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Survey paper

Artificial Intelligence in Healthcare: Review, Ethics, Trust Challenges & Future Research Directions

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ABSTRACT

The use of artificial intelligence (AI) in medicine is beginning to alter current procedures in prevention, diagnosis, treatment, amelioration, cure of disease and other physical and mental impairments. In addition to raising concerns about public trust and ethics, advancements in this new emerging technology have also led to a lot of debate around its integration into healthcare. The objective of this work is to introduce researchers to AI and its medical applications, along with their potential pitfalls, in a comprehensive manner. This paper provides a review of current studies that have investigated how to apply AI methodologies to create a smart predictive maintenance model for the industries of the future. We begin with a brief introduction to AI and a decade's worth of its advancements across a variety of industries, including smart grids, train transportation, etc., and most recently, healthcare. In this paper, we explore the various applications of AI across various medical specialties, including radiology, dermatology, haematology, ophthalmology, etc. along with the comparative study by employing several key criteria. Finally, it highlights the challenges for large-scale integration of AI in medical systems along with a summary of the ethical, legal, trust, and future implications of AI in healthcare.

1. Introduction

To make better decisions in complex and uncertain systems, AI has been introduced as a technology with the potential to transform medical practices (Jiang et al., 2017; Tekkeşin et al., 2019). It is all too common for humans to be overlooked when discussing AI's role in real-world applications. Electronic health records (EHRs) (Häyrinen et al., 2008) and clinical decision-making (Musen and Shahar, 2006) are just two of the many benefits (Buntin et al., 2011) of incorporating information technology into the healthcare industry. Typically as health regulators data is thought of as randomized clinical trials (Benneyan et al., 2017), however, data is being generated in multiple formats, for instance, pharmacy dispensations, digital sensors which are ubiquitous across the population, lab results, electronic health records, diagnostic registries, patient registries and so forth as shown in Fig. 1.

It is possible to analyze medical data in a variety of ways and at a variety of levels. When values on heart electrocardiography (ECG) monitors, for example, fall outside of the normal range, conventional alerting systems are able to help bring the situation to the user's attention. Second-level processing involves merging and analyzing data from multiple sources in order to feed it into a system that generates diagnostic and inference recommendations based on a priori rulesets. This allows the result to be used in a feedback loop to improve the accuracy of the system. These types of systems are able to provide assistance in the process of finding a plausible explanation for the symptoms that have been entered by constructing a tree-like hierarchy on the basis of the data that has been provided. "Expert Systems" are the name given to these rule-based systems. Expert systems are computer programs that are intended to simulate the decision-making capabilities of humans by gaining knowledge from their previous experiences. Improvements are currently being made to intelligence systems in order to give them the ability to reason more effectively and make better use of the data they collect. In contrast to the approach of looking backwards, in which systems only provide diagnoses and conclusions, The goal is to allow decision-making systems to run ahead of schedule so that they can provide early diagnosis.

There is no clear definition of how AI works, how it functions, or what its role is, unlike other technologies (Siau and Wang, 2018). Security, privacy, and patient and healthcare professional [HCP] trust in AI are all tied together. Humans must have faith that their personal data will be used ethically and effectively if AI is to have a positive impact on society (House Of Lords, 2018; Luxton, 2014; Mohandas, 2017). By providing patients with adequate information about how their data is being used, they can have confidence in the technology and decide whether or not to consent or reject its use (Bollier, 2017; Hengstler et al., 2016). Human-to-human interactions, as well as those involving AI, are heavily influenced by trust. It is critical in fields like medicine, where people's lives are on the line, to understand how AI and humans build trust with one another. Human characteristics,

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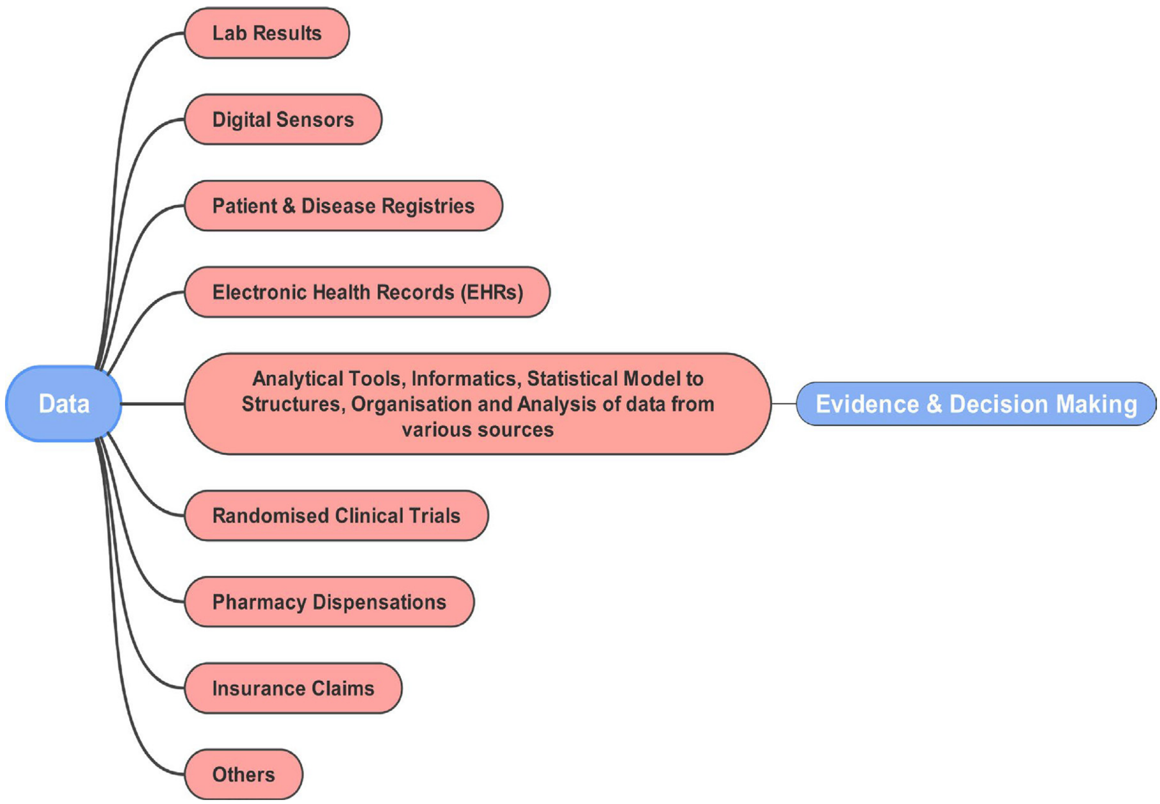

Fig. 1. Data to evidence.

environmental characteristics, and technological characteristics all play a role in determining how much people trust technology.

After considering in all these aspects, it becomes increasingly challenging to get a comprehensive understanding of medical and healthcare sub-fields using ML and DL algorithms. Nevertheless, numerous review and survey publications on AI based medicine have appeared in the recent few years. In most cases, they are designed to be used in narrow medical contexts, such as the automatic detection of a cardiovascular disease in computed tomography angiography acquisitions (Pepe et al., 2020) or the analysis of specific medical images comprising certain illnesses. The goal of this study is to provide a comprehensive introduction to healthcare that covers the latest ML and DL techniques. The focus is on giving a high-level overview of these approaches. As a result of the global trend toward digitalization of the health-care system and the ongoing development of AI in healthcare, there is a significant demand for in-depth analysis of this new emerging technology in order to better understand its implications and key details. In this domain, all previous studies conducted to date did not cover the overall aspects of issues. Therefore, in this paper we are providing the study for better understanding of AI in healthcare services so that it can benefit the research community as well the policy makers associated with healthcare industry around the world.

1.1. Methodology

This survey was conducted in accordance with the standards of a systematic review (Bordoloi et al., 2022). It consists of a series of clearly articulated and documented actions that promote the repeatability of results. In brief, these are:

- The formulation of research questions.
- The selection of keywords and literature databases.
- The screening and selection of articles.
- The discussion and interpretation of the results

The remaining section is a detailed explanation of the approach that was taken.

The first stage is formulating a set of research questions. As a result, we established the following as our primary research questions for this work:

1. In healthcare, what are the different applications of AI technology?
2. To what extent does the widespread use of AI in healthcare raise social, ethical, legal, and trust concerns?
3. To what extent do the benefits and drawbacks of these techniques depend on the specific context in which they are employed?
4. What are the primary research gaps that are either currently being investigated or that ought to be investigated?

Keywords for mining literature databases for raw corpus can be defined by starting with research questions. Terms that are relevant to the overarching study issue are included in the keywords, along with their most natural synonyms. When searching for articles, we choose literature databases that are most applicable to the domains of computer science and health. Typical keywords involved "artificial intelligence" $\wedge$ ("healthcare" $\vee$ "medicine" $\vee$ "deep learning" $\vee$ "machine learning") and various combinations. The databases utilized in this analysis are shown in Table 1. A total of 250 articles in their raw form were gathered using these parameters as the basis for the initial literature corpus.

In the next step of the process, the raw corpus will be analyzed and filtered to produce the final corpus for the suggested literature study. Through a series of checks, irrelevant findings are discarded out of the literature review in the filtering phase. Specifically, it consists of the following factors: To ensure that the review is focused on the most recent research in the field, the corpus should only contain publications that were published during the last five years (from 2016 to 2021). Review of titles and abstracts to filter out publications that are not

Table 1
Literature corpus databases for primary data extraction.

Name	Address
ScienceDirect	https://www.sciencedirect.com
ACM	https://dl.acm.org
SpringerLink	https://link.springer.com
PubMed	https://www.ncbi.nlm.nih.gov/pubmed
JMIR	https://jmirpublications.com
IEEE Xplore	https://plore.ieee.org
arXiv	https://arxiv.org
Nature	https://www.nature.com

specifically about the application of AI in healthcare. Articles from many databases are combined, and any duplicates are purged, as part of the "duplicate removal" process. Articles that do not meet the criteria for a well-rounded research paper should be culled at step four i.e., quality Assessment. 53 articles remain after applying the filtering criteria. All of these articles together make up the comprehensive database for this analysis.

