Healthcare Revolution and Integration of Artificial Intelligence

S. Saranya and S. Priya

1 Introduction

1.1 Healthcare Revolution in the Past Century

Though technological revolution dates back to the decade revolving around 1860, it was not until 1895, that it found a foothold in healthcare with the discovery of X-rays [1]. Since then, the quality of medical diagnosis has seen an accelerated improvement including the notable lifesaving technologies for cardio-pulmonary assistance that were invented in the 1950s. Following the hardware revolution, the invention of computers and the vision of connecting computers to share information were evident in the 1970s. Clinical database management systems collectively called hospital information or medical information systems were initiated by individual hospitals to handle patient-centric data [2]. These series of revolution since the first publication in the domain of AI in biomedicine in 1958 have sowed the seed for the present-day artificial intelligence (AI)-driven healthcare [3].

With the advent of computers, healthcare entered the digital era as a process driven by need. The beginning of the twenty-first century has recognized the role of computer technology to evaluate the clinical processes prior to which it was predominantly used for hospital administration. In the next 10 years, computers became physician's best friend. The volume of data in healthcare is massive, but its potential

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C. Ram Kumar, S. Karthik (eds.), *Translating Healthcare Through Intelligent Computational Methods*, EAI/Springer Innovations in Communication and Computing, https://doi.org/10.1007/978-3-031-27700-9_5

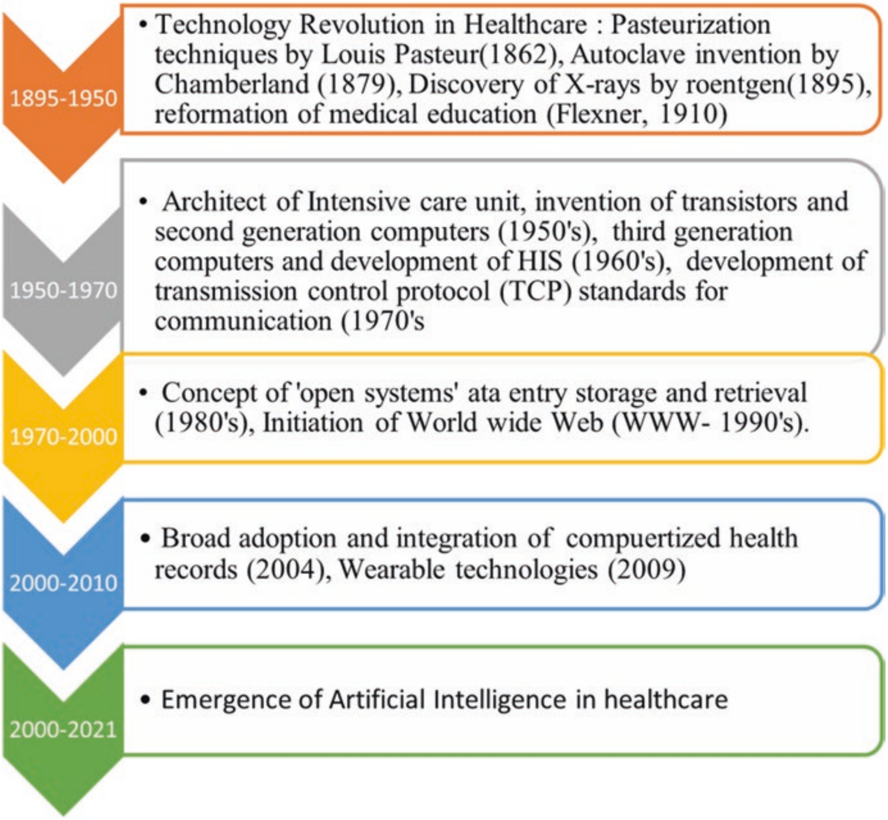

Fig. 1 Timeline of events pertaining to healthcare revolution

to provide insight into patient care was still in its infancy. In 2004, the United States included a goal for broad adoption of computerized health records. These are essentially a digital version of a patient's health record to avoid medical errors and to provide cost-effective healthcare and improved patient care [4]. The timeline of events that led to healthcare revolution is shown in Fig. 1.

Furthermore, the growth of data-intensive medical specialties, wearable technologies, and electronic health records has provided a wide array of real-world data. Early years of last decade saw multiple sources contributing to big data in large amounts, but it was difficult to collect, organize, and analyse the data. With access to continuous digitized data streams the potential for a personalized, precise, and a proactive form of healthcare decision support system was necessitated [5]. Since then, scientists have curated knowledge for the development of machines with intelligence capable of performing tasks analogous to the complex human brain leading to the development of AI.

