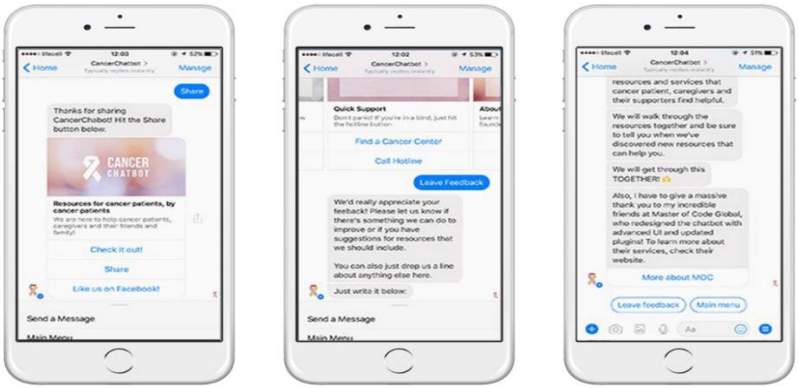
5. Patient Care

Ultimate goal is to provide better care to the patient. With the implementation of machine learning and artificial intelligence application like chatbot and healthcare gadgets has been introduced. Chatbot is an application of Deep learning and neural network. Whereas monitoring devices are application if big data and IoT.

5.1 Chatbot

The chatbot works as a pre-consultation chatbot, which also refers to as a robot doctor. While using a chatbot patients can describe their symptoms, once the chatbot collects the information, it sends it to dedicate doctors. It helps a doctor to find the condition of patients in advance. In the pre-consultation phase, the chatbot collects all information by asking for details from a patient just like a doctor. And when a patient visits the doctor to get a consult. It is easy for a doctor to treat a doctor more effectively. (Rosruen & Samanchuen, 2018). Another type of chatbot that is used for consultation is for mental health. The digital health of psychological counseling has emerged as a new development trend in psychological treatment. the chatbot may also pose questions to consumers depending on the context. Cognitive behavior therapy and powerful natural language processing technologies have been coupled to assist users in recording their feelings and detecting early indicators of depression. (Chung & Park,2019).

Figure 5: Chatbot

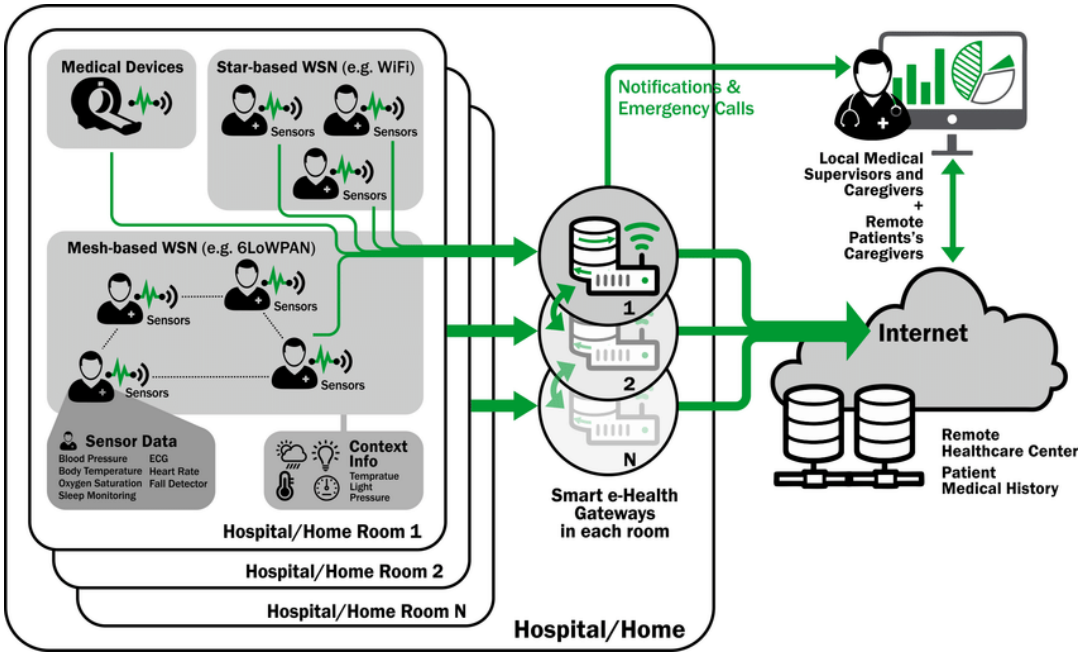


Images of Cancer Chatbot exchange sourced from Chatbots Magazine.