1.2. Contribution

The contribution of this work is to provide information and raise general awareness about AI in the healthcare sector, with the intention of facilitating the operation of decision systems in a prospective manner and delivering an early prognosis to patients. Specifically, we wanted to know if there is a broader issue with current emerging technologies, or if healthcare service transformation is the only issue at hand? Below are the contributions of this work:

– An overview and background of AI technology is presented in order to make the frontier ideas more understandable.
– Context of AI in medical systems along with a summary of the ethical, legal, trust issues are discussed in detail for better understanding for the possibility to raise public confidence in AI.
– We provide in-depth analysis of the reliability and utility of AI technology for healthcare applications along with the comparative study of all the most recent works that use the AI paradigm for numerous downstream tasks across various domains.
– Following an examination of the challenges and opportunities presented by the extensive integration of AI in healthcare, various potential areas for future study have been identified.

1.3. organization of paper

This work is set up in the following manner: Section 2 provides the comparative analysis of all the major previous surveys done on applications of AI in healthcare in recent times. AI and its frontier concepts are introduced in Section 3 & 4, and a general procedure and context in the healthcare setting, as well as their relevance to the evolution of various industries are discussed. Starting with a formal framework description, we then present various ways in which the field can be divided based on various domain of applications in Section 5. A variety of opportunities and challenges are then covered in Section 6 & 7. A taxonomy of overall work is shown in Fig. 2. To wrap up the paper, we discuss about a few hot button issues and how they might play out in the future in our concluding section.

2. Related work

The most recent findings on AI's potential in the medical field are summarized here in this section.

In order to make sense of all the data being collected in the healthcare industry, numerous AI methods have been put to use during the past decade. Automated early diagnosis of cardiac disease was achieved, for instance, by employing a prediction model based on logistic regression (Kumar and Gandhi, 2018). Recent years have seen an explosion of research utilizing DL and demonstrating its capabilities in a wide range of fields and applications, including healthcare and health informatics (Abdel-Jaber et al., 2022), to better the efficiency of sensorless FOC (Gutierrez-Villalobos et al., 2015), motor imagery classification (Ortiz-Echeverri et al., 2019) and a novel strategy for an FPGA-based self-tuned controller with backwards compatibility (Cruz-Miguel et al., 2020). The field of medical imaging has also made use of ML to aid in the automatic detection of object features (Rav'ıet al., 2016).

Many researchers are focusing their efforts on deep neural network (DNN) based algorithms, in particular for analyzing large datasets. In DL, data is filtered via a series of layers, each of which represents a separate stage in the feature-learning process. While many traditional ML models struggle to scale to huge datasets, DNN models improve in accuracy as they do so, allowing them to surpass their more traditional counterparts (Bordoloi et al., 2022). Furthermore, DNN-based methods have shown promising results in NLP and image processing (Abdel-Hamid et al., 2014; Cho et al., 2015). There are a number of methods available for assessing, tracking, and controlling healthcare workers' actions. Many different viewpoints are represented in these methods, all of which contribute to a more complete answer. To explore how ambient supported living can motivate and assist patients with heart disease in self-managing their condition to reduce mortality and morbidity, the authors of Qureshi et al. (2022) conducted a systematic review of the literature on ambient supported living solutions and tools. The review provides a comprehensive overview of the topic. Motwani et al. (2021) presented a comprehensive overview of ubiquitous network and systems of smart healthcare to track a person's lifestyle and chronic illness. The method introduced a new framework for intelligent patient monitoring and recommendation using cloud-based analytic tools and DL. In Zhao et al. (2019), Zhao et al. conducted a comprehensive review of the literature on DL for automated health monitoring. By training DNNs with multiple layers of nonlinear variations, health monitoring ML systems (MHMS) are able to extract hierarchical signals from input data. Industrial vacuum pumps have become increasingly important but have not received sufficient attention from researchers. Authors in Ainapure et al. (2020) presented a DL-based cross-machine health identification approach for these pumps. This research used a real-world dataset of vacuum pumps, and the outcomes were encouraging.

Different ML techniques, including sensor-based and wearable methods of automatic feature extraction, were explored by authors in Nweke et al. (2018) from the context of mobile and human activities. In Alam et al. (2017) the authors conducted a thorough literature review on data fusion in IoT, paying special attention to computational and mathematical techniques such as methods in AI, probability, and the theory of belief, specified IoT ambiances like nonlinear, decentralized, non-homogeneous, and environments where objects are tracked. The full layer-by-layer structure of convolution networks has been reviewed by Karkra et al. (2019). They pointed out some of DL's drawbacks, namely its expensive calculation and lengthy training on processing units. For example, in Debauche et al. (2019), Debauche et al. presented a cloud-based health monitoring framework for fog IoT that makes use of physiological and natural signs to deliver useful data about people's day-to-day routines. Providers of medical services to the elderly or the socially isolated will benefit greatly from this system's ability to monitor health status and respond accordingly. The method described in this paper also evaluates current clinical practise and healing times. Applications of AI in the medical imaging (MI) were discussed by authors in Ranschaert et al. (2019). The data mining and DL strategies for bioinformatics-specific domain knowledge were proposed in a survey by authors in Lan et al. (2018).

In Benyelles et al. (2021), the authors suggested a plan to assist medical professionals in handling a COVID19 outbreak by establishing investigation procedures for the initial patient diagnosed with the disease. These procedures could also be useful for epidemiologists in

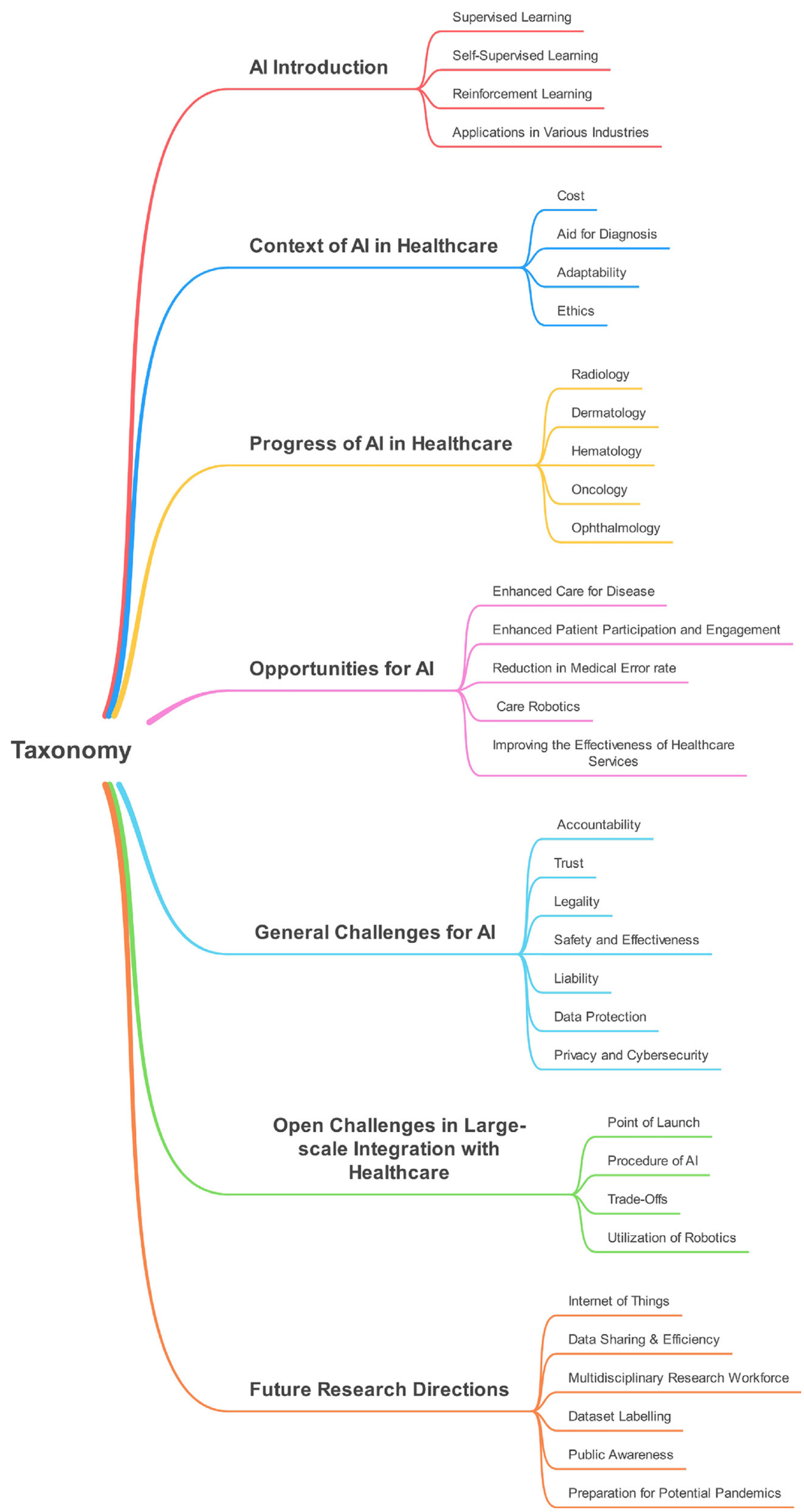

Fig. 2. Taxonomy of this review.

determining how to address the spread of the virus Autoencoding architectures that took into account multi-omic and clinical data from cancer patients were studied in Simidjievski et al. (2019). The methods, tools, and strategies currently in use for health monitoring that make use of DL and transfer learning are reviewed in detail by the Wang et al. (2021a). In Manickam et al. (2022), authors critically examine the role that AI plays in enhancing the detection accuracy, performance, risk assessment, and decision-making ability of IoMT devices. This analysis also takes into account the technological and engineering opportunities and constraints inherent in the development of AI-based