1.2 Artificial Intelligence: A Transformation in Healthcare Delivery

Artificial intelligence learns from a vast amount of data using algorithms to do a specific task. Specific to healthcare, it is the process of applying artificial intelligence to mimic human cognition in discovering, analysing, presenting, and comprehending complex medical and healthcare data. It plays a key role in decision support for clinical interventions aiding in diagnosis, treatment planning, and health management. This capability is creating waves of change, as AI in healthcare proves to be a critical component in many aspects. First, the superpower of these AI systems is to automate diagnosis by building powerful models using accumulated healthcare data [6]. Second, they also enable tailor-made highly precise patient-specific treatments [7].

Simply put, they make use of large amounts of data and select right information/predictions that clinicians may miss or do not have direct access to. The rate of growth of AI market in healthcare as rightly predicted by Frost and Sullivan [8] shows a drastic increase (Fig. 2) in less than 10 years. Section 2 discusses in detail how AI and its components are applied in healthcare.

2 Artificial Intelligence in Healthcare

Artificial intelligence powered by enormous availability of healthcare data and sophisticated analytic techniques has brought a paradigm shift to healthcare. Some of the major use cases are, but not limited to, the discovery of diseases/disease patterns especially cancer, neurology, and cardiology [9]; early diagnosis, prediction, and treatment of medical conditions; personalized medicine and patient monitoring;

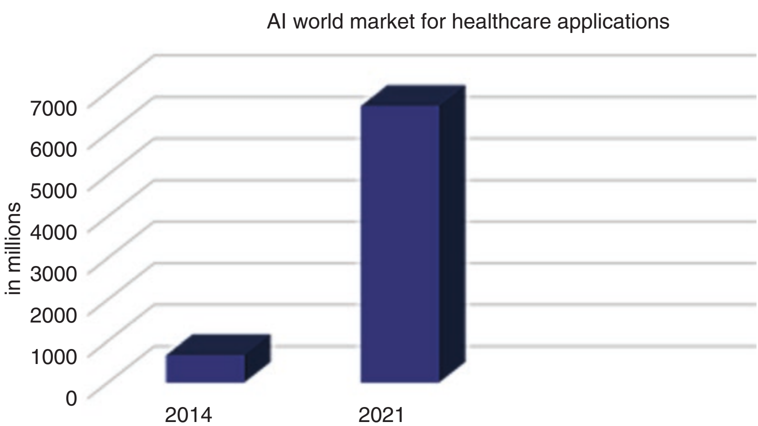

Fig. 2 Growth prediction of global AI healthcare market (2014, 2021)

understanding and explaining complex conditions to medical experts and patients which otherwise would be complex to comprehend or conclude [10]. Healthcare data can be either structured or unstructured and AI can be effectively applied to either of these. While support vector machine and methods like neural networks (NN), fuzzy logic, and evolutionary computing grouped under computational intelligence techniques are popular learning methods considered for structured data; modern deep learning and natural language processing are more predominantly used for unstructured data. The broad application areas of AI in healthcare include image analysis, rule-based systems for encoding clinical guidelines and protocols using electronic health records, predictive analytics, etc. [10].

2.1 Components of Artificial Intelligence

Artificial intelligence covers a multitude of technologies, and some of the major components that AI revolves around are shown in Fig. 3. The upcoming subsections discuss each of these components and their significant role in healthcare.

2.1.1 Machine Learning

Machine learning (ML) can be considered as one of the most popular forms of AI applications in healthcare. Machine learning refers to the ability of the machines to learn and perform on par with human intelligence and enables the machine to learn by experience without explicit programming with massive amount of data [11].