5.2 Monitoring Patient Health

Healthcare monitoring and diagnostics have become an integral part of society. In the city people are so busy, they don't feel to visit doctors for a minute health issue, which can be lethal. Early diagnoses are vital to the treatment of many diseases. (Chaudhury et al., 2017). We can challenge many healthcare issues by introducing an intelligent healthcare system. The innovation and implementation of the Internet of thing (IoT), data science, big data analytics, and cloud computing helps the healthcare industry to meet expectations. (Chaudhury et al., 2017).

Figure 6: Working of medical devices based on IoT



Source: Dash et al., 2019

Nowadays the healthcare industries are facing major challenges in data collection and data storage. Data analytics and data collection play an important role in health screening. Cloud computing plays an important role. The IoT benefits patients, hospitals, doctors, families, and insurance companies. It also tracks how well a patient responds to the treatment and how they follow their treatment plans. IoT has gotten a lot of attention over the past few years, leading to big improvements in how healthcare monitoring works. The IoT in healthcare employs wearable sensors that collect a tremendous quantity of data, and cloud computing is the most effective method for dealing with this large amount of data.

Computing and IoT are becoming more popular, which help to make operations smoother making all assets involved in the healthcare industry happy and making it easy for the patient. The customized healthcare system provides e-healthcare services to provide healthcare accessible to each individual. (Dash et al., 2019). IoT not only gathers information regarding early forecast but also help to take proper precaution to make better decision-making steps for better life quality. The fundamental concern of the physician is that he must make judgments on a patient's healthcare, which requires separating information about a single patient from a flood of medical data related to a huge number of patients. In this instance, a controller of the IoT would be used to transport medical data to the cloud, which would manage the huge amount of data and enable big data analysis. This data processing and analytics allow for continuous patient condition monitoring. (Chaudhury et al., 2017). The growth of big data analytics, which includes the IoT and cloud computing, helps people make better decisions and plan, coordinate, lead, command, and manage things better.

Conclusion

Data science algorithms have proven that innovation in data science brings innovation to healthcare sectors. Healthcare adopts new techniques like Artificial intelligence, Machine learning, Deep Learning, and Big data to find new insight and make bold ideas into reality. Healthcare has seen exponential growth since the introduction of data science in health care and continuously evolving.

In this work, I have discussed a prospective used case that is present in numerous healthcare industries such as Image processing, Genomics, Virtual Assistance for patients, and Monitoring Patient Health. With the introduction of machine learning in medical image processing, doctors can detect small tumors and other deformities formed inside the human body which are not difficult to detect.

The Genomics department of healthcare has seen drastic changes with the introduction of artificial intelligence, big data, and deep learning, the researchers are not only able to detect genetic diseases, but they are also able to find a cure and help to pharma industry create vaccines. Combining genetics and drug-protein binding databases allows for the development of discoveries in this field.

Data Science has brought innovative patient aid platforms and made it easy for patients to access his/her medical records. The acquired data has been analyzed with the help of data science. With tools like an interactive voice response system, health app, and health kiosks. Hospitals may be able to predict when a patient's health will start to get worse and take preventative steps or start treatment early to make it less likely that the patient's health will get worse even more.

With the introduction of IoT and cloud computing, health monitoring gadgets are widely adopted by people to monitor blood pressure, heart rate, oxygen level, and blood sugar level on the confidence rate. Using data science algorithms, hospitals may be able to predict when a patient's health will start to get worse and take preventative steps or start treatment early to make it less likely that the patient's health will get worse even more.

The breakthrough in data-driven technologies which had benefited various phases of the drug discovery cycle. It also helps in rapid screening of virtual compound libraries to predict the molecule’s physical properties and surveillance of patients during clinical trials.

Overall, data science has significantly transformed the healthcare and medical industry and the future appears bright and optimistic.

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