Current Research in Biotechnology 7 (2024) 100164

Contents lists available at ScienceDirect

Current Research in Biotechnology

journal homepage: www.elsevier.com/locate/crbiot

From machine learning to deep learning: Advances of the recent data-driven paradigm shift in medicine and healthcare

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ARTICLE INFO

Keywords:
Deep learning
Machine learning
Artificial intelligence
Medicine and health care

ABSTRACT

The medicine and healthcare sector has been evolving and advancing very fast. The advancement has been initiated and shaped by the applications of data-driven, robust, and efficient machine learning (ML) to deep learning (DL) technologies. ML in the medical sector is developing quickly, causing rapid progress, reshaping medicine, and improving clinician and patient experiences. ML technologies evolved into data-hungry DL approaches, which are more robust and efficient in dealing with medical data. This article reviews some critical data-driven aspects of machine intelligence in the medical field. In this direction, the article illustrated the recent progress of data-driven medical science using ML to DL in two categories: firstly, the recent development of data science in medicine with the use of ML to DL and, secondly, the chabot technologies in healthcare and medicine, particularly on ChatGPT. Here, we discuss the progress of ML, DL, and the transition requirements from ML to DL. To discuss the advancement in data science, we illustrate prospective studies of medical image data, newly evolved DL interpretation data from EMR or EHR, big data in personalized medicine, and dataset shifts in artificial intelligence (AI). Simultaneously, the article illustrated recently developed DL-enabled ChatGPT technology. Finally, we summarize the broad role of ML and DL in medicine and the significant challenges for implementing recent ML to DL technologies in healthcare. The overview of the data-driven paradigm shift in medicine using ML to DL technologies in the article will benefit researchers immensely.

1. Introduction

In the recent era, medicine field is changing very fast. The paradigm shift in medicine was noted in the area of cutting-edge diagnostics of diseases, advanced treatment procedures, targeted drug therapy, and surgery with the recently evolved artificial intelligence (AI) technology like deep learning (DL) technologies. The recent progress of machine learning (ML) plays a crucial role in the paradigm shift in medicine. The ML is a form of AI that uses algorithms to predict outcomes precisely. In medicine, these algorithms use medical data to provide new outcomes. Presently ML systems are frequently used in the medical field (Rajkomar et al., 2019; Goecks et al., 2020; May, 2021; Haug and Drazen, 2023). The first AI-based cardiac MRI software, "Cardio AI," was approved by the FDA (food and drug administration) in 2017 (FDA approved no. K163253), which was developed by Arterys Inc., USA. Subsequently, several AI-based products were approved from time to time (Benjamens et al., 2020; Ebrahimian et al., 2022). The approval of AI technologies boosted AI research. Significant AI-related algorithms have been published during the last decade, demonstrating AI in medical science. The information about AI-related algorithms boosted AI-related research in medical science. DL is a subfield of ML that mainly uses algorithms of neural networks to predict outcomes more accurately. In medicine, DL-based algorithms are more efficient and robust which are mostly used in medical images to solve diagnostics challenges (Kurokowa et al., 1987; Castiglioni et al., 2021). In 2016, Gulshan et al. developed a DL-based algorithm for identifying DR (diabetic retinopathy) using the

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https://doi.org/10.1016/j.crbiot.2023.100164
Received 18 August 2023; Received in revised form 19 November 2023; Accepted 21 November 2023
Available online 22 November 2023

development dataset of 1,28,175 retinal images. The DL algorithm showed high specificity and sensitivity (Gulshan et al., 2016). In the following year, using DNN (deep neural networks), Esteva et al. developed an algorithm for the classification of skin cancer using a dataset of 1,29,450 clinical images (Esteva et al., 2017). Again, in 2018, Rajpurkar et al. formulated and validated a DL algorithm named 'CheXNeXt' for chest radiograph diagnosis where the researchers used 420 images to classify the clinical abnormalities in chest radiographs (Rajpurkar et al., 2018). Thus, in three consecutive years, these three DL algorithms have created examples in medical diagnostics.

Looking back, it is noted in 1950, Alan Turing was the first to explain the concept of simulating intelligent behavior and critical thinking using computers. After six years, John McCarthy coined AI. The computer scientist defines AI as the engineering and science of creating intelligent machines (Chahal and Byrne, 2020; Kaul et al., 2020; Yasnitsky, 2020). Several AI developments occurred between the 1970s and 2000s. In adition to that, several computational problems were solved before 2000 by computer scientists. Although, had calculation speed limitations, all these inventions occurred in the computer laboratory. In about 2000, the vanishing gradient problem of DL was appeared. Although in the 1950s, the concept of DL was first developed, its medicinal application was started in 2000 along with several limitations (Yang and Bang, 2019; Kaul et al., 2020). However, in 2017, the first US FDA-approved cloud-based DL was developed, Arterys, an application in healthcare. A DL-based medical imaging platform was also developed as Cardio AI, which can quickly analyze cardiac ejection fraction through magnetic resonance, maybe within a second. In 2007, the IBM developed an open-domain question-answering computation system entitled as 'Watson,' usually called 'IBM Watson.' However, another technology was developed, named DeepQA, to give evidence-based medicine. Arterys, CardioAI, IBM Watson, and DeepQA were excellent examples of AI-based medical technology which were developed between the year 2000 to 2020 (Kaul et al., 2020). After 2020, the progress of AI-based technologies in the medical field was noted very fast.

The contribution of AI and biosensors in the medical field is significant. In this connection, Qureshi et al. explored recent advancements in AI and biosensors within the medical and life sciences domains. The paper highlights the crucial role of ML in enhancing medical imaging, thereby enabling more accurate diagnostic procedures. Furthermore, the paper delves into the concept of precision medicine, which involves tailoring treatments to individual patients. It emphasizes the contribution of ML in analyzing large datasets to provide personalized care. Integrating biosensors into the Internet of Things (IoT) ecosystem is also discussed, highlighting their real-time monitoring capabilities for physiological and chemical signals. Additionally, the paper addresses technological advancements, such as accelerated AI and edge computing. It outlines the challenges, potential issues, and prospects in applying AI and biosensors in the healthcare industry, emphasizing their transformative impact on medical science and patient care (Qureshi et al., 2023). In a separate study, Phatak et al. proposed a comprehensive framework that combines wearable sensors, real-time location systems, and AI/ML algorithms for data collection and analysis in sports and healthcare. A vital feature of this framework is the provision of real-time feedback to users, which enhances data-driven decision-making processes (Pathak et al., 2021). Jin et al. delved into the applications of AI in diabetes management, specifically using closed-loop control algorithms, glucose predictions, and calibrations within continuous glucose monitoring systems. The study examines the challenges and opportunities associated with individualized and proactive medicine (Jin et al., 2023). In another study, Lu et al. emphasized AI's pivotal role in analyzing data collected from various biosensors. Their article underscores how AI contributes to the long-term and in-situ monitoring of physiological information, aligning with the broader landscape of IoT technologies in healthcare (Lu et al., 2023a). Collectively, these articles reflect the increasing significance of AI-driven biosensors in shaping the future of healthcare. They facilitate data-driven decision-making, personalized medicine, and continuous monitoring, which is crucial in advancing the healthcare industry.

Although ML-based algorithms have enriched the different medical fields, at the same time, along with the advancements in ML-related algorithms, there is a considerable advancement in data science and big data analytics in the field of medical science. Researchers are trying to evaluate and find the correlations between real-world medical datasets and big data. Researchers use ML occasionally in clinical, multi-omics, and pharmaceutical R&D (research and development) data in this direction (Wang and Preininger, 2019; Ahmed, et al., 2020; Alizadehsani et al., 2021). Big data in the medical sector can transform data into knowledge. Datasets has been were analyzed for personalized medicine (Millman et al., 1989; Dicuonzo et al., 2022).

Recently, ML, and DL models have used to detection of different diseases and assessed through the randomized clinical trials (RCTs). Wang et al. created a colonoscopy computer-aided detection system (CADe) by DL-based platform to detect the adenoma. The colonoscopy with the CADe system was registered in a clinical trial on chictr.org.cn (Clinical Trial ID: ChiCTR1800017675) (Wang et al., 2020). Hollon et al. developed a diagnosis method for detecting brain tumors using deep CNN (convolutional neural networks). The technology was tested through the multicenter clinical trial with many patients ($n = 278$) (Hollon et al., 2020). Moreover, the US FDA and other advanced countries have approved several ML or DL-based algorithms and medical devices for the clinic. Aisu et al. have listed the ML and DL-based medical devices approved in Japan. They found 11 ML and DL-based devices received regulatory approval. Among them, five were related to gastroenterology, and six were related to radiology (Aisu et al. (2022).

This article discusses the journey from ML to DL and data-driven patient care. In the review article, we illustrated the ML and DL technologies in medicine in two directions: first, advancement in data science; second, chabot technologies in healthcare and medicine. To illustrate the progress in data science, we discuss medical images data, ML and DL interpretation, data from EMR (electronic medical record) or EHR (electronic health record), big data in personalized medicine, data for medical research, and dataset shift in AI. Chabot technologies with recently developed ChatGPT technology have been discussed. Finally, we illustrated the broad role of ML and DL in medicine and future challenges.

2. The journey from ML to DL and data-driven patient care

In 1943, a neural network model was developed by McCulloch and Pitts , which started the journey of ML (Wang et al., 2021). Early neural networks could have been more helpful and insightful. After its origin, ML models continued to evolve. Data-driven ML was built by the research of Hinton. Subsequently, it improved as a DL technique and was popularized in 2012.

However, first, the different ML models have been used in the medical field to analyse the medical data (Table 1). At the same time, the evolved DL models were utilized to analyze the medical data in a more accurate way (Table 2).

Recently, data-driven ML was popularized as a specific application of AI. Using algorithms, data-driven ML permits computers to trained and improve from data and experience (Ng et al., 2020). Dinh et al. developed a data-driven ML approach for an automatic mechanism to identify patient's risk of cardiovascular diseases and diabetes (Dinh et al., 2019). Zhao et al. developed Chinese diabetes datasets (both type-1 and type −2 patients) for the development of data-driven ML models (Zhao et al., 2023). Similarly, Liu et al. performed a data-driven population segregation analysis using a ML model for clinical use (Liu et al., 2023).

Along with the popularization of ML techniques, data-driven DL is currently gathering enormous attention for patient care. Oh et al. developed a cluster-based deep reinforcement learning (DRL) approach for the treatment of T2D (type-2 diabetes) using electronic health records (EHR) of the South Korean population. The model shows high-

Table 1
A list of different ML methods used for the recent data analysis of medicine and healthcare.