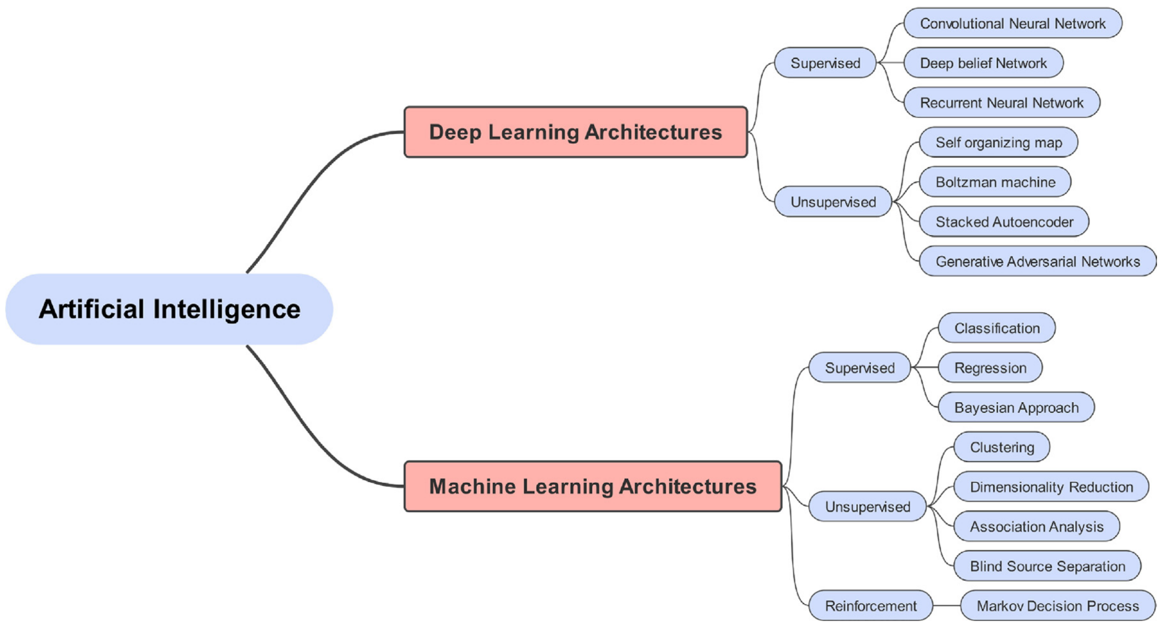

Fig. 3. Categorization of AI, ML, and DL architectures.

cloud-integrated personalized IoMT devices for the development of effective POC biomedical systems appropriate for the delivery of next-generation intelligent healthcare. In Antunes et al. (2022), the authors present a generic framework for federated learning as it relates to healthcare data. The authors argue that due to the sensitive nature of medical data, there should be extensive research on the privacy and confidentiality considerations of sharing training data and models. They also examine ways to improve the aggregation processes for creating learning models from distributed contributions and provide case studies using different types of medical data.

3. What is AI?

AI refers to the way in which computer software emulates human cognitive processes. Like the human brain, an ANN (artificial neural network) is a network of interconnected layers that connects input and output signals (Rosenblatt, 1958). The various types of AI paradigms are summarized in Fig. 3. Many studies have shown that artificial neural networks are superior to logistic regression models when it comes to making decisions in cardiology. Researchers from the University of Texas Southwestern Medical Center in Dallas found that ANN had a higher accuracy rate in predicting myocardial ischemia in patients with chest pain who were admitted to the hospital's emergency room (Baxt et al., 2002). ML is another popular type of AI, which is defined as the ability of computers to learn from data by building algorithms. By automating the process of creating models for constructing patterns or decision support using the data examined, the algorithms in ML can improve performance (Johnson et al., 2018). The process of using AI in healthcare can be divided into several steps, which may vary depending on the specific use case and context. Fig. 4 shows a general flowchart that illustrates the interactions between different components in the process of using AI in healthcare. Throughout this process, there are interactions between different components, such as the data, the AI model, and the humans involved in the process. For example, the data collected and preprocessed by humans may be used to train an AI model, which in turn may be used to make predictions or decisions that are used by healthcare professionals to inform their treatment recommendations. There are four main types of ML methods: supervised, semi-supervised, unsupervised, and reinforcement approach. These are the most widely used methods.

– Supervised Learning: A supervisor, who is typically a human expert, gives instructions to a computer program, telling it to learn associations by analyzing data samples that the supervisor has defined (in this case, a computer program). After prior associations have been learned, a method known as Testing can be utilized to predict what future examples might entail (Panch et al., 2018).
– Unsupervised learning: Using Unsupervised Learning, computers are able to discover patterns in data without being explicitly taught how to do so. It is frequently used for clustering, which is the process of finding previously unknown correlations among sets of input data in order to create new sets of data with shared characteristics.
– Reinforcement Learning: In the process of Reinforcement Learning, reward and punishment signals are used to instruct the system on how to behave. One interpretation of punishment is that it functions as a negative reward signal, encouraging the kinds of behavior that lead to its non-delivery. This is one way to conceptualize punishment Doya (2007).

Risk stratification and prediction are achieved using a variety of algorithms, including Bayesian networks, ANNs, logistic regression, and ridge regression (Seetharam et al., 2019). Clinical and echocardiographic variables are used to compare nonlinear ML and linear logistic models in terms of predicting survival. There are no training and testing categories in unsupervised ML. As a subfield of ML, DL is a recent development. The volume and complexity of big data are constantly evolving, necessitating the use of DL techniques. DL techniques are based on neuronal networks that contain many layers of hidden neurons (Johnson et al., 2018).

3.1. Applications of AI in various industries

Numerous industries have benefited from AI's contributions and successful integration, which has led to higher productivity and lower costs. Several of the sectors that have benefited greatly from the development of AI technologies are discussed here.

3.1.1. Smart grids

Semantic interoperability and inter-connection of power data have received a lot of attention since the era of electric power big data.

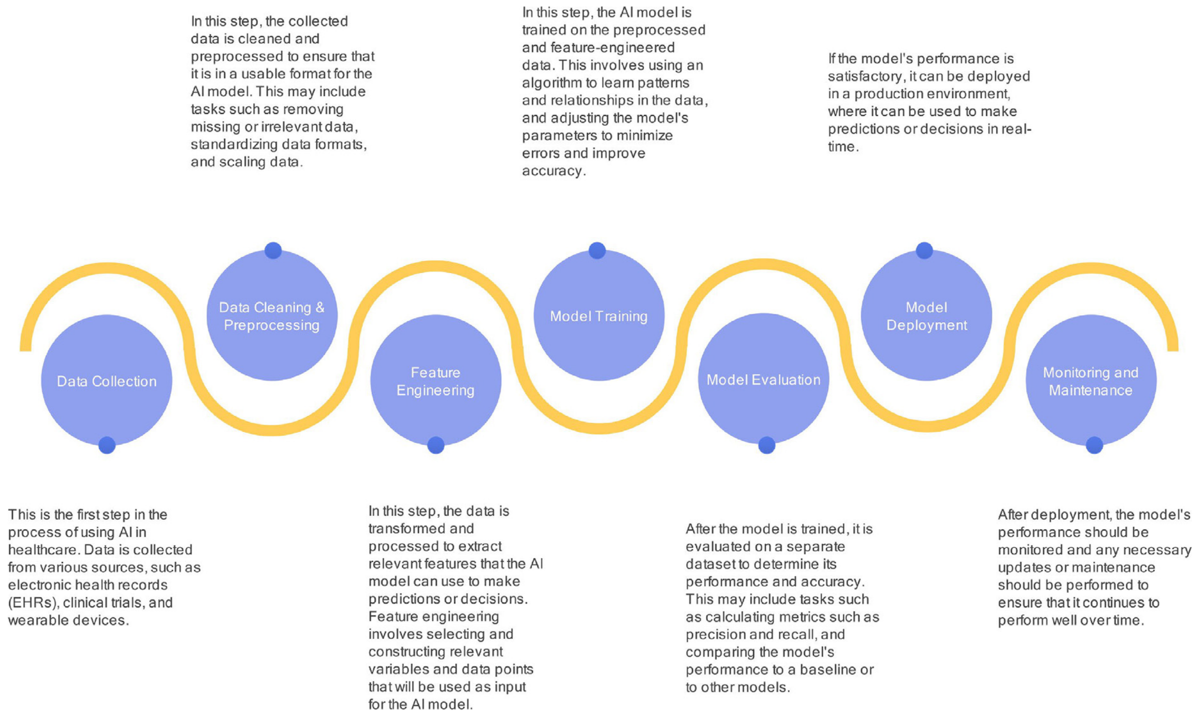

Fig. 4. Process of AI in healthcare.

Knowledge graph technology is a novel approach to describing the intricate interconnections of ideas and objects in the real world, and it has garnered a lot of attention due to its powerful knowledge inference capabilities. KG4SGs is the first step toward the next generation of electric power AI because it introduces a new data integration paradigm that combines massive data processing with strong semantic technologies (Wang et al., 2021b). AI's strong capabilities in computational intelligence, cognitive intelligence, and perceptual intelligence make it one of the most disruptive technologies globally. The use of AI in power systems will improve system reliability, alter how businesses deliver their services, and significantly bolster the next generation of power grids. That is to say, AI applied to electric power will emerge as both a crucial strategic path and an unavoidable answer to the problems facing the evolution of power grids (Yang et al., 2019). The knowledge graph (KG) (Pujara et al., 2013) offers us a practical means of accomplishing this goal, which is essential for easing the intelligentization of power grids. If we look at the management of power equipment as an example, the KG can help with things like better planning, tracking, scheduling production, executing orders, and keeping track of suppliers (Tang et al., 2019).

3.1.2. High-speed railway

Overhead contact lines (OCLs) on high-speed railways are particularly vulnerable to lightning-related failures, which can have disastrous consequences. To account for the recurrence of OCL failures due to lightning strike, it is helpful to be able to predict the probability of such failures so that predictive maintenance decisions can be made. In Wang et al. (2022), the authors present a data-driven Bayesian Network (BN) approach with a spatiotemporal fragility model for predicting lightning-related failure risk. The proposed method demonstrates its remarkable robustness in predicting over the imbalanced dataset and noisy data, and in doing so, guides predictive maintenance decision-making and procurement of OCL components, which ultimately helps with lightning-related risk mitigation. Authors in Ma et al. (2019) used the BN to quantify the level of dynamic flashover risk, combined with the risk propagation chain of OCLs, to investigate the effects of the humid and polluted environment on OCL failures. The other researchers primarily analyzed risks associated with lightning (Xiang et al., 2016; Bian et al., 2013). The studies calculated the probability of a lightning trip-out under varying bridge heights and located the weak spot in the lightning protection performance of OCLs.