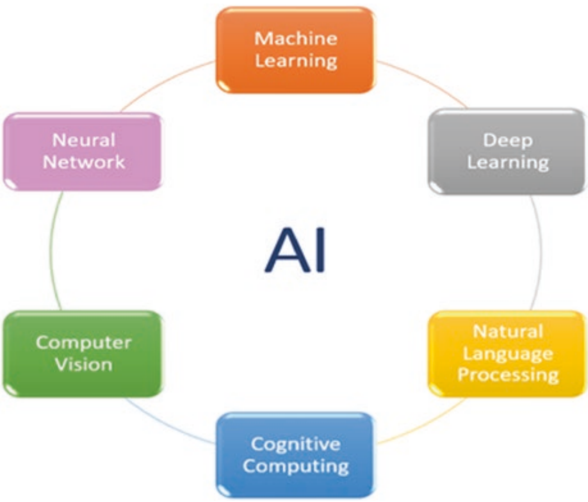

Fig. 3 Pictorial description of AI and its associated components

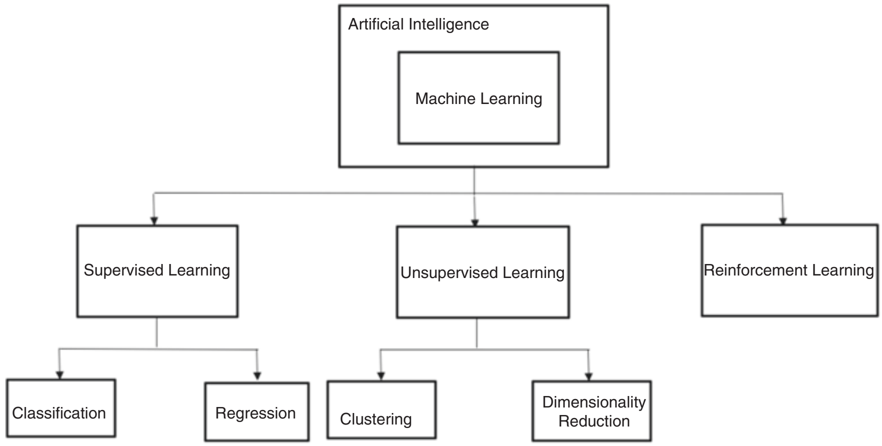

Fig. 4 Types of machine learning approaches

Contrary to the traditional approach where the model acts as an input to the machine, ML approach is data driven and the output is a model used in the analysis of new data. The five major processes involved in the ML pipeline are data acquisition, pre-processing, feature extraction, feature selection, and learning (supervised/unsupervised/reinforcement) task. The choice of the learning method is based on the amount of human intervention and the way in which a machine learns. The various subsets of machine learning are shown in Fig. 4.

In supervised learning, the ML algorithm learns on a labelled dataset, i.e., a certain degree of ground truth is available for performing the expected task. This is further classified into classification and regression based on the task to be performed.

On the other hand, in unsupervised learning, the algorithm deals with unlabelled data and tries to extract features and patterns on its own. They can be further classified into clustering and dimensionality reduction. Reinforcement learning is typically a trial and error method with feedback for learning from new situations using an interactive environment. The notion is to maximize rewards that are provided for favourable outputs. In this work, clustering, an unsupervised ML, as well as classification, a supervised ML technique, are further explored through experiments.

Feature engineering is one of the challenges in traditional ML methodologies. This requires intensive human effort to translate raw patient data into higher level feature representations usable for interpretations. Clinical data types obtained from radiology (X-rays, CT, MRI, PET, SPECT, and photographic images), biosignals including ECG, EMG, EEG, EOG, EGG, etc., and unstructured data from electronic health record (EHR) are some of the most common data types used by ML for diagnostic predictions [12]. Prediction of patient-specific treatment procedures based on their health conditions and genetic makeup is a huge leap forward and seems to be promising for many healthcare organizations.

2.1.2 Computational Intelligence

Computational intelligence (CI) encompasses a number of nature-inspired computational methodologies that can be classified into three main categories namely artificial neural networks (ANN), fuzzy logic, and evolutionary algorithms such as swarm intelligence, genetic algorithms, and their hybridization for addressing real-world problems. CIs are preferred to specific problems to which conventional modelling cannot be used, due to reasons such as complexity, existence of uncertainties, and the stochastic nature of the processes. The discussion in this section is limited to a very popular CI method, the ANN, which uses artificial neurons that depict the biological neurons of the human brain through which learning is made possible to solve AI problems. The technique is an extension of linear regression and unfolds the complex and non-linear input–output relationship.

ANN is multi-layered with a number of hidden layer combinations that determine the associations between the output and the input layer. The layers are made of a predefined number of neurons interconnected by weights between them. The goal of ANN is to develop a model to estimate the weights between the layers from input through output that satisfies the criteria of minimizing the average error between the actual target and predicted output. ANN is one of the initial techniques that gained popularity in AI-related healthcare applications and the advanced version of which is the present-day deep learning networks. Applications of ANN started off with disease diagnosis, monitoring, and classification. These included processing of biomedical data involving image analysis, clinical diagnosis, drug development [13], and speech processing [14]. However, their applications extended to informing healthcare management decisions. Particularly, in the years spanning 1994–2003, cancer diagnosis, prognosis, and guided therapy using ANN-based decision support systems were reported emphasizing the need for rigorous methodologies [15]. It is also noteworthy to mention that the use of ANN for clinical diagnosis based on classification and prediction majorly spans the areas of cardiovascular, telemedicine, and organizational behaviour [16].