Sl. No.	Significant concept of ML	Description
1.	Bayesian learning	This method combined the preceding knowledge information in addition to data, to accomplish ML.
2.	Ensemble learning	Ensemble learning approaches build many models and use the average of all the models to create predictions. Collective ensemble approaches include the gradient-boosting, random forests, and with the stacking/meta-ensembles.
3.	Unsupervised, supervised, and semi-supervised learning	Unsupervised learning identifies the structure, generally clusters, among the unlabeled data. Whereas, the supervised learning predicts labels or classes on future data, based on past data that holds labels/classes. Semi-supervised learning initially accomplishes unsupervised learning, and humans label structures that found from the unsupervised learning.
4.	Dimensionality reduction	It reduces the number of features or attributes of a dataset by choosing vital features or merging the features to capture variance in a dataset. Frequently used to increase the machine learning models performance and to support visualization.
5.	Deep learning	Deep learning is the multi-layer artificial neural networks that can learn the complex non-linear functions. It is too much useful for unstructured data like speech, images, or text. But, usually it does not provide insights in to the aspects of the data which are driving the functions.
6.	Federated learning	This approaches used for incrementally learning from data distributed in numerous locations. It cannot be united into a single dataset. It is useful when data are positioned in multiple clinical systems, or when the learning occurred from sensitive personal data.
7.	Regression and classification	These are the supervised learning methods. Regression predicts real-valued outputs such as response to therapy. The classification can predicts discreet categories such as normal vs. diseased.

quality performance when it resembles existing DRL models (Oh et al., 2022). Therefore, a recent paradigm shift was constantly noted in data-driven patient care using the ML and DL models, which are changing the scenario of health care.

2.1. Progress in ML

The speedy progress of ML was recorded in medicine and healthcare, and researchers have contributed to the progress immensely (Table 3). The progression of ML algorithms and models has been incredible, with the development of novel techniques to tackle different problems. An example is graph machine learning (GML), which represents a new classification of ML methods that harnesses the structural characteristics of graphs and other irregular datasets to acquire effective feature representations of nodes, edges, or even entire graphs (Gaudelet et al., 2021). ML has applications in various sectors, including drug discovery and development, education, drought hazard monitoring and forecasting, and cancer research. In drug discovery and development, using repurposed drugs through in vivo studies suggests that GML is on track to become the preferred modeling framework within the field of biomedical ML. GML has piqued the interest of the pharmaceutical and biotechnology industries due to its capacity to model biomolecular

Table 2
A list of different DL methods used for the recent data analysis of medicine and healthcare.

Sl. No.	Significant concept of DL	Description
1.	Generative adversarial network	The neural network with generative approach,where two neural networks are trained. One neural network, thegenerator mainly provided with a set of randomly generated inputs, and tasked with producing samples. The second, the discriminatoris trained to generated, differentiate and real samples. Afterwards the two neural networks are trained against each other, the resulting generator can be used to produce new important examples
2.	Neural network	A ML approach mainly conceptualized by biological neurons, the inputs are fed into one or more layers, and producing an specific output layer
3.	Restricted Boltzmann machine	The neural network having generative from of neural network that forms the building block for support to many deep learning approaches, having a single input layer and a single hidden layer. In this approaches no connections developed between the nodes within each layer
4.	Recurrent neural network	One type of neural network with cycles in between the nodes inside a hidden layer
5.	Supervised learning	The ML approaches with the goal of prediction of labels or consequences/outputs
6.	Autoencoder	The neural network where the training objective is to reduce the error in between the output layer and the input layer. This kind of neural networks are unsupervised and are frequently used for the dimensionality reduction
7.	Feed-forward neural network	The neural network that does not consist cycles between the nodes in the same layer
8.	Denoising autoencoder	The special type of auto encoder comprises a phase where noise is incorporated to the input during the stage of training process. The denoising step actions as smoothing and may permit for effective use on input data,this is inherently noisy
9.	Variational autoencoder	One of the special type of auto encoder generative AE learns a probabilistic latent variable model
10.	Unsupervised learning	ML approaches with the aim of pattern identificationor the data summarization
11.	Convolutional neural network	The neural network consist with layers, where connectivity is preserves local structure. Even the data meet the underlying assumptions performance is often good, and this networks can require less examples to trainefficiently. Because they holds rarer parameters and also offer improved efficiency
12	Deep neural network	The neural network consists with multiple hidden layers. Training occurs over the network, and accordingly such architectures allow for feature construction to performed combined with to optimization of the complete training objective
13	Deep belief networks	The generative neural network with numerous hidden layers, which can be acquired from combining of the multiple of Restricted Boltzmann Machine
14	Long short-term memory (LSTM) neural network	This special type of recurrent neuralnetworkhaving features that enable models to capture the longer-term dependencies
15	Multilayer perceptron	One type of type of feed-forward neural network having minimum one hidden layer,in

(*continued on next page*)

Table 2 (*continued*)

Sl. No.	Significant concept of DL	Description
		where each deeper layer is a nonlinear function of every earlier layer
16	Adversarial training	The specialized process by which artificial training examples are nastily designed to fool an neural network and then input as training examples to make the resulting fool an neural network robust
17	Generative neural network	The neural networks that fall into this class of neural network can be used to produce data similar to input data. These models can be sampled to produce hypothetical examples
18	Data augmentation	A procedure by which transformations doesn't affect appropriate properties of the input data, and are applied to training examples to upsurge the size of the training set

structures, elucidate the functional relationships between them, and integrate multi-omic datasets. ML techniques have been implemented in research and education to augment teaching, learning, assessment, and educational support. In one study, Cao et al. have highlighted the importance of geometric machine learning in several research application areas (Cao et al. (2022). Several other milestones and breakthroughs in ML research are available.

Sarker et al. explored the convergence between AI, the internet of medical things (IoMT), and blockchain in healthcare. The research delves into the potential utilization of these technologies to enhance patient care through data-driven approaches. AI plays a crucial role in this technology use as it facilitates the processing of extensive healthcare datasets, leading to improved patient outcomes and the implementation of predictive analytics (Sarker et al., 2023). Bharati et al. conducted a study in breast cancer prediction utilizing various classification algorithms. Their work demonstrates the practical application of ML techniques for early detection and diagnosis, which marks a significant advancement from traditional ML to more sophisticated models in the healthcare domain. The WEKA tool's comparative analysis offers valuable insights into the performance enhancements (Bharati et al., 2018). In a separate study, Bharati et al. focused their research on diagnosing polycystic ovary syndrome (PCOS) through utilizing ML algorithms. PCOS is a complex and challenging medical condition to diagnose accurately, and this study showcases the potential application of ML in addressing such complexities within healthcare. The research reflects the shift from traditional ML to more advanced techniques in managing intricate medical conditions (Bharati et al., 2020). Further, in another study, Bharati et al. conducted a comprehensive review of the role of explainable artificial intelligence (XAI) within the healthcare domain. This multidisciplinary area of research is relevant in transitioning from traditional ML to advanced methods, as it highlights the importance of understanding the decision-making processes of advanced AI models (Bharati et al., 2023). In the domain of data-driven care, Ibtisum S. conducted a comparative study on various big data tools. This research holds significant value in handling and processing the vast amounts of healthcare data required for data-driven patient care (Ibtisum, 2020). In another study, Rahmani et al. provided a comprehensive review of the applications of ML within the field of medicine. This paper covers the evolution of ML within healthcare, ranging from its applications in diagnostics to the associated challenges and limitations. By understanding the applications and limitations of traditional ML within healthcare, this paper acts as a stepping stone towards adopting more advanced techniques, thereby paving the way for a data-driven approach in patient care (Rahmani et al., 2021). Rubinger et al. have also discussed the role of ML and AI in research and healthcare. They emphasized the increasing adoption of AI technologies within healthcare, showcasing their potential to revolution patient care and research. It serves as a

Table 3
Recent performance of ML in medicine and healthcare.

Sl. No.	ML model and its area of application	Remarks	Reference
1.	Weka-based classification algorithms on breast cancer prediction	It is used to diagnose breast cancer disease using various ML data mining tools and is considered a new aspect of medical progression. It was explored to evaluate the cancer disease dataset collected from the UCI ML repository.	(Bharati et al., 2018)
2.	Logistic regression, and hybrid random forest and logistic regression (RFLR) are applied to the diagnosis of polycystic ovary syndrome dataset	Data-driven diagnosis of polycystic ovary syndrome using the ML algorithms to a dataset freely available in the Kaggle repository.	(Bharati et al., 2020)
3.	ML utilized in the field of personalized medicine to integrate clinical data and genomic information of patients	The multiple ML algorithms utilized in clinical and genomic medicine for implementation of AI in clinical medicine, drug discovery, and genomic medicine.	(Chafai et al., 2023)
4.	ML driven approach for large amounts of complex healthcare information	Focus on the ML-driven approach's potential need, role, and limitations to analyze complex healthcare evidence of big data sectors.	(Cammarota et al., 2020)
5.	ML and its potential role in cardiovascular healthcare	ML refers to learning independently and making accurate predictions in cardiovascular healthcare. Additionally, applied in automated imaging interpretation, natural language processing and data extraction from electronic health records, and predictive analytics.	(Kilic, 2020)
6.	ML technologies in oral healthcare	The ML is used for new perspectives on diagnosing, classifying, and predicting oral diseases, treatment planning, and assessing and predicting outcomes, reducing the possibility of human errors.	(Leite et al., 2020)
7.	ML used in pediatrics and neonatology healthcare	ML can assist in healthcare data, high-resolution medical imaging, biosensors with continuous physiologic metrics output, and the OMICS science for pediatrics and neonatology.	(Matsushita FY et al., 2022)
8.	Utilization of ML in clinical hematology laboratory	ML used in laboratory hematology will increase standardization and efficiency by reducing staff involvement in automatable activities and fewer resources.	(Obstfeld AE, 2023)
9.	ML application in astroenterology and hepatology	The ML also contributes to health imbalances in gastroenterology and hepatology, including the diagnosis of oesophageal cancer, management of inflammatory bowel disease, liver	(Uche-Anya et al., 2022)

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Table 3 (*continued*)

Sl. No.	ML model and its area of application	Remarks	Reference
		transplantation, and screening of colorectal cancer.	
10.	ML strengthen in the geriatric medicine	ML algorithms are offered to improve diagnosis, risk stratification, and individualized approaches to patient management, specifically in geriatric medicine.	(Woodman RJ and Mangoni AA, 2023)
11.	ML supportive to cardiac surgery	ML technical and clinically applied to cardiac surgery comprises diagnostics, surgical skill assessment, postoperative prognostication, augmenting intraoperative performance, and accelerating translational research.	(Ostberg, 2021)
12.	ML domain in dermatology	It contributed to dermatologists in diagnosing and treating skin diseases, thereby improving patient care.	(Adamson AS, Smith A, 2018)

testament to the ongoing evolution in this field, highlighting the shift towards DL, big data analysis, and data-driven approaches in healthcare (Rubinger et al., 2023). Despite the substantial progress in ML research and education, numerous challenges persist and necessitate attention. Ethical considerations, privacy concerns, and the imperative need for effective collaboration between humans and AI are among the obstacles to integrating AI into education (Kumar et al., 2023a).