3.1.3. Sparse cyber attacks

DL is a relatively new subfield of ML that has seen widespread interest and application in areas as diverse as data mining and wind speed prediction (Zhang et al., 2015). Prior research has shown that DL, in contrast to shallow learning models, can reveal previously hidden nonlinear features and structures in time series data. Therefore, this paper's third contribution is the introduction and design of a typical DL algorithm—the stacked auto-encoder (SAE)—to reduce the impact of ELF's inherent uncertainty and, in turn, reduce the breadth of state variables, which improves the efficacy of the interval state estimation (ISE)-based defense mechanism. Both the scenario-based cyber-attack strategy and the ISE-based defense mechanism have been extensively validated and demonstrated on IEEE benchmarks. The findings shed light on the inner attacker's tactics and emphasize the criticality of protecting critical infrastructure from cyber attacks (Wang et al., 2018).

3.1.4. AI of things (AIoT)

Traditional AIoT paradigms necessitate moving users' IoT-generated energy data to a centralized storage (like the cloud or edge device) in order to extract knowledge, which can pose serious privacy violation and data misuse risks. An appealing privacy-preserving AI paradigm, federated learning allows energy data owners (EDOs) to jointly train a shared AI model without disclosing the local energy data. However, low-quality shared local models, non-independently and identically distributed (non-IID) data distributions, and unpredictable communication delays continue to pose potential security and efficiency concerns that prevent the widespread adoption of federated learning-based AIoT services in smart grids (Su et al., 2021). Specifically, in AIoT, private energy data must be migrated to a central storage for knowledge extraction in traditional AI models (Zhang and Tao, 2020; Tran et al., 2019a; Pandey et al., 2020). When it comes to users' personal energy data, federated learning stands out as a promising privacy-preserving AI paradigm because it allows ESPs to extract knowledge and insights from such data while allowing individual energy data owners (EDOs)

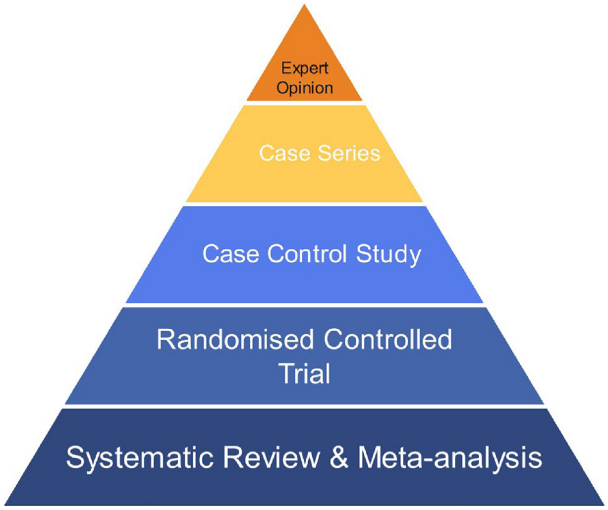

Fig. 5. Hierarchy of evidence.

to keep their training data securely stored on their own devices (Taïk and Cherkaoui, 2020).

3.1.5. Circuit faults

Three-phase pulse width modulation (PWM) rectifiers have been widely adopted by industry due to their superior properties and potential benefits. Open-circuit faults in IGBTs do not cause instantaneous system failure, but they do cause performance degradation due to things like voltage and current fluctuations and harmonics. For fault diagnosis, the authors of Kou et al. (2020) propose a deep feedforward network equipped with temporary synthetic features to reduce reliance on inaccurate mathematical models. As well as introducing a new OCF diagnosis method that utilizes a deep feedforward network with temporary synthetic features, they perform an in-depth analysis of the characteristics of OCF in 3-phase PWM VSR IGBTs. As a data-driven technique, the deep feedforward network is taught to recognize faults from the past using the actual data that caused them. Because it is so challenging to establish a reliable fault mathematical model for a power electronics circuit, this can lessen the importance of using one.

3.1.6. Smart wind farms

The use of wind power has led to a surge in both the number and size of wind farms in recent years. The wind power industry all over the world is quickly adopting a new strategy that involves the construction of wind farms in offshore locations due to their many benefits, including stable wind speed, clean energy production, renewable resources, pollution-free operation, and minimal impact on agricultural land. There has been a shift toward increased digitization and intelligence in offshore wind power operation and maintenance. The authors in Papatheou et al. (2015) proposed using ANNs and a Gaussian process-based method to monitor the wind turbines that are a part of offshore wind farms. In order to construct a reference power curve for each wind turbine, the method that was proposed was selected; however, there are some additional features that can be taken into consideration to improve the method's performance. Governments are making great strides in many areas of offshore wind power development around the world. Cloud computing, big data, IoT communication, AI, and various other recent technologies greatly aid in the building and expansion of smart offshore wind farms (Helsen et al., 2016).

4. Context of AI in healthcare

Compared to other technical fields, AI research in health care presents unique challenges. Physical system models are mathematical representations of engineering applications' underlying technical behavior. Medical diagnostics (e.g. the precise relationships between diseases and their causes) is one area where such quantitative models are lacking, and this poses a significant problem. When it comes to the same clinical cases, the responses of doctors can be vastly different. As a result, training AI-based tools with subjective responses that carry over individual bias from clinicians who are unaware of the truth of the real world would be challenging. In addition, research in AI needs to take into account the various characteristics of medical problems that can be found in a variety of applications within the health care industry. It is possible that the process of training a mathematical model for an AI that is tailored to cardiovascular applications, for example, cannot be generalized in order to train an AI model for applications that are specific to cancer. This would prevent the training of an AI model for applications that are tailored to cardiovascular applications. In addition, there is a possibility that the outcomes will not be accurate if the requirements of underserved communities and individuals with disabilities are not taken into consideration during the development of the AI system. There is a possibility that a specialized AI process will be required for each application. This will be determined by the nature of the health care decisions that need to be made, as well as the patient population that is being targeted, the amount of variability and useful information contained within the data, and the amount of useful information.

There is a hierarchy of evidence starting from the expert opinion which is the lowest and going up to randomized controlled trial and systematic review and meta-analysis as shown in Fig. 5. Expert opinion has turned out to be a dated way of making decisions. Expert opinion may actually be incorrect, and often experts do not agree. As a result, it occupies a low position in the hierarchy. A series of cases is described as a set of patients with common features to identify certain aspects of a disease, a treatment or diagnosis, whether clinical, pathophysiology or operation, which comes next in line after expert opinion and so on. According to the literature (Burlacu et al., 2020; Lake, 2019), the last two usually change practice. So that was the ultimate in preview & practice for the patients. If anyone wanted to look into something which might look like new, basically a new drug, then there are stages of phased evaluation going from something called pre-clinical to what is normally considered as a kind of gold-standard randomized controlled trial and ultimately a phase 4 trial where the larger population is safely analyzed (Ghogawala et al., 2019).

As long as the doctor is confident in their expertise, they should not use information provided by an intelligent medical device as a basis for their decision. Independent information evaluation is part of their skill set, and the greater the ramifications of a decision, the greater their need to question their assumptions (Molnár-Gábor, 2020). It also needs to be efficient so clinicians always want to have a stage where they want to abandon early medicines that do not work and never have then any research waste and finally, never want to use medicine that does not have an evidence base because that is a waste of money if clinicians are buying something which does not work (Fountzilas and Tsimberidou, 2018). So after the introduction of new concepts they have a pipeline for assessing any new proposal that is in health, say it works pretty well, there are some problems, they have heard about them, but what is going to be appreciated is that it goes beyond accuracy. So when clinicians think about AI they often think about the accuracy but when they think about healthcare they think about efficacy, cost-effectiveness, and safety (Gopal et al., 2019). The truth is that this pipeline does not work well for lots of things especially not for AI because of the four following main reasons as shown in Fig. 6.

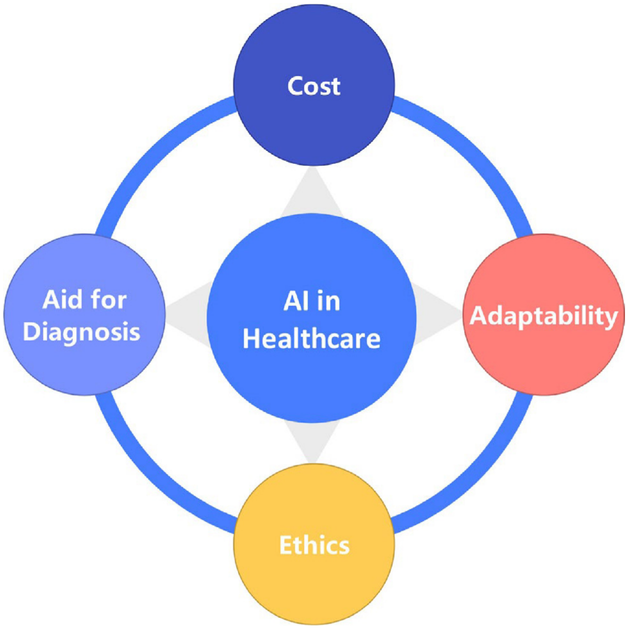

Fig. 6. Fundamental impediments to the full integration of AI in healthcare.

4.1. Cost

The costs of data collection, cleaning, and annotating data are all part of the data acquisition and preparation process. The quality of the data used to build an AI application is, in most cases, the primary factor that determines how good that application will be. As a consequence of this, this stage is extremely important, time-consuming, and costly depending on the granularity of the information that needs to be extracted from the data that was collected. How much a randomized controlled trial costs and how long it takes, so to think about doing that for everything that a clinician might want to do an AI model for, it is almost behabitive. Precision medicine and ML both require a training dataset with a known outcome (such as the onset of a disease). One of the biggest challenges in using AI in healthcare and medicine is the lack of large clinical datasets for training AI models. Datasets with labels, such as those created by doctors or medical experts, are particularly time and money-intensive to collect (Tran et al., 2019b). Recent developments in AI have been made possible as a result of the convergence of powerful computing resources and an abundant supply of data. To put this another way, recent advancements in computer hardware, such as graphics processing units (GPUs), have made it possible to process the massive amounts of calculations needed to train and run artificial neural networks at a much faster rate than was previously possible. As computing power and available data increase, so does the accuracy of a model's predictions.