2.1.3 Deep Learning

As a subset of ML, deep learning (DL) is an extension of classical ANN with many layers and with a capability of exploring more complex non-linear patterns in data. The two most widely used DL techniques are convolutional neural networks (CNN) and recurrent neural networks (RNN). Deep learning was introduced to overcome the hiccups faced by classical ML algorithms in handling the issue of data with more dimensions and with many traits. For instance, the DL models perform better in scenarios that employ images as input where the dimensions are naturally high due to pixels as traits. CNN can take the normalized pixel values on the images as input and processes it by alternatively weighting and sampling in the convolution and subsampling layers, respectively. This results in a recursive function which is

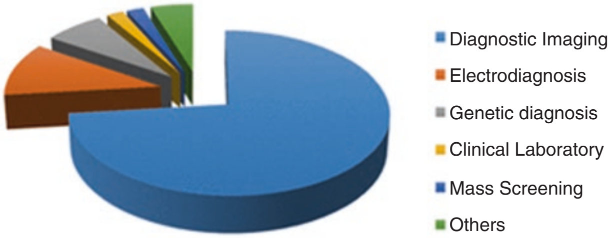

Fig. 5 Major applications of deep learning in medicine

the output of the weighted input values. As in the case of ANN, the weights are trained to minimize the average error between predicted and the actual outcomes [9].

Deep learning is also used for speech recognition which is popularly known as natural language processing (NLP), a promising application in healthcare. One major limitation of DL models is the difficulty in interpreting the features arrived as they usually have little or no meaning for delineating manually. Figure 5 shows various applications of DL in medicine most common being diagnosis, screening, and imaging.

2.1.4 Natural Language Processing

Natural language processing is a method by which useful and insightful information is extracted from textual data. In healthcare, electronic health records and clinical data are in the form of unstructured written records or reports. Examination reports, laboratory reports, operative notes, and discharge summary are inexplicable for the computer program. NLP is capable of extracting information from these unstructured texts aiding in clinical decision making. NLP pipeline generally comprises the following processes: (1) text processing and (2) classification. Text processing enables the identification of a series of relevant keywords based on the available clinical databases. This is followed by examining a subset of relevant keywords and the effects on normal and abnormal case classification are deduced. The validated keywords now serve as a structured data support in clinical decision making [9].

Speech recognition or text analysis followed by translation is one of the common processes followed by NLP systems. The major application of AI in healthcare using NLP application involves a method of understanding and classifying clinical documentation. These unstructured clinical notes give a promising insight for clinicians to better diagnose and understand treatment quality, improving the process and providing better results for patients. NLP also assists in creating alert systems during treatment arrangements, monitoring adverse effects, etc., which form a key role in clinical decision making [9].

2.1.5 Cognitive Computing

The thin line of difference between cognitive computing (CC) and AI is that the former works to replicate or mimic the human way of solving problems while the latter creates alternate ways to solve problems and potentially outperform humans. Hence CC aims at creating automated systems to solving problems without human intervention. These techniques perform a sort of data mining operation using a variety of data from appropriate streams of information. These systems follow a process of continuous knowledge acquisition and fine-tune their methods of pattern matching and data processing. This makes them capable of predicting new problems and modelling suitable solutions. To simply put, these are self-made systems based on continuous learning by incorporating techniques such as data mining, pattern recognition, and NLP thus mimicking the human brain. Cognitive computing forms a part of AI application that includes but not limited to natural language programming, expert systems, neural networks, virtual reality, and robotics to name a few [17].

In healthcare, cognitive computing paves way for the development of AI systems capable of augmenting the role of physician by providing virtual assistance to patients. This will in turn help improve telemedicine and personalized medicine. With the increasing access to clinical data through EHR it is possible to build such systems that are cost effective, accessible, and with improved care outcomes. The CC system processes large amount of varied data almost instantly based on an intelligent query response approach to make customized recommendations. From areas of advanced personal training to patient-specific treatment, clinical trial matching to individual treatment plans for cancer treatments, cognitive computing transforms the way in which organizations impact health and wellbeing [17]. Cognitive computing in healthcare provides an interface between machine and man where both brainstorm to improve clinical decision making [18].