2.2. Progress in DLmodels in healthcare

A few significant contributions and developments of DL in medicine and healthcare are summarized in this subsection. The noted researchers' contributions to the development and progress of DL in medicine and healthcare have been incredible (Table 4). As it is known, DL models, which are also referred to as DNN, have an essential advantage, i.e., these attempt to resemble human brain functioning and can comprehend highly complicated patterns in vast datasets. DL can be employed in several areas, such as health monitoring, image investigation, prediction of protein interactions, and detection of viruses. With DL, many unsupervised datasets can be comprehended and analyzed. Therefore, it undoubtedly becomes a precious tool for undertaking big data analytics where the raw datasets are mostly not categorized or labeled. Najafabadi et al. studied the use of DL in handling notable issues with big data analytics, such as extracting complicated patterns from enormous datasets, tagging data, retrieving swift information, semantic indexing, and doing more straightforward discriminatory jobs. This group further explored the requirement of more research in the DL domain to tackle the exact challenges that crop up from time to time in big data analytics (Najafabadi et al., 2015). In another study, Kaul et al., in their book chapter, highlighted the contribution of DL techniques when vast volumes of medical data need to be processed and analyzed. They noted the DNN working mechanism concerning big data analytics and the capacity of DNN in detecting and treating human diseases (Kaul et al., 2022). The contribution of DL in the healthcare domain was also assessed by Shamshirband et al. They studied DL models used in healthcare by considering novel network architectures and their applications. They highlighted the use of DL models in healthcare to unite DL technologies and healthcare interpretation (Shamshirband et al., 2021). Jin et al. made an elaborate study on DL use in COVID-19 research. Their study concluded that DL has the potential not only to diagnose COVID-

Table 4
Recent performance of DL in medicine and healthcare.

Sl. No.	DL model and its area of application	Remarks	Reference
1.	The application of DL strengthen ChatGPT in the drugs and its target discovery, drug development process	Such a model helps to recognize the structure of proteins, the structural domain in the protein, the drug-binding pocket, and the active site of the protein-based drug target.	(Chakraborty et al., 2023a)
2.	DL for cancer diagnosis, prediction and treatment	DL is used in the analysis of the complex biology of cancer, methylation and transcriptomic data, and histopathology-based genomic inference.	(Tran, 2021)
3.	DL strengthen ChatGPT for biomedical engineering and research	It provides error-free, more accurate, and updated information and advances the biomedical engineering design of a medical device.	(Pal et al., 2023a)
4.	ChatGPT support the application in medical science	It offers greater applicability in medicine, architecture and training methods, medical diagnosis and treatment, and research ethical issues.	(Chakraborty et al., 2023b)
5.	DL based support system in ophthalmology	The DL was performed to detect diabetic retinopathy and prematurity retinopathy, glaucoma-like disc, macular edema, and age-related macular degeneration. Moreover, it uses optical coherence tomography and visual fields.	(Ting DSW et al., 2019)
6.	Deep learning (multi-layered neural networks) based application for cardiovascular medicine	Dl is accomplished to automate medical image interpretation, identify novel phenotypes, enhance clinical decision-making, and select better treatment pathways in complex cardiovascular diseases.	(Krittanawong and Johnson, 2019)
7	DL for COVID-19 diagnosis and prediction	Dl has been used for thoracic imaging to diagnose, predict, and manage COVID-19 patients with moderate to severe symptoms.	(Liu et al., 2022)
8	DL model (deep neural network) for echocardiographic assessment of diastolic dysfunction	This model integrates multidimensional echocardiographic data to identify distinct patient subgroups having heart failure with preserved ejection fraction.	(Pandey et al., 2021)
9.	DL system for differential diagnosis of skin diseases	The deep learning system (DLS) to provide a differential diagnosis of skin conditions using 16,114 de-identified cases (photographs and clinical data) from a teledermatology practice.	(Liu et al., 2020a)
10.	DL approach used for accurate eczema and psoriasis skin detection	Large and diverse datasets of skin images are used to study the deep learning approach to detect multiple skin diseases and improve the efficiency and accuracy of dermatological diagnosis.	(Hammad and Pławiak, 2023)

19 but also to judge the progress and prognosis of the disease, suggest treatment plans, and assist federal governments in formulating intelligent steps to control and prevent the spread of the disease (Jin et al., 2023). Another detailed study by Zvarikova et al. discussed the role of ML and DL techniques, tasks involving computer vision, and IoT-based health checking systems in handling COVID-19, i.e., detecting, testing, treating, and preventive measures. It was pointed out that biometric data could be deployed to diagnose remote COVID-19 (Zvarikova et al., 2022). Concerning COVID-19 screening, Mondal et al. have also mentioned the role of DL and federated learning in their review paper (Mondal et al., 2023). In a different application area, Kumar et al. have also highlighted the prospects of ML and DL in health monitoring systems in their book chapter. They proposed a robust model that would deliver superior confidence and precision compared to traditional ones (Kumar et al., 2023b). In another interesting work, Wu et al. proposed an IoT-enabled DL-based health monitoring unit that works in real-time. As a protocol, medical devices need to be put on, and the proposed unit would gauge vital signs and utilize DL techniques to comprehend precious information on health conditions. The case study was conducted on Sanda athletes, and the monitoring system can deliver precision prediction during real-time transmission conditions, monitoring, storage, and examination of datasets (Wu et al., 2023). DL has also played in information extraction of protein–protein interactions (PPI). In this connection, Zhao et al. developed a DNN model that can extract PPI information from biomedical literature. The model first utilizes the training method of auto-encoders for parameter initialization of a deep multilayer neural network (DMNN) and second, the gradient descent technique to train the DMNN model. The experimental results indicated better performance than multilayer neural networks (Zhao et al., 2016). In another work on PPI extraction from biomedical literature, Peng and Lu conceptualized a model that functions on a multichannel dependency-based convolution neural network (McDepCNN). The McDepCNN model can utilize high-quality information procured from various channels, and it can easily generalize on various corpora, as well as record lengthy features of sentences (Peng and Lu, 2017). A detailed study on the status of PPI prediction with DL was undertaken by Soleymani et al., and they highlighted the latest DL technologies employed in predicting functions associated with proteins, PPI and their corresponding sites, binding among proteins and ligands, and design of proteins (Soleymani et al., 2022). Furthermore, DL technologies have contributed to clinical image analysis considerably, and this field is gaining increased attention with new research developments. As mentioned in the introduction section, many research groups have worked on employing DL methods in medical image analysis to tackle diagnostic hurdles, retinopathy for diabetic patients, classification of cancer in the skin, and investigation of chest radiographs (Castiglioni et al., 2021; Gulshan et al., 2016; Esteva et al., 2017; Rajpurkar et al., 2018). Comprehensive reviews giving a detailed overview of the use of DL techniques in comprehending and analyzing clinical photographs have been carried out recently (Suganyadevi et al., 2022; Shen et al., 2017; Razzak et al., 2018; Zhou et al., 2021).

DL has been proposed for used in solving global health problems like antibiotic resistance. Chakraborty et al. proposed to use DL to solve the problem of antibiotic resistance. They have shown a path to explain the prospect of DL to solve antibiotic resistance. Chakraborty et al. also proposed using DL in the different surgery processes (Chakraborty et al., 2022a). DL-enabled tools and methodologies have emerged as a powerful technique to characterize and learn from rapidly accumulating medical and healthcare data. Several researchers have used DL-enabled tools in different fields of biological science research, especially in medicine and healthcare (Chakraborty et al., 2022b; Chiu et al. (2020). Recently, DL-enabled ChatGPT has emerged as a powerful LLM means. It has been used in different fields of medicine and healthcare, occasionally (Pal et al., 2023a). However, we have illustrated the application of ChatGPT in medicine and healthcare in a separate section in this article.

2.3. The transition requirements from ML to DL

The transition from ML to DL in the healthcare field is a multifaceted and transformative journey, encompassing many intricate challenges that require close attention. One of the primary challenges is the protection of data privacy and security. As the healthcare industry increasingly relies on large and diverse datasets, it becomes crucial to establish strong encryption, access controls, and anonymization techniques to safeguard sensitive patient information. Compliance with stringent regulations such as the health insurance portability and accountability act (HIPAA) and the general data protection regulation (GDPR) is indispensable to mitigate data breaches and avoid legal consequences. Furthermore, achieving interoperability is a pressing concern. The seamless exchange of data between healthcare systems and devices necessitates the utilization of standardized data formats and protocols, such as the fast healthcare interoperability resources (FHIR), to ensure smooth data sharing and integration. Without interoperability, the potential advantages of DL may be hindered by fragmented and isolated data, limiting the comprehensive understanding of a patient's medical history. Ensuring the long-term maintenance and updates of DL models is another critical aspect. These models require ongoing attention to adapt to evolving medical knowledge and data patterns. Establishing dedicated teams to maintain the models and address ethical implications and regulatory compliance is vital to prevent the obsolescence of DL applications. Gaining patients' trust and acceptance depends on transparency in the use of their data and obtaining informed consent. Educating patients about the benefits and risks of DL in healthcare and how their data is utilized is crucial in fostering trust and acceptance of these technologies. The issue of data ownership and governance is multifaceted. Determining who owns healthcare data and has the authority to access and utilize it is a fundamental question. Establishing clear governance policies that address data ownership, access, and sharing can help resolve conflicts and ensure responsible data usage. Promoting interdisciplinary collaboration is also essential for effectively implementing DL in healthcare. It necessitates the seamless collaboration of healthcare professionals, data scientists, and domain experts. Encouraging interdisciplinary training and fostering a culture of collaboration can bridge knowledge gaps and facilitate the integration of DL technologies into healthcare workflows. Another significant challenge is determining liability in adverse events involving DL systems. When these systems are used in patient care, it is vital to establish legal frameworks and guidelines that determine responsibility in case of system failures, errors, or adverse outcomes. Regulatory compliance, particularly with agencies such as the USFDA and the European Medicines Agency (EMA), is imperative to ensure that DL applications meet rigorous standards for patient safety. Adhering to these guidelines is vital to mitigate risks and legal liabilities associated with healthcare AI. Ethical considerations play a significant role in the transition to DL in healthcare. These encompass issues related to bias in algorithms, discrimination, and the equitable distribution of benefits. To address these ethical concerns, it is essential to establish robust ethical frameworks, ethical oversight, and ongoing monitoring to ensure that AI systems are fair, transparent, and accountable. Finally, incorporating DL in healthcare is contingent upon education and training. The assimilation of DL technologies necessitates healthcare professionals and data scientists to possess the requisite knowledge and expertise. In this regard, extensive training programs, workshops, and courses can bridge the knowledge disparity and ensure that the workforce is adequately prepared for the forthcoming AI-centric era of healthcare.

3. Advancement in data science in medicine in the journey of ML to DL: From clinical data to big data

Initially developed computers were quite slow and huge in the 1950s. The storage capacity was meager, which was below 5 MB. The first hard drive with 1 GB in capacity was introduced in 1980. The data storage capacity was increased daily, and the computation speed was increased every day. Therefore, there is a huge improvement in the data storage systems and computer devices such as memory, speed, and the circuit. All these increase the data processing capacity. Even today's pocket-sized devices are more powerful than the supercomputers of the 1980s. With the advancement of the computer system, both the cost per unit of data storage and the device's size was reduced considerably. In terms of data, today computers are having high processing capacity and faster more (Fig. 1a and Fig. 1b) (Leiserson et al., 2020; Haug and Drazen, 2023).