4.2. Adaptability

Because the health care sector is so heavily regulated, the creation of adaptive AI technology that is in line with applicable regulations is a challenging endeavor. An adaptive algorithm is one that modifies its behavior automatically based on what it has learned over the course of its usage without requiring any human intervention. When an adaptive algorithm learns and updates from a given set of inputs, it may produce different results each time. In order to guarantee a secure and dependable performance even when the AI is exhibiting adaptive behavior, the design of the AI must incorporate a credible validation and verification plan (Asan et al., 2020). Every time it changes clinician cannot do a randomized controlled trial, its impossible. When examining the evaluation of AI, clinicians developed these kinds of models of how things could work if they wanted an efficient pipeline to assess new medicines and models of AI (Gilvary et al., 2019). For instance, one might develop a model, one might validate it, one might benchmark it as illustrated in Fig. 7, one might run a trial and one might have safety which looks fairly similar according to the other pipeline that they had a look at apart from the idea of benchmarking (Wenzel and Wiegand, 2019). Now what is it mean and why do clinicians think it is important, the premise around bench-marking for AI for health is that if a developer is having its AI model trained on his/her data and trained on his/her data and he/she brings it to the bench-marking platform where there are a number of other data i.e., data-sets from other developers, data-sets from other hospitals, data-sets from other countries and he/she can submit the model and benchmark against it (Harutyunyan et al., 2019).

Fig. 7. Illustration of a typical benchmarking procedure.

So why is that important? It is for a number of reasons.

- Clinicians know that if they want to do any kind of prognostication, it has to be validated in an independent data-set, otherwise, it might just work in one hospital (on the data-set developed there) and it would not work for any other and would be useless. So this keeps the power to entry pretty low because one might have just his/her data-set but one can also do this independent validation that is required in your data-set.
- The other reason it is important is that it allows you to do some kind of quality assurance or comparative efficacy. So if the human doctor has about 70% accuracy and the models that anyone submitted is between maybe 65%–75%. Then it is known that it is probably good enough.

In intensive care medicine, prognosticating the course of disease is crucial for making informed decisions. New AI and ML methods have already outperformed traditional prediction models for a number of medical applications. For the intensivist, these methods will bring new ethical challenges due to their technical characteristics (Beil et al., 2019). It also then would allow one to have this kind of gold standard of a trial (Shankar et al., 2006), but it does not mean that they have to do it every time because some people who are working on the same use case might to get together, they might have a trail really this is probably the best way anyone would ever know that something works and changes hard clinical endpoints like morbidity and mortality (Yu et al., 2020). It is known that if this algorithm performs well and then it is bench-marked against it. If the algorithm is adopted, no further test is necessary, as the results are understood to be sufficiently close. Robust assessment is AI's biggest health challenge, but perhaps not entirely true. Perhaps creating a pipeline like this that is a robust assessment for AI in health is one of the greatest opportunities, because there are many challenges in the way clinicians are currently evaluating new clinical drugs, any new technique or device, and if they get this right at that point in time, it creates an efficient pipeline and they just need to keep going to be sure, yes, it works for anyone (Xu et al., 2019).

Assuming an algorithm is 80% accurate, what is the real purpose of the algorithm? Are people saved, mortality is decreased, and morbidity is increased as a result of this? These are the actual endpoints to be concerned about. No one has a trial proof that AI works for any of those meaningful full-endpoints, according to the majority of the population when discussing it. It is not that clinicians do not want to conduct a randomized control trial because it is not the right thing to do. Utilizing DL algorithms on raw patient monitoring data may make it possible to arrive at more accurate clinical predictions and to make decisions more promptly. This may be the case (Yu et al., 2018). It cannot be seen as not to do it because one is going to invent some other data set that gets round the accountability that everyone is kind of holding on to. It should be seen how AI redefines our role, for instance, elevating the role of radiology (Dilsizian and Siegel, 2014). What is to be learned is that there are certain things that AI can do better which are not necessarily the most intelligent tasks (e.g. routine tasks conducted by a radiologist). We need evidence and better comparative studies in able to move forward with knowledge. There is a better opportunity for better communication indeed or coordination at the global level at least at this point in time. We need to provide more clarity to the stakeholders (here patients), the more clarity one can provide across the spectrum the better it is.

4.3. Aid for diagnosis

Technologies supported by AI and their applications will now include lifestyle operation and daytime reminders using digital devices for a person's key signs. The AI innovations in health organizations are designed to change the operation, optimization and interaction of health systems with patients dramatically and to deliver healthcare services to raise the overall performance of patient outcomes. The diagnosis of patients with special needs should be supported by AI. According to Taylor (Lee and Yoon, 2021), between 40 thousand and 80 thousand people lose their lives in American hospitals every year as a direct result of preventable diagnostic errors. Thus, the application of AI-based technology in various fields can aid in reducing the impact of human error.

4.4. Ethics

For the most part, ethical considerations are what come to mind when discussing moral right and wrong, as well as what should be done versus should not be done when making decisions or formulating new legal norms or contesting the status quo. Actors can take advantage of the social benefits of digital technologies by using ethics as an opportunity strategy. In this way, the advantage of being able to recognize and take advantage of new opportunities that are socially acceptable or preferred can be realized, while also balancing any precautionary principle with the duty not to overlook what could and should be done. As a result, ethics provides a risk management strategy. Even if a course of action is legal, it can still be rejected by society if it is considered socially unacceptable. Using ethics can also reduce the cost of missed opportunities and missed chances because of fear of making mistakes.

AI is the key topic of distributing the future faster. Making sure of what has shown to be a great standard to make it applicable everywhere, it is not necessarily the "new" thing which has never been done before, but when it comes to making possible for 7 billion people what currently is only possible for some, that is the biggest promise of AI. AI in healthcare is likely to bring about a slew of ethical, medical, occupational, and technological shifts. Institutions in healthcare and government and regulatory bodies must create structures to keep tabs on key problems and to respond responsibly, while also establishing governance mechanisms to limit negative consequences (Davenport and Kalakota, 2019). During the last decade, both in academic as well as business communities, the ethics sector of AI in health care has become an important concern. In their laboratories, many organizations and hospitals recruit AI ethicists to adapt to AI's ethics guidelines. Finally, there are a number of ethical implications of applying AI in healthcare. Health care decisions have traditionally been made by humans, and the use of intelligent machines to make or assist with them raises questions of accountability, transparency, permission, and confidentiality.

There are technical and non-technical barriers when it comes to an AI-based solution. They can be organizational in nature, cultural nature, regulatory, data access, interoperability, and security (Kelly et al., 2019). The policy framework which primarily has three-axis under which AI should be operating in healthcare is, firstly *access to data* which is basically to provide access of data to people and entrusting giving them the possibilities to control that data and then to decide with whom they want to share and for which purpose as shown in Fig. 8 (Khalique et al., 2019). Secondly, *generating new kinds of data* i.e., working on data that for instance is not aggregated or linked then third once you have that data streamlined or defined, you work on that data to make sure that you deliver innovation. Data set is the backbone of whatever is going to be done in AI. In terms of opening and accessing the data, it is very important in addition to the regulation for general data protection (i.e., regulations that gives the right to people for accessing data) to make sure that one can access and use the data and if you look at the healthcare sector today, data is locked in solutions that are not inter-operable (Kim et al., 2019). For achieving the same it takes into account the regulations and standards that are already in place but it gives a framework for under which using that it makes sure that the data can actually flow across borders in a semantic and technological way.

The use of AI in healthcare has numerous potential benefits. In routine clinical practise and research, AI can be a huge help. AI's main advantages include easy access to information, increased outreach, and fewer mistakes in disease diagnosis and treatment. The application of AI has resulted in significant advancements being made in a number of important fields, including the delivery of targeted therapies, predictive diagnosis, and precision medicine (Ellahham et al., 2020). It is a continuum that includes the administration, the workflows, the therapeutics, health management, etc., and as clinicians go around there is a lot about the results of AI in healthcare like treating images, digital pathology, Dermatology, Cardiology, Gastroenterology (Yang and Bang, 2019) and of course together with research and innovation comes the question around the guidelines specified on the ethical guidelines (Peters et al., 2020). Some of AI frameworks are described in Table 2. Particular guidelines or strategies should be set up to highlight what are the challenges and means to address AI in healthcare. There could be three elements there, firstly to *increase the capacity* by strengthening the investment for local researchers but also for those who are going to use it for meaningful purposes. Empowering the people to develop and use that technology and then obviously the elements on ethics, a trustworthy society. Hence there could be more balanced approaches where one end seizes the investment and the other end needs to deal with the trustworthiness part. Certainly, there are underlying principles of managing the data and aspects that are very much related to data sharing or how does one integrate these workflows and what could be the repercussions that integration in clinical workflows (Kondylakis et al., 2018). Challenges of which could be *transparency and accountability, data protection and security, safety and liability, expertise, and digital skills*.

5. Progress of AI in healthcare

There are several reasons for the recent rapid growth of AI, including the availability of large amounts of annotated clinical data, the increased affordability and accessibility of computational power and cloud storage, improvements in machine-learning techniques, and the availability of open-source machine-learning packages. Another factor that has contributed to the growth of AI is the availability of large amounts of clinical data. The following are a few of the many areas in which AI has demonstrated great promise.

Table 2
Overview of few healthcare specific AI frameworks.

Framework	Application
Convolutional neural network (Fiszman et al., 2000)	It incorporates the AI-based characteristics and natural language treatment in order to diagnose diseases effectively.
Skytree (Lee and won Hwang, 2009)	More precisely, without downsampling, to manipulate massive structured and unorganisationed data sets.
Apache Mahout (Walunj and Sadafale, 2013)	Provides processes such as grouping, regression and clustering
Cognitive ML algorithm (Sengupta et al., 2016)	Echocardiology data are normalized to distinguish constricting pericarditis from restrictive cardiomyopathy using the master learning algorithm.
ML algorithms (Narula et al., 2016)	To show the difference between heart of athlete and cardiomyopathy hypertrophy.
BigML (Nagwanshi and Dubey, 2018)	It integrates AI-based features with a cloud-based platform to create cost-effective, highly accurate, and scalable applications.
Phenotypic clustering (Lancaster et al., 2019)	In order to analyze echocardiogram clustering, the left ventricular dysfunction and high risk phenotyping patterns can be determined.