2.1.6 Computer Vision

Computer vision is a part of AI that focuses on understanding and interpreting visual data using trained intelligent algorithms without being explicitly programmed. In healthcare, about 90% of the input data is in the form of images, thus providing numerous opportunities to improve patient care. The automated image recognition process can surpass the need for manual interpretation of clinical staff, enabling the human workforce to focus on more complex problems [19]. Computer vision technique has been quite welcoming in the areas of predictive analytics, therapeutic, and surgical procedures. Technologies like three-dimensional (3D) modelling and rapid prototyping have driven the rapid development of medical imaging modalities like CT and MRI which have been widely used in recent times in the field of medicine [20]. Furthermore, computer vision is also extensively used in various healthcare domains like radiology and oncology to track tumour progression, early diagnosis of cancer, bone fractures detection; in cardiology for vascular imaging, artery highlighting, automated cardiac pathology, and anomaly detection to name a few; and for automated lab tests in which blood analysers powered by computer vision are capable of either taking images of blood samples or receiving pictorial inputs of blood-stained slides [19].

Thus, AI has paved way for solving many complex healthcare problems. Each AI component has been widely used in various healthcare domains for different types of input data. A summary of different biomedical data types preferred for AI-based applications in healthcare is shown in Table 1 [11, 12].

3 Impact of AI in Medicine

Undoubtedly AI has the potential to transform healthcare delivery with increased productivity and efficiency. The technological advances in medical science have increased life expectancy with demands being driven by population ageing, lifestyle changes, newly emerging diseases, and changing patient expectancy. The pandemic in late 2019 gave the world a lesson to work towards a shift from a care-based healthcare management to a more proactive and focused healthcare philosophy to cater to the complex needs. AI definitely seems promising to address the challenges outlined above, with better care outcomes and a learned decision support system. This section discusses how AI will impact current medical practices.

Table 1 Biomedical data types and preferred AI approaches

Data types	Subtypes	Preferred AI models
Multi-omics data	Genomics Proteomics Transcriptomics Epigenomics Microbiomics	Integration using ML: Data-based and model-based DL, CC
Clinical data	Images EHRs Physiological signals	Supervised ML, DL, CC Computer vision DL, NLP,CC ML, DL, CI
Behavioural data	Social media data Voice data Mobile health data	Unsupervised ML
Environmental data	Pollution data, metallic reactions, etc.	Supervised/unsupervised ML
Pharmaceutical data	Chemical compounds, clinical trial data, drug interaction reports	ML graph-based approaches

3.1 AI and Traditional Medicine: Combining Impact

Artificial intelligence has set its mark in the healthcare domain with its high-performance computing and superior learning algorithms using huge medical data resources. With the current pandemic impact faced globally, the need for understanding the disease forms, its prognosis, design and development of new drugs has become the prime focus. The rich resources of traditional medicine and its practical references needs to be sufficiently exploited and rejuvenated to address the global crisis faced during the COVID-19 pandemic. Prior to AI, drug development strategies focused on drugs designed to react only with the proteins involved in a particular disease reducing side effects; but can still react with unintended targets thus missing on a multi-targeted approach. AI technologies in the areas of bio and chemical informatics, pharmacology systems, and computational biology when properly linked with traditional medicine can lead to successful implementation of computer-assisted drug design technology with low-cost, high-speed precise solutions to combat disease management and treatments. The various stages of drug design and development where AI can play an integrated role is shown in Fig. 6.

In recent times, big data has extended its application in drug design and discovery. AI-based computer programs can predict how people with different genetic and physiological characteristics react to new therapeutic drugs using a virtual human body. It will enable more chemical combinations to be tested, reducing the number of superfluous trials. One such research led by the research team of Bio-Synergy Research Project has developed CODA (context-oriented directed associations)