Clinical big data are transforming in the medicinal field. Medical data sets are analyzing from ML to DL, and the analyzed datasets were interpreted from time to time (Table 5). Although, the ML algorithms need massive datasets to obtain an acceptable range, often requiring millions of observations performance levels. Obermeyer and Emanuel stated that ML algorithms are high "data hungry" (Obermeyer and Emanuel, 2016). Therefore, a huge quantity of medical data can be used to support the ML algorithms' property of data hungriness. However, clinical data analysis like image data, big data, and dataset shift are the crucial area in which ML, and DL analyze and predict.

3.1. Medical images data and ML to DL interpretation

ML models have evolve and shown substantial improvements in medical image data detection. The recent evolve DL has catalyzed a new phase in the evolution of ML. For radiological image processing, DL systems have shown significant improvements in accuracy in different areas of medical imaging, such as understanding the image of mammography, lung cancer detection, detection in the area of ophthalmology, understanding in the area of gastroenterology, and cardiac function assessment.

3.1.1. Understanding the image and other data of breast cancer

Understanding the images of breast cancer (BC) is an essential field of medical image data analysis using from ML to DL models. Scientists are especially using more efficient DL algorithms for medical and cancer image data. Wu et al. have used a deep convolutional neural network of DL for BC screening. Here, the researchers have trained and evaluated the image data using over 1,000,000 BC images. Here, they have performed the classification of BC images. The researchers provided a hybrid model and compared it with their previous one. Finally, they have shown the hybrid model might predict the malignancy by a radiologist more accurately (Wu et al., 2020). Using DL techniques, Shen et al. have developed an improved detection method of breast cancer screening using mammography. In this study, researchers have used the convolutional network method to classify mammograms. Here, they have used the approach of "end-to-end" training that leverages training datasets efficiently and also the independent test set of FFDM (full-field digital mammography) (Shen et al., 2019) In another study, for the DL model, Jaamour et al. used the divide and conquer-based technique for mammography classification (Jaamour et al., 2023).

Moreover, several researchers have used a hybrid model of DL techniques BC classification and detection. Altaf and Dewangan et al. have worked DL–based hybrid models for cancer detection (Altaf, 2021;

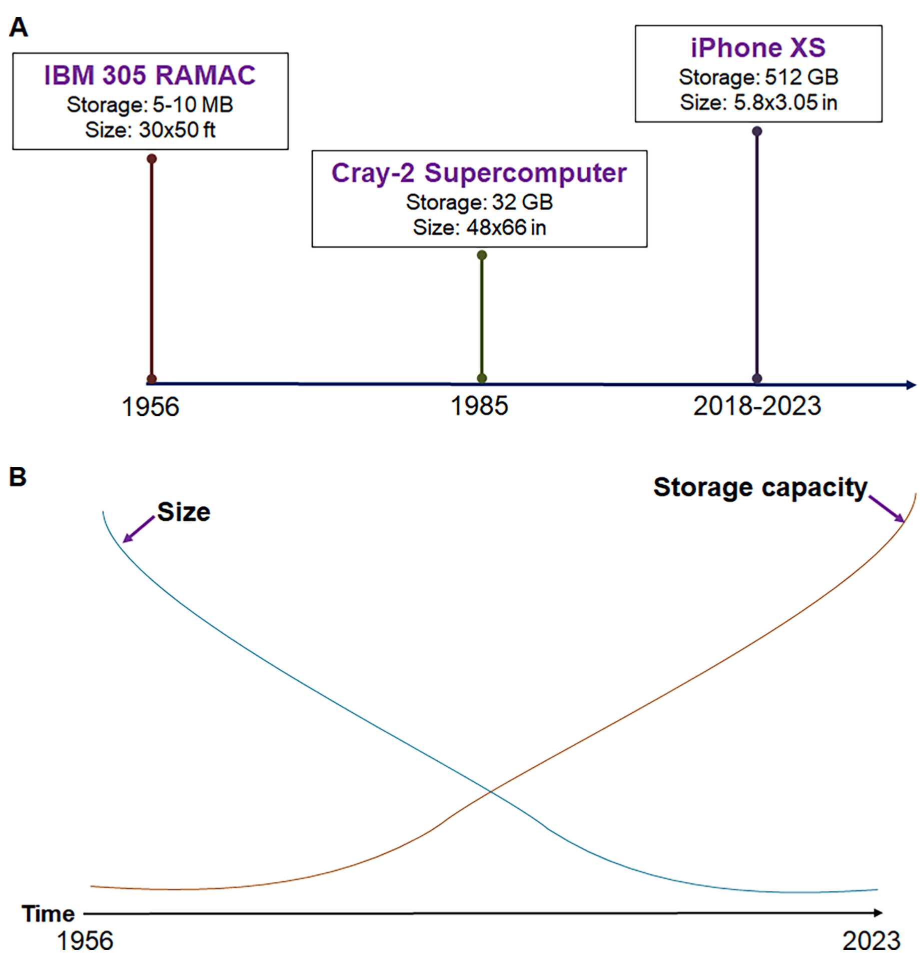

Fig. 1. The timeline and graphical representation show the advancement of computers. (a) the timeline depicts the development of computers from 1956 to 2023. (b) the graphical representation shows computers' advancement in size and storage capacity. these features of computer science cause the recent progress in medicine and healthcare data science.

Table 5
Feature and variability of ML and DL for Medical data determining and outcomes forecasting.

Sl. No.	ML and DL algorithm and its area of application	Objectives	Remarks	Reference
1.	ML and the evolution of human healthcare	Examining the integration of ML in human healthcare	Development of support vector machine model for physiological data segmentation and analysis, prediction of disease progression and diagnosis	(Jones et al. (2018))
2.	Unplanned consequences of ML	Efficient, safe, and effective, humanistic care	DL for development digital imaging, curating datasets, integrative heterogeneous data analysis, identifying the novel associations, and remote monitoring and digital consultations	(Cabitza et al., 2017)
3.	AI, ML and data science, for laboratory medicine	Implementation of data science, AI, and ML for the laboratory medicine	ML used for finding patterns, determining inefficiencies, forecasting outcomes and taking accurate decisions	(He et al., 2019)
4.	DL in health care system	Reporting the unplanned consequences due to the application of ML in present healthcare systems	ML for prediction of modeling in oncology, and pattern recognition in pathology and radiology	(Naylor, 2018)
5.	ML knowledge base with the ontology role for pattern recognition in personalized medicine	Inspecting three main supports integrating the personalized medicine into routine clinical practices, which are categorized phenotypically, population size and statistical analysis	ML methods for pattern recognition and development of statistical models (sample size and effect size). Knowledge base of all present phenotype categories and diseases. It organized the clinical dataset of experimental population size. Specific software platform for statistical analysis of higher-dimensional healthcare and related multi-omics data	(Emmert-Streib and Dehmer, 2018)
6.	Ethical challenges of implementing ML in healthcare	Implementing challenges of ML in healthcare	Addressing the existing challenges in healthcare systems owing to the implementation of ML	(Char et al., 2018)
7.	Finding out the missing link for big biomedical data	Biomedical data combination and analysis located at heterogeneous sources	ML and AI tools improvement to analyze the biomedical data for superior clinical decision-making.	(Weber et al., 2014)
8.	ML for prediction in electronic health record	ML implementation for better understanding of heterogeneous treatment effects to apply precision medicine	ML algorithms for addressing diverse clinical questions by analyzing and finding the nonlinear relationships in the electronic health record	(Rose, 2018)
9.	Intelligent health data analytics	AI for progressive health data analytics	Operation of ML and AI based analysis with the presence of health data preprocessing, choosing of algorithm based on expected outcome, developing analytical models, and interpreting results	(Abidi and Abidi, 2019)
10.	DL to transform healthcare	Transform healthcare by ML application	Operation of DL for the digital image analysis	(Hinton, 2018)
11	Genomics and ML in precision medicine	Significant improvements to address the genomic and clinical data security problems	ML models to address the main challenges of gene variations and similarities among studied patients	(Azencott, 2018)
12.	ML classifies cancer	Identification of novel tumor classes	ML for analyzing the histological data. The supervised ML used for analyzing central nervous system tumor type genome-wide methylation data to detect the methylation patterns. Unsupervised ML to examine the patterns in the data sets for development of categories classification	(Wong and Yip, 2018)
13.	Role of electronic health record and integrated precision medicine in	Primary diagnosis of chronic conditions by the proper extraction of clinical insights	Proactive and predictive involvement in healthcare through AI, and development of	(Sitapati,Kim et al., 2017)

(continued on next page)

Table 5 (*continued*)

Sl. No.	ML and DL algorithm and its area of application	Objectives	Remarks	Reference
	personalized treatment		clinical decision support tool	
14.	Fundamental inference and ML	Studied the implications of advancement in observational research design and healthcare databases	ML for the data classification and prediction in real world evidence to maintenance of clinical and regulatory decision-making	(Crown, 2019)
15.	Use of electronic health record in comparative effectiveness research	Reporting cautions into the existing healthcare systems	Effecting of ML for over whelming of present big data limitations in healthcare systems	(Hersh et al., 2013)
16.	Visualizing and analyzing the knowledge structures of health informatics	Finding of future strands research, comprising new algorithms, tracking tools and Internet of Things-based decision support systems	New ML, DL algorithms and advanced the big data analytics for better-personalized treatment	(Saheb and Saheb, 2019)
17.	ML algorithms and big data for healthcare delivery	AI tools improvement based on incremental learning to enhance the predictive accuracies	Human computer interaction -based AI and ML applications for different clinical developments in oncological	(Ngiam and Khor, 2019)
18.	Intelligent digital pathology	Improving the diagnostic accuracy and efficiency with the usage of ML	DL for analyzing the images of whole-slide pathology	(Acs and Rimm, 2018)
19.	ML in healthcare	Investigating the AI applications in healthcare, and their potential outcome in future days	The ML algorithms used to extract and cluster data, and perform the principal component analysis, support vector machine to determine the model parameters, and identify imaging biomarkers, natural language processing for text classification and processing, and DL for electro diagnosis and diagnostic imaging development	(Jiang et al., 2017)
20.	ML in cancer prognosis and prediction	ML applied to detect crucial features by predictive modeling of complex and heterogeneous datasets for advancement and treatment of cancerous	ML used to model the progression and treatment of cancerous conditions through examining complex datasets and revealing their relevance	(Kourou et al., 2015)

Table 5 (*continued*)