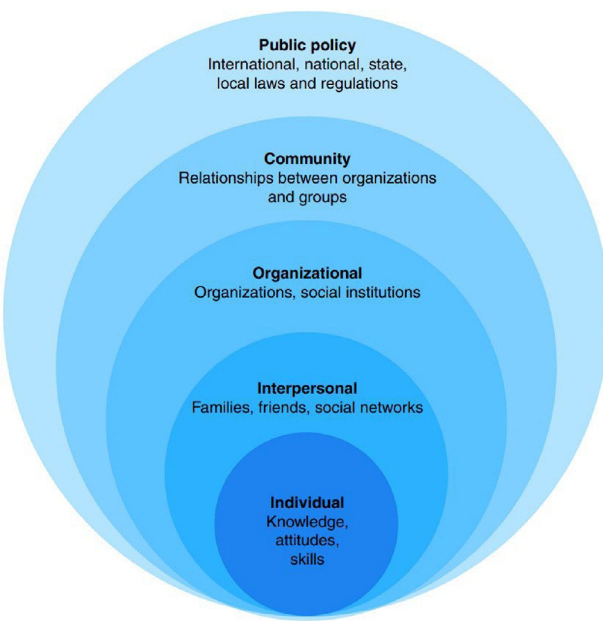

Fig. 8. Health is determined by a complex web of individual and environmental factors, and this model can help you make sense of it all and pinpoint where to exert the most influence (Bronfenbrenner, 1977).

5.1. Radiology

If a physician is using a CT scan or an MRI scan to perform medical imaging, AI techniques can assist him or her in extracting useful insights from the image using guidance and assistance from the machine. Radiologists are able to screen patients for diseases, diagnose those diseases, determine the underlying cause of an illness, and monitor a patient's progression throughout the course of a disease by using a collection of images (Reed, 2010). Using logistic regression as the classification method, Wu et al. (2019) have just recently presented a method that classifies TN i.e., triple negative breast cancer using/incorporating ultrasound images. As a first step, we use ultrasound, which is both the cheapest and most common diagnostic imaging method. Many AI-based clinical uses are waiting for clearance from the appropriate authorities. For instance, the Food and Drug Administration (FDA) (Dubin et al., 2021) gave its stamp of approval to a DL system that analyzes cardiac MRI images in order to diagnose cardiovascular diseases. It is possible to detect lung nodules using computed tomography images (Ginneken et al., 2015), to diagnose pulmonary tuberculosis and other common lung diseases using chest radiography (Rajpurkar et al., 2017), or to identify breast masses by using mammography scans (Arevalo et al., 2015) using modern machine-learning methods, all of which can be accomplished with the aid of AI. DL was used by the researchers in a different study that was carried out not too long ago to determine which X-ray images showed a healthy chest (Wong et al., 2019). While a health expert is still required to use this system effectively, that expert would only need to manually classify half as many cases involving healthy chests. This would be the case even though the specialist would still be required to use their expertise.

5.2. Dermatology

In the diagnosis of many different types of skin lesions, visual inspection is critical. There are distinct visual characteristics that set benign moles apart when it comes to skin melanoma (Rigel et al., 2005). Researchers have spent a significant amount of time and effort over the course of many years attempting to create automated diagnostic systems that are able to differentiate between benign and malignant lesions based on photographs taken of the lesions (Ercal et al., 1994; Wolf et al., 2013). Convolutional neural networks that were trained on nearly 100,000 clinical images were able to diagnose skin cancer (Esteva et al., 2017) with an accuracy comparable to that of a dermatologist, according to a study that was published not too long ago. It is possible to deploy the completed diagnostic model on mobile devices, which has the potential to make skin lesion screening at the expert level more accessible in more places around the world. This is in spite of the fact that the training phase of the deep-learning model can sometimes require a significant amount of computational resources.

5.3. Hematology

The identification of cells for diagnostic purposes is one of the areas in which accelerated development is required most immediately. In recent years, research has been done into the use of contemporary ML methods for the diagnosis of hematological disorders. Previously, these conditions could only be diagnosed based on the results of laboratory tests. One method used all of the available blood tests, while the other method used only a select few of the blood tests that are typically measured during the initial patient intake. Both methods were used. When taking into consideration only the disease with the highest likelihood, the accuracy of the predictions dropped to 59 and 57 percent respectively from 88 when taking into consideration the list of the five diseases with the highest likelihood (Gunčar et al., 2018). In addition, research was carried out on the application of NNs in the field of peripheral blood analysis, which led to the development of two methods that are particularly noteworthy. This was another area of investigation. The use of laser cytometry in conjunction with an integrated isovolumetric sphering system was the initial procedure that was performed in the process of diagnosing haemoglobin disorders. Recent research suggests that gene profiling could be a useful field for classifying a variety of diseases (Turner, 1998). The findings of recent research led the researchers to come to this conclusion. The use of AI models in conjunction with the methodology of DNA microarrays has been helpful in the identification of new pathological categories as well as the investigation of stem cells through both unsupervised and supervised learning. In the process of class discovery, unsupervised learning has been utilized. One application of this technique is the division of multiple myeloma into five subtypes according to the expression of a translocation oncogene and the expression of cyclin Barillé-Nion et al. (2003), for instance. For instance, supervised learning has been

Table 3
A summary of some recent and important research articles on the use of AI in the medical field.

Paper	Year	Area	Methodology	Application	Key features
Esteva et al. (2017)	2017	Dermatology	Neural network	To achieve dermatologist-level accuracy when diagnosing skin cancer	Image recognition
Abramoff et al. (2018)	2018	Ophthalmology	Neural network	Moderate to severe diabetic retinopathy is found in diabetic macular oedema	Image Recognition
Thompson et al. (2018)	2018	Oncology	Neural Networks	Image segmentation as well as optimization of the radiotherapy dose.	Image recognition
Wu et al. (2019)	2019	Radiology	Logistic regression	Ultrasound examinations are used to establish the criteria for the classification of breast cancer known as triple negative (TN).	Image recognition
Wong et al. (2019)	2019	Radiology	Neural network	In order to determine which of the X-ray images showed a healthy chest	Image recognition
Sayres et al. (2019)	2019	Ophthalmology	Neuralnetwork + integrated gradients	Grading diabetic retinopathy more quickly and accurately	Image Recognition (Manual)
Dubin et al. (2021)	2021	Radiology	Neural network	Diagnosing cardiovascular diseases using cardiac MRI images	Image recognition
Sánchez-Reyes et al. (2021)	2021	Neuro-degenerative diseases	SVM + Neural network	The evaluation of brainwave activity using EEG equipment to identify dementia	EEG systems
Al-Waisy et al. (2021)	2021	Chest radiography imaging	DBN + convolutional DBN	For detecting the COVID-19 virus using CX-R images of the chest	Butterworth bandpass filter + Image recognition
Amethiya et al. (2021)	2022	Histopathology	Logistic regression	To diagnose cancer based on images taken with a microscope	Biosensors + Image recognition
Amethiya et al. (2021)	2022	Psychological care	ResNet + CNN + BiLSTM	To determine what kind of cyberbullying is being committed, and identify the individuals involved	Natural Language Processing
Biswas and Dash (2022)	2022	Pathology	LSTM + CNN	Analysis and prediction of real-time COVID-19 data using twitter data	Natural Language Processing
Nancy et al. (2022)	2022	IoMT	Bi-LSTM	Monitoring and accurately predicting the risk of heart disease	Cloud computing
Liu et al. (2022)	2022	Medical event prediction (MEP)	Multi-channel LSTM	To represent medical event that is strongly linked to the prediction task using EHRs	Natural Language Processing

utilized in the context of acute myeloblastic leukemia in order to make predictions regarding which patients will be placed in which class. The latter method is most likely to be used in order to assist in the differentiation of stem cells into specific lines through the use of basic genetic profiling (Ramalho-Santos et al., 2002).

5.4. Ophthalmology

Fundus photography i.e., a non-invasive methodology that involves the capture of images of the patient's retina, optic disc, and macula by retinal cameras that are attached to the patient's eyes. This procedure is also known as a fundoscopy. After that, these cameras are utilized so that a fundus examination can be carried out on the patient. In order to detect and monitor diseases such as diabetic retinopathy, glaucoma, neoplasms of the retina, and age-related macular degeneration, it is essential to determine the factors that lead to avoidable blindness. These conditions can be detected and monitored with the help of an imaging system for the retina (Panwar et al., 2016). According to a different group of researchers, the performance of convolutional neural networks was better than expected; the FDA has approved this system for use by healthcare providers to detect diabetic macular oedema and moderate-to-severe diabetic retinopathy (DR). Ophthalmologists already make use of various machines in order to quickly and accurately diagnose patients who are experiencing vision problems. One of the more common illnesses is DR, an eye complication of diabetes mellitus that is also the most commonly reported diabetic complication (Abramoff et al., 2018). Sayres et al. (2019) have demonstrated that a DL algorithm can assist specialists in grading DR more quickly and accurately than was previously thought possible. This was something that was previously thought to be impossible.

5.5. Oncology

Using AI and ML to fight cancer is an approach that has been met with cautious optimism. Gene therapy, small molecule inhibitors, and engineered biotherapies are just some of the modern medical interventions that have contributed to this success. AI is currently being studied for its potential use in radiation oncology, particularly in the fields of radiotherapy dose optimization and image segmentation, where these methods have shown that they meet or exceed conventional standards and where they have proven to be more efficient than manual planning in most cases (Thompson et al., 2018). Research has shown that using a specific ML technique is the best way to accurately predict the survival outcomes of patients undergoing gastrectomy based on personalized risk assessment (Uhlén et al., 2005). This is something that needs to be done in order to make accurate survival predictions for patients. Research into the use of convolutional neural networks (CNNs), the most popular form of supervised learning, has yielded interesting accuracy results in numerous experiments aimed at measuring and liver tumors in 2D and 3D images and tracking brain tumors/gliomas (Işın et al., 2016; Weizman et al., 2010).

In Table 3, some of the most recent and compelling research on the use of AI in the medical field are encapsulated.