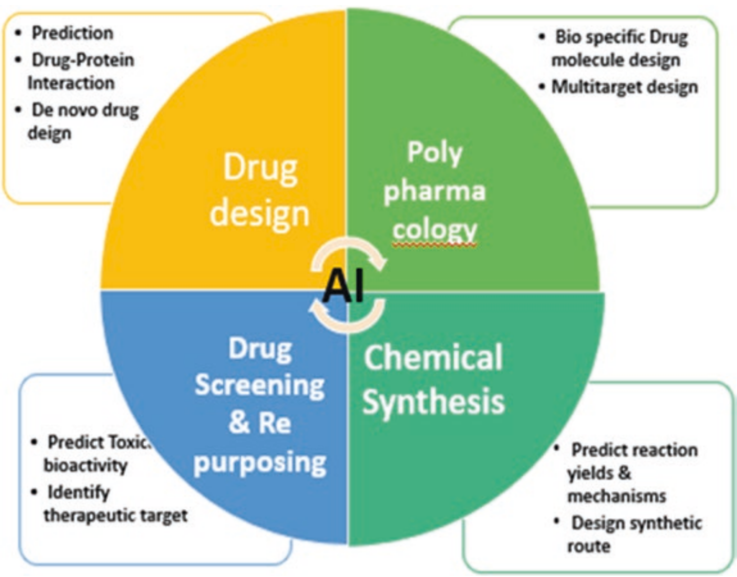

Fig. 6 Role of AI in drug design and development cycle

software to test the therapeutic potential of chemical compounds found in traditional medicines [21].

The researchers first developed an AI-based intelligent program to represent biological interactions. Then voluminous resources from public databases and scientific literature were collected to construct a network of potential interactions between chemicals, proteins, and genes within, and between organs. With this AI has enabled safe, cost-effective, and precise patient-specific drug development methods to combat new disease forms that pose a challenge to survival of mankind.

3.2 Future Role of Physicians

Quantity and quality of data is the basis of any AI system to be effective in learning and making accurate judgements. To simply put, it requires humans to collect data and teach them what to do, so that they learn. AI has a promising role to augment/assist the efforts of clinicians for much faster and less expensive at the same time more accurate decision making. High computational power intelligent systems can search and read through countless medical data, a capability that far exceeds a human physician [22]. A fatigued physician may not recollect the allergies and past symptoms of a particular patient, but that cannot be the case in an AI-based system. Not only limited to diagnosis, surgeries assisted by augmented reality can be provided by AI systems so that, the surgeon can perform a remote surgery with precision and with decreased blood loss due to tactile feedback [23]. AI-based systems can analyse and learn from millions of data in a considerable timeframe. This is particularly advantageous in the fields of radiology, pathology, dermatology, and ophthalmology [24]. In 2018, researchers at Harvard's SEAS in association with Massachusetts General Hospital (MGH) reported that in diagnosing intracranial haemorrhages, an AI-based system was equally accurate as trained radiologists. In 2019, researchers from academic institutions in conjunction with Google, reported an AI-based lung cancer detection system which had 94% accuracy with fewer instances of false positives and negatives compared to the decisions of six radiologists [25].

With AI taking most of the burden, it certainly will minimize the waiting time for appointments and also provide more time for clinicians to spend with patients. All said, an AI-based system will work hand in hand with physicians augmenting their capability and is less likely to interfere with the patient–physician relationship [8].

3.3 Explainable AI

AI solutions, specifically machine learning models, are considered as black box making it difficult to comprehend and interpret the results of the ML models. This has led to the evolution of explainable AI (XAI). XAI is the process of making ML models more explainable as well as a means to testing its reliability and causality with respect to its features. Especially in the field of medicine, it is important for the clinicians to understand why a particular result is obtained and trust the model output in order to help them assist in the treatment of patients. Thus, XAI has gained popularity in recent times.

XAI aims at producing explainable ML models without compromising on the high-level learning performance and accuracy in decision making. This provides an understanding towards how feature engineering is performed within ML, thus making it more reliable [26]. By doing so, it enables trustworthiness of the AI solutions and makes use of the powerful AI solutions in solving the real-world healthcare problems.

3.4 Risks and Safety Challenges

With more and more recognition towards AI's potential value, there is equal concern towards its potential risks. The quality of data is paramount for any AI-based healthcare delivery as "bad data" may put a patient's life to risk. Poorly designed AI systems trained on culturally biased data will incorporate blind spots that lead to misdiagnosis/treatment when applied universally. Having said, the costs of doing it wrong might cost a life. Therefore, both the potential and challenges of AI are equally big. With changing demands and healthcare complexities, AI-based systems require constant fine-tuning to enhance quality, efficiency, safety with reduced health discrepancies and elevated care coordination. A significant number of years may be required to rightfully believe that AI works right for healthcare encompassing a broad range of medical tasks and surpassing the need for physicians.

4 Conclusion

The impact of integration of AI in healthcare is phenomenal, facilitating quality and precision in diagnosis, patient care, and management. AI has integrated the world together by providing a common platform to address healthcare needs. It is undoubtedly a boon which has solutions to all unanswered complexity involved in the identification and treatment of certain deadly diseases.

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