Sl. No.	ML and DL algorithm and its area of application	Objectives	Remarks	Reference
		conditions, outcomes and risks		
21.	Precision medicine with electronic medical records	Using ML to the electronic health records to produce personalized medicine by converting it into consistent risk predictors, and integrating the patient's variability for prevention and treatment of disease	It analyzed patterns into the subset of population who existing similar clinical phenotypes of complex disease	(Nayak et al., 2016)
22	Big data analytics in healthcare	Application of big data analytics in healthcare	ML used for the data mining and analysis	(Raghupathi and Raghupathi, 2014)
23	AI, ML and data science, for laboratory medicine	Prognostic modeling for improved collaboration among hospitals without sharing the patient's data and complying privacy regulation	ML for healthcare data analysis and optimization, cost reducing, improving efficiency of resources and staff	(Gruson et al., 2019)
24	Healthcare problems solving with the precision medicine	Altering the medical treatment with deference to the individualized features of patients	ML implemented to precision medicine, which comprises data analysis and storage for determining the association between disease outcome and risk for identification of patient characteristics and optimum treatment	(Jacob et al., 2023)
25	Intelligent health data analytics	AI for advanced health data analytics	Application of ML and AI based analysis with the addition of health data preprocessing, choosing algorithm based on expected outcome, developing analytical models, and interpreting results	(Abidi and Abidi, 2019)
26	ML in medicine	Investigative the essential structural changes in the healthcare system that are essential to release the full potential of ML in medicine	DL applied on the current electronic health record data to produce associations and meaningful data for personalized treatment and disease diagnosis	(Rajkomar et al., 2019)
27	Data analytics and ML for	Analyzing the electronic health	ML algorithm for the structured	(Stein et al., 2019)

(continued on next page)

Table 5 (*continued*)

Sl. No.	ML and DL algorithm and its area of application	Objectives	Remarks	Reference
	disease identification in electronic health record	record for identification of extensive range of medical conditions and diagnosis	and unstructured big data analysis leading to the identification of wide range of medical conditions and diagnosis	

Dewangan et al., 2022). However, other than the DL models, recently, ML models have been used for breast cancer detection (Izci et al., 2023).

3.1.2. Assessment of the image and other data of lung cancer

Lung cancer detection is important, and from ML to DL techniques were widely used to detect lung cancer. Recently, scientists have been using three-dimensional (3D) DL techniques for cancer and another disease diagnosis where a model has been reconstructed for the 3D view from an object using 2D image collection representing the scene. Ardila et al. use 3D deep learning models for end-to-end lung cancer screening. Their model simultaneously attains a high-level interpretation of 6,716 National Lung Cancer Screening Trial (NLST) cases and an autonomous clinical verification set of 1,139 subjects (Ardila et al., 2019). Similarly, Shimazaki and his colleagues have tried to detect lung cancer using chest radiographs. In this direction, a DL-based algorithm was developed using segmentation methods. The study has detected lung cancers with low mFPI (mean false positive indications) per image (Shimazaki et al., 2022).

3.1.3. Screening the image and other data of cardiac function

Scientists are screening the image and other data of cardiac function by applying ML and DL. These models are making essential advancements in the field. Ghorbani et al. tried to assess the echocardiogram data to understand the cardiac function using DL. The researchers have identified the local cardiac structures and evaluated the cardiac function and cardiovascular risk. They have developed a DL model, EchoNet, which can identify several cardiac parameters such as the ejection fraction, systolic and diastolic volumes, etc. (Ghorbani et al., 2020). Fletcher et al. tried to assess the diastolic function from Echocardiography using the ML technique, which showed evidence that ML algorithms could correctly distinguish cardiac structures (Fletcher et al., 2021). Hu et al. recently developed a wearable ultrasound imager to detect cardiac function and understand cardiovascular health. The researchers developed a DL model that mechanically understands the left ventricular volume from the continuous image recording. It helps direct and real-time cardiac function estimation (Hu et al., 2023).

3.1.4. Assessment of the image and other data of ophthalmology

During the journey ML to DL, several significant models have been used extensively in ophthalmology. In this direction, several new algorithms have been utilized from time to time. Scientists have primarily implemented deep learning systems (DLS) to classify and validate different ophthalmological parts. Milea et al. used DLS to classify optical disks, which were assessed into three categories: normal conditions, papilledema, or further abnormalities. The study uses excellent training and data sets which use 14,341 data of photographs from 6779 patients. The dataset contains about 9156 standard disk photographic datasets, 2148 papilledema disk photographic datasets, and 3037 disk data set with other abnormalities (Milea et al., 2020). Liu et al. developed a DL system to identify the GON (glaucomatous optic neuropathy) with high sensitivity and specificity. The DLS assessed the validation datasets (Liu et al., 2019).

3.1.5. Assessment of the image and other data of gastroenterology

DL has also made advancements in gastroenterology, especially the improvement of colon and endoscopies. ML and DL models have assisted endoscopists and colonoscopists, making endoscopy and colonoscopy a more consistent tool for diagnosis. Scientists are trying to improve endoscopy techniques through these models.

Yuan and Meng developed WCE (Wireless capsule endoscopy) to analyze the endoscopy images to recognize the polyps accurately. In this study, the computer-aided diagnosis used DL-based techniques to detect and characterize the polyp images in a WCE video (Yuan and Meng, 2017).

Similarly, several studies of ML or DL models were noted for image detection in colonoscopy. Wang et al. created a computer-aided DL-based detection system. The study has tried to detect the ADR (adenoma detection rate) during the colonoscopy. The researchers have developed the characteristics of adenomas and polyps identification. The study has been registered for a clinical trial (Wang et al., 2020). Another study by Gong et al. developed an improved colonoscopy technique, the “ENDOANGEL system,” performed through deep neural networks. To understand the effect of the ENDOANGEL system, about 704 patients were randomly done the colonoscopy, where 349 patients used the control colonoscopy ($n = 349$) and 355 patients ($n = 355$) used the ENDOANGEL system. During the colonoscopy, the ENDOANGEL system enhanced the significant adenoma yield (Gong et al., 2020). Similarly, Urban et al. developed DL-based models for real-time polyps detection and localization through colonoscopy screening, and they observed that the model’s accuracy was 96 %. In this study, the technique used ADR to improve polyp detection. The DL model was created using convolution neural networks (CNNs) (Urban et al., 2018).

3.2. From ML to DL and pathology

During the journey from ML and DL, several models have been developed and have made the most significant progress in pathology to understand new disease insights. In this direction, several studies developed models to detect the area of interest within slides and create the proper workflow. Similarly, studies have been performed to understand disease inside using whole-slide imaging. Kather et al. tried to assess the microsatellite instability from histology images to understand gastrointestinal cancer. The study uses the DL models for MSI (microsatellite unstable) screening, which may be very helpful for cancer immunotherapy. Using whole slide images, Campanella et al. detect the area of interest using a learning-based DL system. From 15,187 patients, the study used whole slide images dataset of 44,732 numbers to train and classify models (Campanella et al., 2019). Images of lung tissue were tried to detect occasionally using histopathological images. Using DL, Rajpu and Subasi et al. have developed lung cancer assessment techniques from histopathological images of lung tissue (Rajput and Subasi, 2023).

Besides ML or DL, single-cell pathology is essential for detecting cancer cells. Jackson et al. have tried to identify the intratumor phenotypic heterogeneity using a single-cell pathology landscape. The study has quantified 35 biomarkers using several high-dimensional pathology images ($n = 720$) from using tumor tissue from numerous patients ($n = 352$) (Jackson et al., 2020).

3.3. Data from EMR or EHR

The systematic collections of EHRs can provide patient health information. It contains some structured information and unstructured information. The structured information includes laboratory tests, diagnoses, procedures, and medications. Unstructured information includes free text such as clinical physician notes (Wang and Preininger, 2019). Recently, DL models have been implemented to analyze the HER data (Table 6). To analyze using DL models, several architecture and algorithms have been used, such as CNN (convolutional neural

Table 6
Different EHR models were developed using ML and DL to analyze the EHR data.

Sl. No.	EHR model	ML and DL method	Patients numbers	Remarks	Reference
1.	Deepr	Convolutional neural networks (CNN)	300,000	It use to predict the unplanned readmission of patients	(Nguyen et al., 2017)
2.	Doctor AI	Recurrent neural networks (RNN)	263,706	Predict the medical codes in future visits, and duration until next visit	(Choi et al., 2016a)
3.	RetainVis		63,030	Prediction of heart failure, and cataract	(LeCun et al., 2015)
4.	eNRBM	Autoencoders (AE)	7578	Outcome for suicide rate prediction. Elixhauser comorbidities, diagnosis linked groups, emergency attendances and admissions, demographic variables (age 10 years intervals, gender) are applied	(Tran et al., 2015)
5.	Med2Vec	Feed-forward neural networks (FFNN)	–	Prediction of medical codes in previous/ future visits	(Choi et al., 2016b)
6.	Ensemble model	Recurrent neural networks (RNN)/Feed-forward neural networks (FFNN)	216,221	It studied and calculate the inpatient mortality, unplanned readmission for 30-dy, long length of stay, diagnoses	(Rajkomar et al., 2018)
7.	Deep Patient	Stacked denoising autoencoder (SDA)	704,587	Used for future disease prediction. Demographic variables (age, gender, and race), diagnoses, medications, procedures, along with the lab tests, free-text clinical notes also considerate	(Miotto et al., 2016)
8.	DeepCare	Recurrent neural networks (RNN)	7191	Applied for disease progression, medication and unplanned readmission prediction	(Pham et al., 2017)
9.	RETAIN		32,787	Prediction of human heart failure	(Choi et al., 2016c)

networks), RNN (recurrent neural networks), and FFNN (feed-forward neural networks) from time to time (Fig. 2) (Ayala Solares et al., 2020). Rajkomar et al. used the DL models to predict multiple medical events from a considerable volume of HER data to improve healthcare quality and drive personalized medicine. The data contains 46,864,534,945

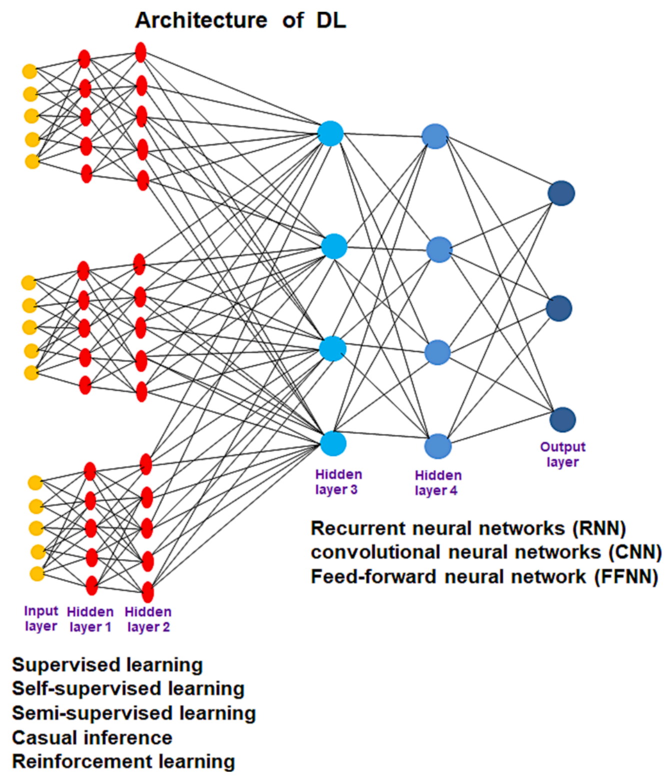

Fig. 2. Different architecture and algorithms used in ML and DL for medicine and healthcare.

data points and clinical notes (Rajkomar et al., 2018). Huang and his colleagues have used the ML approach to evaluate hospital stay timing and mortality using EMR data. Here, the researchers have used a CBFL (community-based federated machine learning) algorithm to evaluate the EMRs (Huang et al., 2019). Using infectious disease EMR, Wang et al. have tried to develop a decision-making system in clinical infectious disease using vast amounts of data. The data contains several cases (n = 20,620) from seven types of infectious diseases analyzed through a DL model. In this study, they developed MIDDM (multiple infectious disease diagnostic model) with two methods (attention mechanism and residual network) to advancement of the system performance. The DL model can predict and multi-class diagnosis of diverse infectious diseases having improved accurateness (Wang et al., 2022).