6. Opportunities & challenges for AI applications in healthcare

AI is defined by computers in health care as the simulation of human cognitive functions (Jha and Topol, 2016). AI draws inspiration from biological neurons and includes the basics of sensing, identifying, and identifying objects so that machines can compete with or surpass human performance. But AI cannot replace medical physicians with the inherent lack of articulation and insights (Shah, 2019). In many instances, AI must be supplemented by medical judgement without universally applicable rules in the field of healthcare. For the diagnosis or monitoring of any illness condition a wide correlation of history and clinical findings is necessary. Studies have shown that AI can perform at or above human levels on key health care tasks like disease diagnosis. Algorithms have already surpassed radiologists in detecting malignant tumors, and researchers are ahead of the game when it comes to assembling cohorts for costly clinical trials. However, it is believed that AI will replace humans in large parts of the medical process in the distant future for a number of reasons (Lee, 2018; Yoon and Lee, 2018). However, the dystopian perspective poses a variety of fresh and dreadful problems. The increasing use of analytical Patient Data would increase the privacy and protection cyber security risks (Coventry and Branley, 2018), the responsibilities for health error and the potential effect on employment loss (Abomhara and Køien, 2015).

6.1. Opportunities

The wider use of AI-based technology in the healthcare sector offers a broad range of potential possibilities as depicted in Fig. 5. Increased knowledge and results in health care plays an important role for AI. AI has broad applications for disease prediction and diagnosis, data management in large volumes and the synthesis of insights, and efficiency and results maximization for health management in disease states (Duggal et al., 2018). AI has a comprehensive application. Fig. 9 shows an examination of the interconnections between the many prospects of AI in the healthcare sector. Following are some of the relevant opportunities:

6.1.1. Enhanced care for diseases

The development of science and technology has led to a surge in the use of AI and other forms of ML in contemporary medical practice (Kermany et al., 2018; McFarland, 2020). AI has emerged as a crucial force that propels the future and development of industry, making it an integral part of healthcare's progress and medical diagnosis's innovation. 4.0. In order to better understand symbolic illness models and relationships, doctors can now use algorithms and programmes made possible by medical AI technologies to analyze patient signs and symptoms (Koh et al., 2011; Wimmer et al., 2016; Ramesh et al., 2004). Researchers in the field of AI have paid a lot of attention to the diseases that are the most common causes of death. By 2030, 80 percent of human lives are expected to be caused by chronic diseases globally and cause serious global disease burdens (Nuño et al., 2012; Rosen et al., 2016). In particular, the death rate due to carcinoma has risen by 6 percentage points over the past decade (ReFaey et al., 2019). Then, researchers employ cutting-edge technology in the hopes of making an early diagnosis and effectively treating the condition (Houssami et al., 2019; Martinez-Millana et al., 2019). The AI is moving from classification to prediction of tumor behavior, into cancer treatment (Ueyama et al., 2021; Leatherdale and Lee, 2019).

6.1.2. Enhanced patient participation and engagement

For accurate disease diagnosis and patient protection, the patient's participation in the medical care process is crucial. Moreover, it is a useful and supportive opportunity for patients themselves to participate in sessions with medical personnel. The positive experience of patients in their involvement in the therapy phase has stated that Boulding et al. (2011) has had a positive effect on treatment outcomes and the protection of patients. Therefore, healthcare providers should make patient participation a strategic goal in order to enrich patient service and improve the quality of treatment Lee (2018, 2019).

6.1.3. Reduction in medical error rate

Wang et al. (2019) stated that, with the AI help, doctors in China have found 20 percent more polyps than doctors without AI. in colonoscopy examinations. AI architectures increase physicians' ability to eliminate issue small polyps that can cause potential complications, improve treatment, and decrease the possibilities of medical errors.

The implementation of AI technology in the field of healthcare promotes disease forecasting, diagnosis and treatment that benefits both patients and health workers (Reddy, 2018). AI can assist doctors in their work, allowing them to spend less time diagnosing patients and more time treating them. By using AI, large amounts of data can be quickly and comprehensively analyzed, allowing for quick and accurate decision-making (Ellahham et al., 2020). Medical services will not be fundamentally improved or significantly reduced in the near future due to the application of AI, even if it does improve patient disease treatment outcomes (Miyashita and Brady, 2019). As part of their ongoing efforts to decentralize care and optimize administration, medical organizations are increasingly turning to AI-enabled technologies to achieve previously impossible feats (Lee and Yoon, 2021).

The introduction of IBM Watson was a turning point in medical history, sparking widespread interest in the potential of using innovative digital technologies to boost public health and the standard of care for individual patients (Lee and Yoon, 2021). In the case of anticoagulant therapy for stroke patients, for instance, a randomized clinical trial found that an AI platform increased adherence by 50% (Labovitz et al., 2017). Additionally, the AI system's accuracy surpasses that of human radiologists. So doctors can use the amount of time saved by the AI system for improving the quality of the treatment service as the AI system increases their radiologists, to conduct more fun and fruitful conversations with the patients. Furthermore, medical personnel can avoid potential medical mistakes in advance by extracting more precise data by AI.

6.1.4. Care robotics

Individuals who are already socially isolated may benefit greatly from increasing the amount of "social" interaction they have in their lives thanks to the excellent opportunity provided by robots (Sharkey and Sharkey, 2012; Sorell and Draper, 2014). Care robots, for instance, could allow care recipients to keep up their social skills (Sorell and Draper, 2014) while also allowing human caregivers more time to focus on providing meaningful interactions with those they are caring for, as suggested by the National Institute on Aging (Borenstein and Pearson, 2010). This would allow human caregivers to spend more time engaging in meaningful conversations with the people they are caring for. The question of good care, including what constitutes good care and whether or not robots are capable of providing it, is closely related to the dilemma of deception (Torresen, 2018). Some have argued that deception by care robots is fine as long as it improves people's lives and makes them more humanlike (Coeckelbergh, 2010, 2016).

6.1.5. Improving the effectiveness of healthcare services

As AI continues to develop, it may be possible to improve the efficiency and effectiveness of processes across an expanded public health continuum, making it possible to personalize predict and prevent approaches that can be applied differentially across populations, allowing preventive services to be tailored to individual needs. This approach has the potential to result in a radical expansion of the scope of public health, and many of these activities will be led by organizations other than the traditional public health institutions. It is possible that the impact of AI on public health will be primarily indirect, as has been suggested previously. It is possible that widespread automation of manual jobs through AI will result in near-term unemployment in low-income communities, as well as negative health consequences (Panch et al., 2019). Automation, on the other hand, will almost certainly increase the efficiency of logistics and human resources, resulting in significant benefits through increased productivity and performance of health-care systems. However, it is difficult to predict the overall impact of these trends, particularly in the context of political and economic uncertainty.

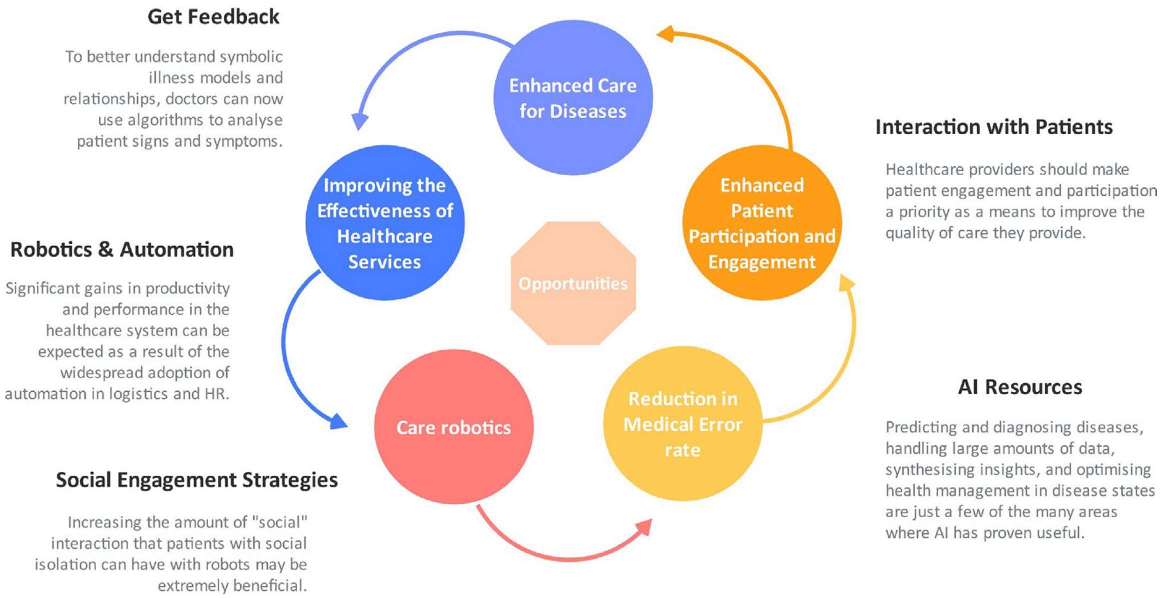

Fig. 9. Association analysis between various opportunities provided by AI technology in healthcare domain.

6.2. Challenges

Although AI provide new opportunities to enhance everyday life for people, they also present challenges which need to be effectively handled. The successful adoption and smooth implementation of AI is subject to several limitations as shown in Fig. 10. AI's health efficacy and safety are lacking evidence-based studies (Kao and Liebovitz, 2017). For example, clinicians are often resistant to AI in medical practises and reticent to it. Privacy concerns, patient anonymity, ethical considerations, and medical law all arise when using AI-enabled systems in clinical practice and research (Keskinbora, 2019; Vellido, 2019). Following are some of the prominent challenges to be tackled before complete integration of AI in healthcare system:

6.2.1. Accountability

While technologies related to AI are rapidly advancing and their implementations are common, the ethical aspects of AI have not been investigated relatively little. Accountability and safety practices that are currently in use around the world have not yet been adapted to account for the possibility that decisions made by an AI-based clinical tool could cause patients to suffer harm. However, moral accountability must be distinguished from legal liability. Despite their close relationship, one can exist without the other, and the other way around. As AI-based technology/systems will likely grow considerably in future in a variety of fields, they should be built to match their performance on people with social standards and values. As the reach and scope of digital health systems continue to expand, the practices currently in place for safety assurance and the clinical accountability models that have been developed are being put to the test (Habli et al., 2020). The difficulties associated with providing assurance of safety and being morally accountable help explain why industries that place a premium on worker protection, like aviation and nuclear power, are hesitant to consider the applications of AI. The relationship between the physician and the patient is guided by associative and lateral thinking. In addition, the influence on disease outcomes of a variety of factors (e.g. psychosocial, emotional) goes beyond AI. As a component of any sophisticated healthcare system, clinicians and health care organizations make an unspoken commitment to patients that they will exercise sound judgment, carry out their duties in an expert manner, and facilitate the patient's recovery (Pellegrino, 2004). Professional complacency can be avoided by holding people to a higher standard of moral accountability. This also helps patients have confidence in the clinicians who are providing their care. Patients often believe that their doctor has their best interests at heart. Goodwill, on the other hand, has no bearing on the decisions made by a computer programme.