3.4. Big data in personalized medicine

Big data, complex or too large dataset, primarily include three types of data: structured, unstructured, and semi-structured. In biological science, several scientists have tried to transform big data for healthcare and personalized medicine. Marshall et al. have integrated DSM (Dynamic Simulation Modelling) and big data toward personalized medicine. They have finally explained the synergies between the DSM and big data (Marshall et al., 2016). The big data management of genomic data is a considerable challenge. At the same time, it is very much essential to perform big data Analytics in the field of biomedical omics-data (glycomics, metabolomics, transcriptomics, proteomics, genomics, etc.), which might help to improve personalized medicine (Hassan et al., 2022). However, scientists are trying to analyze the big data for the development of personalized medicine, and several review articles have been published to jot down the works and ideas in this field (Ristevski and Chen, 2018; Cirillo and Valencia, 2019; Hulsen et al., 2019). Work has been performed on personalized medicine using big data. In this work, Kang et al. developed a DCP model to forecast dental caries using a labeled dataset of 22,287 samples containing the features such as gender, region, age, etc., from South Korea. In this study, researchers have used the Random Forest (RF) model of ANN (Kang et al., 2022). Recently, Zhang et al. have developed a hybrid algorithm based on ML in precision medicine for clinical decision support. Here, they have used two methods: an improved BM25 algorithm and luster-based abstract extraction. The study used two data sets namely TREC2018 and TREC2017 to train the proposed model. Subsequently, to validate, the one dataset (TREC2019) (Zhang et al., 2023). Scientists are trying to use QSAR approaches and also developing new models during drug discovery using different ML to DL algorithms. Beam and Kohane illustrate how ML algorithms can handle a large number of patient data. They also discussed DL algorithms, high rank on the ML algorithms, and help in diagnosis procedures using huge raw pixel data (Beam and Kohane (2018)). Recently, DL applications have been handling the challenges in big data. In a review article, Najafabadi et al.. Shows the direction to application of using fast information retrieval, data tagging, semantic indexing, simplifying discriminative tasks, etc. (Najafabadi et al., 2015).

3.5. Data for medical research

Other than image classification, ML and its highly efficient DL-based models are applied in protein structure and function prediction, antibiotics discovery use and resistance, drug discovery and development and several other areas of medical science.

3.5.1. Protein structure and function prediction

Recently, DL models have been executed in the different areas of protein structure and function prediction-related research, such as de novo protein modeling using DL (Greener et al., 2019), biochemical properties of protein using self-supervised autoencoders of DL models entitled DiffNets (Ward et al., 2021), improved protein structure prediction applying DL model like AlphaFold, (Senior et al., 2020), rational protein engineering through deep representation learning algorithm (Alley et al., 2019), understanding the interaction landscape from protein molecular surfaces using geometric DL (Gainza et al., 2020).

3.5.2. Drug discovery and development

Drug design is an important field of medical research. Machine intelligence and DL models have been implemented in the different arenas of drug discovery and development, such as optimization of hit selection in virtual screening driven by machine intelligence (Kumar and Acharya, 2022), lead optimization model development using DL (Green and Durrant, 2021), lead optimization through the 3D ligand information using AI/ML methods (Bleicher et al., 2022), the web server for drug discovery using DL-based web screening entitled DeepScreening (Liu et al., 2019), the drug toxicity screening using DL models (Jimenez-Carretero et al., 2018; Lee and Chen, 2021), etc.

3.5.3. DL models from antibiotics discovery to resistance

DL-based models are used in diversified areas of research to study the antimicrobial substance such as antibiotic discovery (Stokes et al. 2020); understanding the antibiotics resistance genes (Arango-Argoty et al., 2018; Li et al., 2021); diagnosis and treatment of antibiotic resistance (Chakraborty et al. 2022); rapid identification of the resistance UTI pathogenic bacteria (Fu et al., 2021), etc.

3.5.4. Several other areas of medical science

ML and /DL-based models are helping in different another area of medical research, such as surgical practice (Chakraborty et al. 2022). Recently, CRISPR/Cas9-research has been an important area in biomedicine. Here, ML to DL moles have been developed from time to time. ML approach was used to understand the anti-CRISPR protein families (Gussow et al., 2020). DL models were applied for two high-adhere Cas9 variants to optimize the CRISPR guide RNA design (Wang et al., 2019). Similarly, ML algorithms were developed SeqCor to manage the resulting biases potential initiated by the arrangement of gRNA sequences. CRISPR/Cas9-based screening was used to organize gRNA in the library (Liu et al., 2020b). Other than the CRISPR/Cas9, and DL models have been utilized in DDR1 kinase inhibitors (Zhavoronkov et al., 2019), pathogenic infections (Zillmer, 1986), etc.

3.6. Dataset shift in AI

Dataset shift is a challenging situation AI model where the joint distribution of the training and test datasets changes. This situation is known as “dataset shift” (Fig. 3). It is a significant problem in the AI medical field (Finlayson et al., 2021). Several scientists indicated the medical dataset shift is noted due to changes in the medical dataset distribution due to the change in the training dataset and test dataset. Therefore, dataset shift will be challenging during the implementation of ML to DL models. Recently, Subbaswamy and Saria indicated that shifts are a prevalent condition when a model moves from the training phase to the test or deployment phase due to the change in different conditions such as patient demographics, equipment, timing, disease prevalence, treatment patterns, measurement pattern, and more (Subbaswamy and Saria, 2020). Sometimes, it is referred to as changes of classification, the concept of drift, the concept of shift, etc.

4. Chatbot technologies in healthcare and medicine

Chatbot technologies, a computer program that can recognize questions and provide automated responses, use AI and NLP (natural language processing) (Haug and Drazen, 2023; Jackson-Triche et al., 2023). The first chatbot was developed by J. Weizenbaum, a computer scientist, in 1966 at MIT, and it was named ELIZA. Since 1966, several chatbot technologies have been developed in till today from time to time (Fig. 4a and Fig. 4b). Chatbot technologies have also been applied in medical research (Table 7.).

Chatbots are conversational agents powered by AI that can guide users to perform multiple tasks by responding in natural language (Jia, 2003). In several industries, including healthcare, they are becoming more prevalent recently (Jovanović et al., 2020; Caldarini et al. (2022). Chatbots can be used for self-diagnosis by patients who want to look through their symptoms before seeing a doctor. Online symptom checkers fall far short of AI-powered chatbots like OpenAI’s ChatGPT, Microsoft’s Bing, and Google’s Med-PaLM regarding accuracy. Patients can utilize the chatbot to describe their symptoms, and the chatbot can then provide a grim diagnosis and advise them to see a doctor. Health coaching is another chatbots application that offers patients personalized advice and support (Mitchell et al., 2021). For instance, Ariana is a chatbot that assists patients with therapy, provides information about their disease and treatment, and renders helpful guidance on managing daily activities.

CoachAI, a conversational agent-assisted progressive health coaching platform, enables health intervention delivery to individual patients and groups (Fadhil et al., 2019). Chatbots of this type can help patients manage their health and wellness by recommending what to eat, how to exercise, and how to reduce stress. Chatbots can also be used to improve the readability in online mode for informed consent forms. In a recent experiment, participants were given information from consent forms using Rumi, an AI-powered chatbot (Xiao et al., 2023). Compared to form-based engagement, the chatbot decreased the power imbalance among the participant and the researcher and improved consent form reading.

Furthermore, chatbots can be used to provide patients with mental healthcare. One example is Wysa, an AI-powered bot that helps people manage their emotions by utilizing cognitive behavioral therapy and dialectical behavior therapy (Nicol et al., 2022; Devaram, 2020). The empathic chatbot is another type that can recognize the user’s emotional state and alter conversations to help people receiving mental healthcare (Devaram, 2020). Physicians can interact with existing and potential patients by adopting chatbots for remote patient monitoring (Sabour

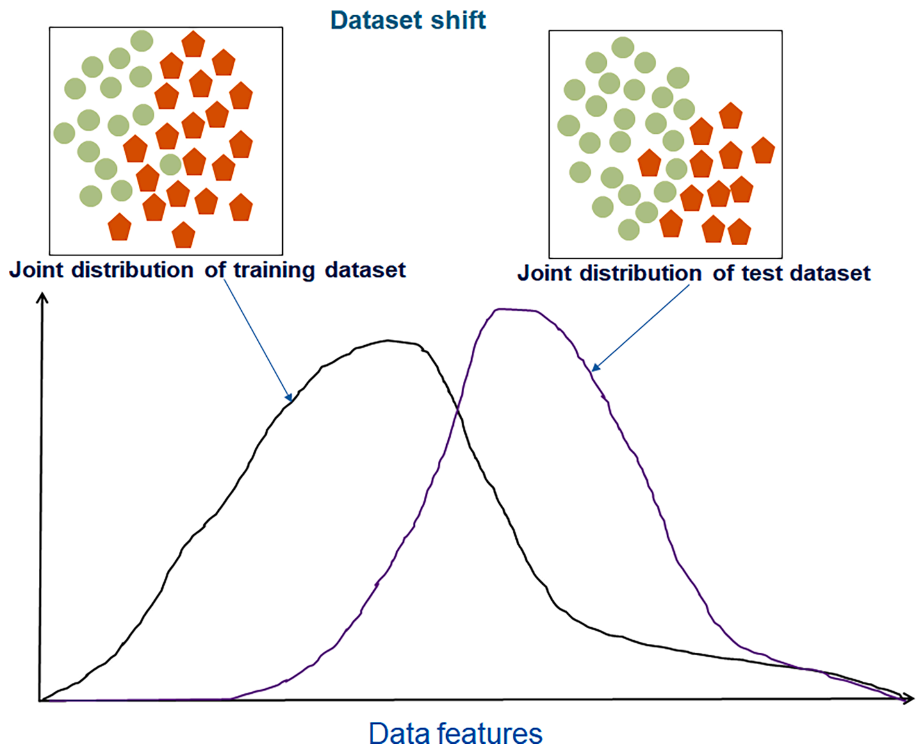

Fig. 3. The figure shows the dataset shift. It is a challenging situation for the AI model where the joint distribution of the training and test datasets changes.

et al., 2023). Telehealth services can be delivered through facilities like the SmartBot360 platform, and video chat can monitor patients from a distance (Dias et al. (2022). Health-designed chatbots allow patients to schedule visits with doctors and receive prescription reminders. These fantastic, constantly accessible health monitoring tools have impacted healthcare (Fadhil and Schiavo, 2019). Therefore, chatbots can transform healthcare by providing patients with customized and efficient services. Numerous medical services are available, including self-diagnosis, health coaching, informed consent, support for mental health, and remote patient monitoring. Chatbots arerojectted to perform a more prominent function in the healthcare industry as they develop.

5. ChatGPT: A recent chatbot technology developed using DL, LLM and NLP models

An intense effort was put forth for several years by research and development teams of DL- based chatbot and chatbots of specific capabilities were introduced. In 2022, a unique Chatbot named ChatGPT was launched by OpenAI to generate informal talk remarkably similar to humans. The initial ChatGPT model was based on GPT-3.5, and now the updated ChatGPT version runs on GPT-4. ChatGPT is an advanced language-based bot that has changed contemporary natural language processing and human–computer interaction (Biswas, 2023). ChatGPT uses deep neural network to produce human-like text (Hashana et al., 2023). Large language models (LLMs) use recurrent neural network (RNN) models to comprehend text, a DL model. Using transformer architectures, it can use trillions of parameters. The transformer topology was developed in 2017, a breakthrough in this direction. The transformer is a deep bidirectional transformer entitled Devlin and her colleagues (Devlin et al., 2018; Benjamens et al., 2020; Ebrahimian et al., 2022). It works with GPT model methodology, and this GPT is an extensive language model that has been trained on tons of data and can be used for many multiple tasks, which includes text creation, question answering, and language translation (Joublin et al., 2023). Reinforcement learning from the human feedback concept works in ChatGPT, and the DL system's output is adjusted utilizing the proximal policy optimization method. The ChatGPT can learn from a considerable amount of data using DL approaches, particularly transformer-based topologies, and produce human-like responses (Pournaras, 2023).

ChatGPT's competence has an opportunity to alter statistical process control (SPC) practices, instruction, and research. However, since the technology is still in the primary stages of development, it is prone to misuse or misinterpretation. The investigation has looked into ChatGPT's capability to deliver code, describe critical concepts, and generate knowledge pertinent to SPC practices, education, and research (Megahed et al. 2023). ChatGPT has become quite popular in the medical field due to its capacity to simplify radiological reports, facilitate communication between patients and healthcare providers, and generate academic papers at an acceptable standard (Sedaghat, 2023). Medical students can practice their communication skills and diagnosis methods in a secure setting using ChatGPT, replicating patient encounters (Amri and Hisan, 2023).

Additionally, ChatGPT can help researchers and medical students read and write academic articles by effectively summarizing a given topic and producing an unbiased abstract. For patients and healthcare teams to better comprehend radiological findings, ChatGPT can be utilized to translate the records into plain language (Lyu et al., 2023). ChatGPT (with GPT-4) may even produce fictitious medical images, such as electrocardiogram graphs and X-rays, free of consent and copyright, allowing medical students to practice and improve their interpretation abilities. By providing medical advice and medical information databases, including symptom checks, fitness, and health counseling, ChatGPT serves an essential purpose. The system also provides a few unique medical functions, such as appointment scheduling, notification alert, and reminders for regular medication to satisfy the demands of patients or users (Chung and Fong (2014)). ChatGPT can enhance mental health by simulating patient interactions and assisting with mental health issues (Hisan and Amri, 2023). In addition, social networking services like ChatGPT can support communication and furnish resources for college students' mental health (Vornholt and De Choudhury, 2021). While discussing ChatGPT's benefits, it is essential to mention that ChatGPT's use in clinical settings remains challenging, and

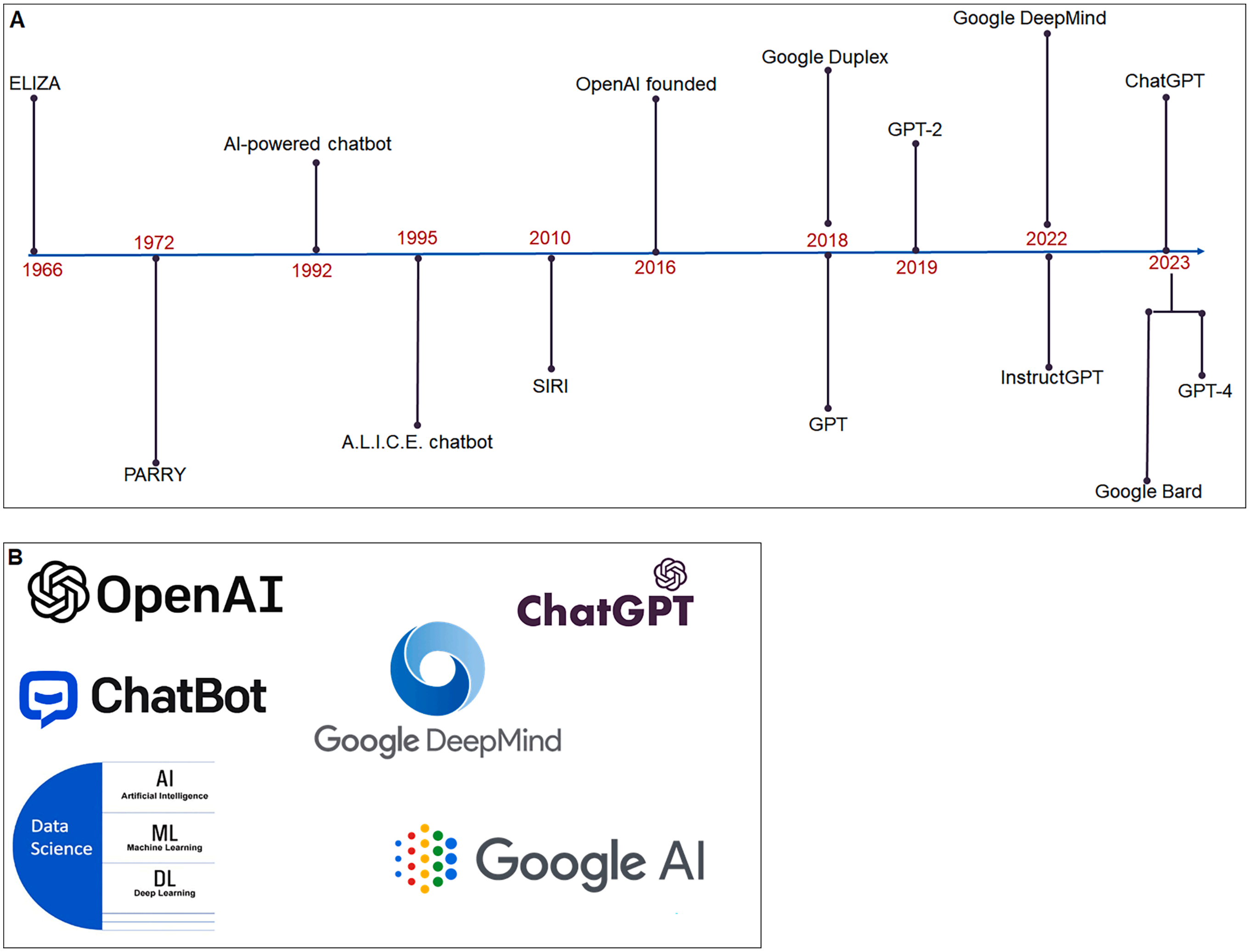

Fig. 4. The timeline and graphical representation show different chatbot technologies and their origin time. (A) The timeline shows different chatbot technologies and their origin time point. (B) It depicts different chatbot technologies.

its performance in the medical field is comparable to that of third-year medical students who achieve marks that are just below the passing standard (Gilson et al., 2023). More developments are needed to achieve its widespread medical use (Li et al., 2023). Despite ChatGPT's possible benefits for the healthcare system, its application has genuine ethical concerns. Utilizing ChatGPT, the potential for misusage of academic articles is one of the crucial problems in this direction (Hisan and Amri, 2023).

It is very clear that ChatGPT has been applied in different fields of medicine and healthcare, from medical education to research (Chakraborty et al. 2023). It has been noted that the tool has been applied to diverse branches of medical sciences, such as oncology, radiology, ophthalmology, orthopedics, rheumatology, etc. (Chinnadurai et al., 2023; Ramamurthi et al., 2023: Bajaj et al., 2023; Chakraborty et al., 2023a). It is also used in diseases, diagnostics, and therapeutic purposes. It has been used for patient clinical letters' writing (Ali et al., 2023). This tool has been used in the nucleic acid research (Chatterjee et al. (2023)). The DL-enabled powerful tool is also used in drug discovery and development (Chakraborty et al., 2023b; Pal et al., 2023b). However, the use of this powerful tool is increasing very fast daily.

Furthermore, there are doubts about the accuracy of ChatGPT's translation findings because the program periodically displays unpredictability in its responses and occasionally omits or oversimplifies the important details. Depending on ChatGPT's response could create conflict with the in-person counseling recommendation of doctors, which they suggest after years of experience in their respective medical specialties. There are also worries regarding the security and privacy of patient data while using ChatGPT. Before implementing ChatGPT in clinical practice, it is critical to investigate and resolve all these ethical issues to a certain acceptable standard.

6. The broad role of ML and DL application in clinical practice and healthcare management

In the medical domain, ML and DL is playing crucial roles across the medical field, which includes diagnostics, therapeutics, patients' health management, administration and regulation of hospitals, and countries' regulatory activities of healthcare management (Fig. 5 and Fig. 6) (He et al., 2019; Jassar et al., 2022; Rajpurkar et al., 2022; Haug and Drazen, 2023).

6.1. Diagnostics

ML and DL are performing several diagnostics activities, including clinical and omics-data, medical image detection such as early cancer diagnostics, quick detection of infectious diseases, diagnostics applications in different fields of gastroenterology, cardiology, ophthalmology, etc. They can be applied to diagnose pathology-related data. Besides these diagnostic activities, ML and DL models are used to analyze the EMR or HER data (Fig. 6) (He et al., 2019).

Table 7
Different chatbot technologies to study different medical issues.

Sl. no	Different Technologies	Medical issue and application	Reference
1.	Chatbot	Mental health support in China	(Zhang et al., 2023)
2.	ChatGPT	Support tool for breast tumor board.	(Sorin et al., 2023)
3.	Chatbot	Mental health self-care discovery	(Moilanen et al., 2023)
4.	ChatGPT/GPT-4	Support for intensive care unit medicine	(Lu et al., 2023b)
5.	Chatbot	Stress and health-related parameters	(Schillings et al., 2023)
6.	Chatbot	Behavioral health during COVID-19	(Jackson-Triche et al., 2023)
7.	Vickybot	Support for anxiety-depressive symptoms and work-related burnout in primary care and healthcare professionals	(Anmella et al., 2023)
8.	Chatbot	Improving the well-being of type 1 diabetes	(Boggiss et al., 2023)
9.	ChatGPT	Forthcoming diabetes technology prediction	(Huang et al., 2023)
10.	Chatbot	Support for cognitive behavioral therapy	(Wang et al., 2022)
11	Chatbot	Mental healthcare and assessment	(Schick et al., 2022)
12	Chatbot (Otis)	Used for health anxiety management	(Goonesekera and Donkin, 2022)

6.2. Therapeutics

ML and DL can guide physicians and might help in treatment procedures considering the HER. It also helps medical surgeons with machine intelligence inspired surgery. It might help data-driven precision medicine. These models also help in pharmacogenomics–based medical therapy (Fig. 6).

6.3. Patients/population health management

ML and DL models are trying to generate patient-centric information for healthy lifestyle information and promotion. These models might be helpful for the diseases detection in early stage. Simultaneously, these models will help public education about healthcare. The chatbot technologies like DL inspired ChatGPT are helping people to solve health-related questions (Fig. 6) (Dave et al., 2023; Shahsavar and Choudhury, 2023).

6.4. Hospital administration and regulation

ML and Dl algorithms can guide the day-to-day activity of hospital administration and regulation. It also helps preserve and analyze the EMR or HER data. Finally, it might help in disease monitoring (Fig. 6).

6.5. Regulatory activity in health regulatory bodies

Regulatory bodies can check and measure all the regulatory activity related to health using different moles of ML including DL. Regulatory bodies such as FDA can first review the product-related application using those models.

7. Future challenges during ML to DL implementation in health care

There are numerous critical challenges for those models, such as data standardization, establishing norms, policy, proper regulatory environment, adequately trained and educated AI-related workforce, financial implication, Ethical concern for data securities, implementation challenges, etc. (Fig. 6).

7.1. Data standardization

ML to DL results could be more accurate. Therefore, data standardization, model training and testing is crucial before it implements in the patient's diagnosis. We already discuss the dataset shift, a crucial problem for training and test data (Finlayson et al., 2021). Recently, Finlayson et al. described real-time problems of those models' implementation of a sepsis-alerting model at the University of Michigan Hospital in April 2020 (Finlayson et al., 2021). Kruse et al. have described that big data management and improved decision-making are the key challenges in the healthcare sector (Kruse and Goswamy, 2016). Therefore, it is necessary to have proper standards of ML or DL models before implementing them into the actual medical field.

7.2. Establishing norms, policy, and the regulatory environment

ML will be applied in the real world in medicine. Sometime, the technologies might be data-biased. Therefore, ML or DL technologies can be implemented considering the risk of illness. The regulatory bodies must control to ensure effectiveness and safety. Therefore, each country should have norms and policies in those directions to ensure

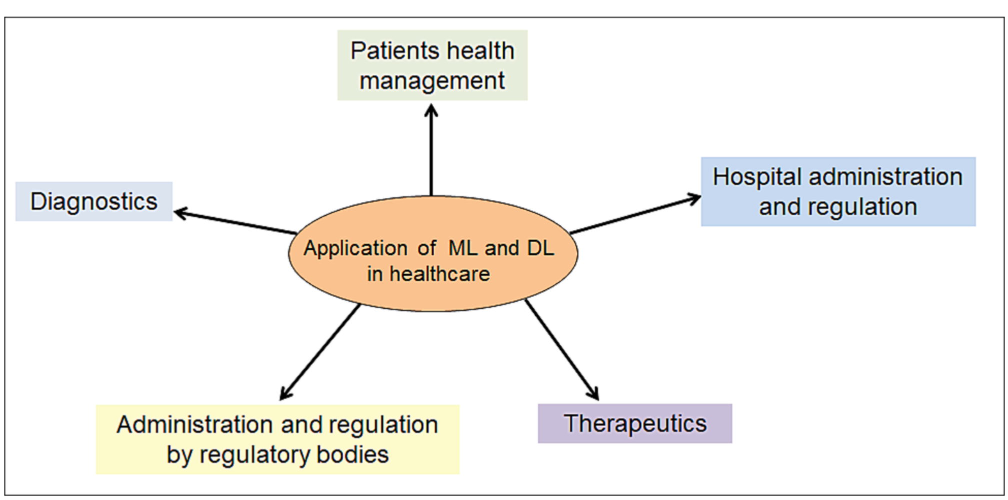

Fig. 5. The broad role of ML and DL in medicine and healthcare.

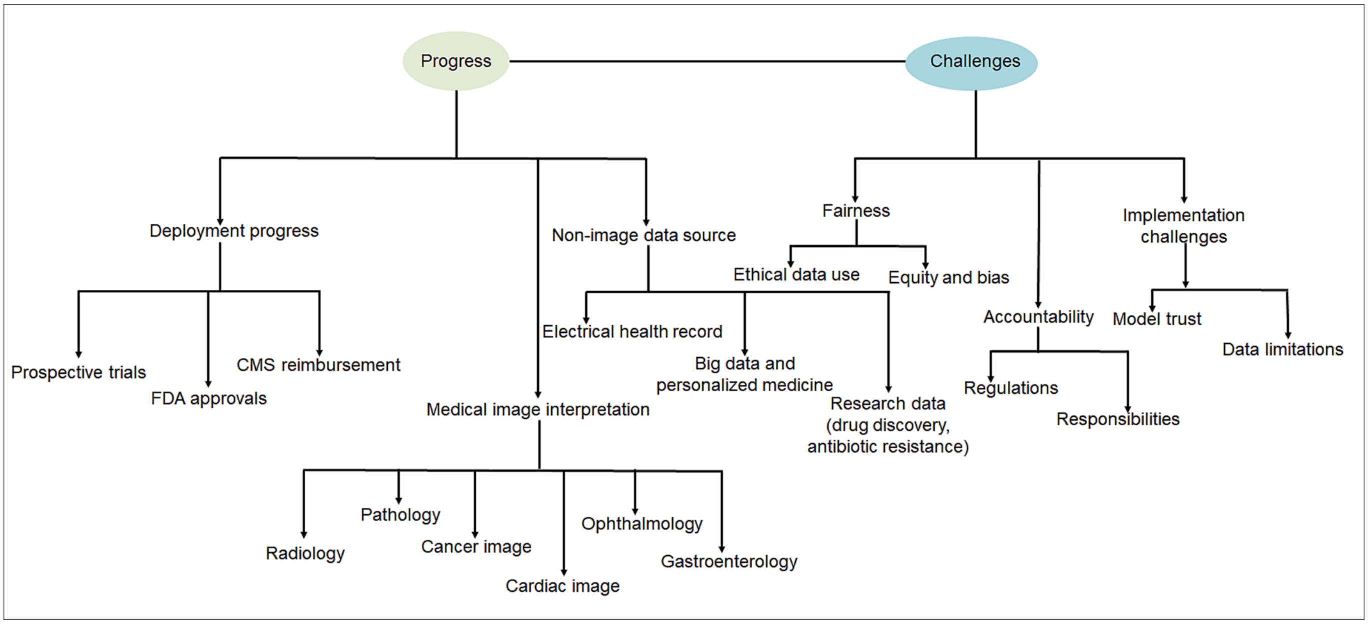

Fig. 6. The challenges and progress of ML and DL in medicine and healthcare.

effectiveness and safety. Therefore, it is necessary to create a regulatory environment.

7.3. Need adequately trained and educated workforce

The workforce should be adequately trained and educated before implementation of ML or DL technologies. The curriculum of bachelor's and master's courses in medical schools must be updated and include the topics like statistics, computer science, and health informatics (Tang et al., 2018). All fellowships of residency need to go through dedicated training programs and projects of informatics. Nurses should also be trained in this direction.

7.4. Technology implementation and financial implication

These systems are expensive. Therefore, all the technologies implementation needs a considerable amount of cost. At the same time, the systems need ongoing maintenance, such as software updates, algorithms-related software updates, hardware maintenance, and substantial financial implications associated with these technologies. Therefore, before implementing the technologies, proper budget allocation should be needed.

7.5. Ethical concern for data securities

ML technologies need cyber security measures related to patient safety. The misconduct might take place, and hackers can hack the medical datasets. It should consider that it includes sensitive information from real-time patients. Therefore, it is necessary to maintain the patient's privacy.

7.6. Other implementation challenges

There is a concern for large image sizes because neural networks can increase the model complexity and, thereby, the number of pixels. Hence, there is an increased amount of memory required. Another limitation of the dataset is the risk of noise in some weak-supervision setups (Rajpurkar et al., 2022). It is also a need for a technological bias system when data is collected from different sources.

8. Conclusion

The ML and DL technologies have made significant progress in medicine and healthcare. Ongoing progresses in research from ML to DL areas are creating the recent paradigm shift in medicine and healthcare. However, the implementation of these technologies in real-world medical fields is still in its infancy and huge concern. These technologies are in the early stages of development. All recent AI–based research technologies need to scale up for use. At the same time, all the technology needs proper validation and implementation. Therefore, the technologies must be scalable and applicable. Similarly, during technological implementation and use, there should be collaboration among computer scientists, physicians and data scientists, healthcare providers, and engineers, which is essential now. At the same time, new and diversified algorithms are needed with numerous medical applications and to improve the quality of diagnostics and therapeutics.

The successful integration of ML and DL technologies in the healthcare sector requires a multifaceted and flexible approach. The foundation of this approach lies in fostering interdisciplinary collaboration among experts in AI, medicine, data science, and engineering. Establishing regulatory frameworks and standards tailored explicitly to AI in healthcare is crucial, and international cooperation is essential to ensure consistency and comprehensiveness. These standards should encompass important ethical considerations such as data privacy, transparency, and accountability. Rigorous validation protocols should include randomized controlled trials and assessments using real-world data and comparing the performance of these algorithms against existing clinical practices to ensure the reliability of AI algorithms. Comprehensive education and training programs should be implemented to cultivate talent and expertise, targeting both healthcare professionals and AI specialists. Design principles that prioritize the patient's needs should not only focus on the accuracy of diagnostics and therapeutics but also on enhancing the overall patient experience, emphasizing empathy and accessibility. Open-source initiatives can be employed to expedite research and development. Government and industry support, including funding, incentives, and regulatory cooperation, will be vital in scaling up and widely implementing AI technologies in healthcare. Lastly, maintaining a culture of continuous learning and improvement is paramount as AI technologies evolve rapidly. Healthcare systems should include flexibility and adaptability, with a commitment to staying at the forefront of technological advancements and embracing change to enhance the quality of care. This comprehensive strategy for ML to DL-based medical technologies will address the current concerns surrounding the implementation of AI in healthcare but also ensure a brighter future for the field as it enters a new era propelled by cutting-edge technologies.

CRediT authorship contribution statement

Chiranjib Chakraborty: Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Manojit Bhattacharya:** Validation, Formal analysis. **Soumen Pal:** Investigation, Formal analysis. **Sang-Soo Lee:** Validation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgement

This study was supported by Hallym University Research Fund and by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2020R1I1A3074575).

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