6.2.2. Trust

A person's willingness to put their faith in another person in the face of uncertainty and danger is referred to as their "trusting beliefs", while their willingness to put their faith in another person's competence, integrity, and predictability is referred to as their "trusting intention". In a human–technology relationship, the trustee could be either the technology itself or the technology provider, as opposed to trust in an interpersonal relationship where the trustor and trustee are both humans. In addition, the relationship between technology trust and trust in the service provider will influence each other. Despite the fact that the characteristics of people and the environment are similar regardless of the trustee, the characteristics of AI, ML, and robotics that impact trust are distinct from those of other objects or humans. The performance, process, and purpose of AI must be defined and considered because it has many new features compared to other technologies.

Trust is the only mechanism shaping clinician's use and adoption of AI in the evolving relationship between humans and AI. Machinery can be more precise, reliable and complete, with lower risks of prejudicial behavior, but there is still a lack of confidence and empathy (Goldhahn et al., 2018). Because AI is evolving so quickly compared to other technologies, it is difficult to define the process, functionality, and role of AI (Siau and Wang, 2018). There is increasing concern that AI systems can learn and perform more than humans when they are repeatedly trained. Understanding the trust dynamics that exist between AI and humans is absolutely necessary in fields such as healthcare, where patients' lives are literally on the line. AI advances will allow this technology to play a larger role than just automating routine, well-defined tasks. In the long run, it will act as a guide when making decisions in the face of uncertainty, which is something that only trained medical professionals can do at the moment. Because medical professionals are becoming more reliant on AI, it is imperative that a trusting relationship be "calibrated" in order to accommodate this growing dependence (Hoffman et al., 2013). AI adoption in healthcare has been slowed by a lack of trust in the technology's algorithms. Trust in AI can be affected by a wide range of human characteristics, including level of education, life experiences, user preferences, and attitudes toward automation. Trust in AI can also be affected by characteristics of AI systems, such as the degree to which they are

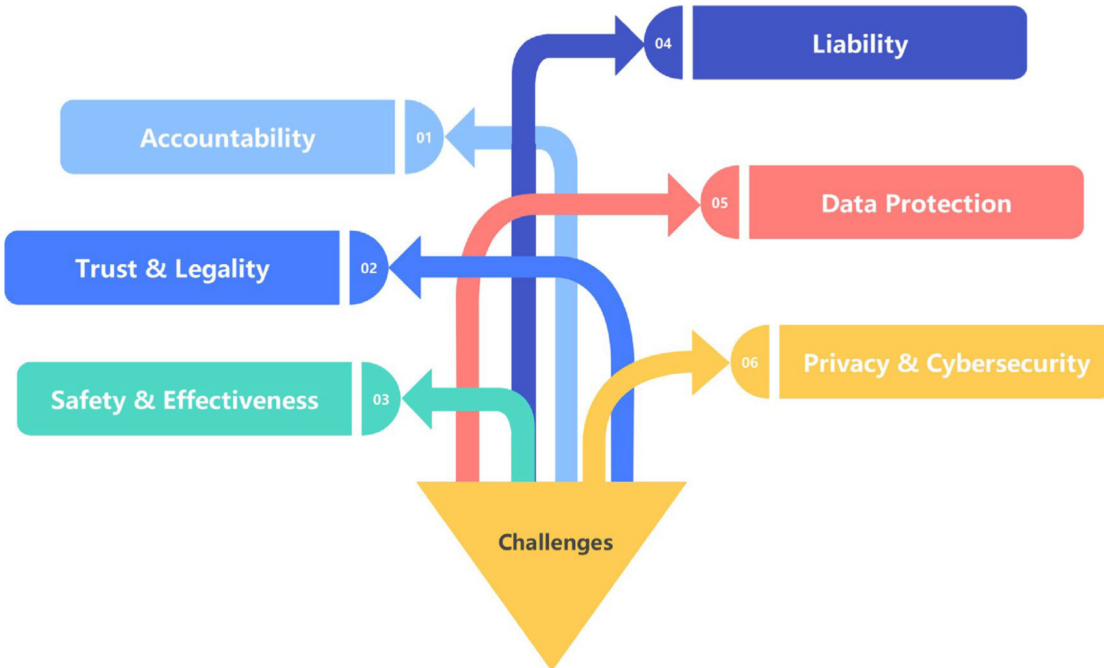

Fig. 10. Challenges to be effectively addressed in order for AI to be adopted and implemented successfully.

controllable, transparent, and complex, as well as the risks that are associated with using AI.

AI advocates argue that freeing health-care professionals to focus on patients and build trust with them by delegating routine tasks and decisions to rational machines will result in better patient outcomes (Kerasidou, 2020). Reimagining healthcare assumes that the importance of empathy, compassion, and trust will remain high even if AI takes over specific, specialized tasks while allowing health-care professionals more time to communicate and empathize with their patients. There is a chance that patients and the health-care system place a higher value on precision and efficiency than they do on empathy and judgement, which could lead doctors to lose sight of the need for human-specific skills (Susskind and Susskind, 2015).

6.2.3. Legality

A large number of people are of the opinion that AI will have a significant impact on the healthcare industry, particularly in clinical applications such as imaging and diagnostics, as well as in the optimization of hospital workflow and the utilization of health apps to evaluate an individual's symptoms. The AI health market is expected to grow more than tenfold between 2014 and 2021 (Gerke et al., 2020), according to an economic forecast. AI's rapid expansion brings with it a slew of new issues, so it is critical that it be integrated into the healthcare system in a way that is both ethical and legal.

6.2.4. Safety and effectiveness

AI developers should be open and honest about the data they use and the software's flaws, for example (e.g., data bias). To successfully implement AI in clinical practice, it is essential to build trust among all stakeholders, especially clinicians and patients. Adding more "black-box" systems (i.e., systems with multiple hidden layers) raises additional questions. It will be difficult to figure out how to achieve transparency in this context. Despite the fact that the model could be reduced to a straightforward mathematical relationship between symptoms and diagnoses, it is possible that this process still involves complex transformations that clinicians (and patients in particular) are unable to comprehend. However, there is a possibility that the "black box" is not required. If positive results are obtained from randomized trials or other forms of testing, this might be enough to demonstrate the safety and effectiveness of AI in some cases. According to the discussion paper published by the FDA, AI and ML-powered SaMD are medical devices that are able to adapt and optimize their performance in real time. This enables the devices to continue improving their performance while also ensuring their safety and effectiveness (Food, Drug Administration et al., 2019).

6.2.5. Liability

In addition, new technologies based on AI present challenges for the existing legal framework governing liability. The process of identifying and allocating responsibilities is absolutely necessary in order to design the most effective liability structure. It is expected of clinicians to treat their patients with the utmost skill and compassion, and to do so, they must adhere to a set of professional standards. It appears that clinicians could be held liable even if they relied in good faith on a "black-box" ML algorithm, as AI-based software is considered a tool under the control of the health professional who makes the final decision. So, instead of blindly following its recommendations out of fear of legal repercussions, doctors can use it as a confirmatory tool to aid in their current decision-making processes and still avoid medical malpractice claims (Price et al., 2019).

6.2.6. Data protection

Having adequate data protection laws in place is critical in the world of big data, especially when it comes to protecting the privacy of patients. Current legislation (Price and Cohen, 2019) leaves significant gaps in today's healthcare environment because it only covers certain health information created by "covered entities" or their "business associates". There is also a restriction on the scope of the definition of "covered entities", which does not go much further than naming insurance providers, insurance services, healthcare clearinghouses, and healthcare providers. Amazon, Google, IBM, Facebook, and Apple will not be considered "covered entities", so they will be exempt from the current laws that govern the use of AI in healthcare. These companies are all making significant investments in AI applications in the healthcare sector. In light of the foregoing, these measures are insufficient to protect patients' health privacy. When it comes to protecting health-related data that is not covered by such acts, federal law should take it more seriously.

6.2.7. Privacy and cybersecurity

Since AI technologies and systems rely on large data sets, privacy concerns have emerged as a major obstacle to data collection and sharing. Medical care administration is made easier with the help of this cutting-edge technology. Healthcare is a difficult area to predict because of the benefits and challenges associated with AI. As AI advances, many questions arise, including whether it can exercise doctors' rights and obligations or protect privacy concerns. The law as it currently stands has not caught up (Sunarti et al., 2021). Due to the fact that patient records contain personal information, it is very difficult for data related to diseases to be shared and regulated across various databases. This means that software developers must comply with the confidentiality regulations that may hinder AI development. Patients' individual circumstances are not considered in the decision-making process because it is predicated on an understanding of the accumulated data and does not take into account special circumstances that raise ethical and legal concerns. The rules and norms to be followed by AI technology, such as ethics, laws and individual values which govern the conduct of people in the society, must therefore be discussed. In terms of privacy, health service data are the most private and personal information anyone has about another. Patients' autonomy or self-government, personal identity, and well-being (Reddy et al., 2020) are all entwined with respecting their privacy as a fundamental ethical principle in health care. Respecting patient confidentiality and ensuring adequate processes for obtaining correct consent are therefore ethically significant.

7. Challenges in large scale implementation of AI

One of the greatest challenges facing AI in the medical field is not determining whether or not the technologies are useful; rather, it is ensuring that the technologies are adopted in daily clinical practise. AI systems need to be approved by regulators, integrated with EHR systems, standardized so that similar products all function in the same way, taught to clinicians, paid for by public or private payer organizations, and kept up to date in the field over time. Only then will they be widely adopted. Even though these problems will be solved in the end, it will take a lot longer than expected for the technologies themselves to become fully mature. Medical image analysis is currently the most successful use of AIin medicine. Using retinal fundus and skin cancer images, DL algorithms can detect diabetic retinopathy (Gulshan et al., 2016) and skin cancer (Esteva et al., 2017) automatically and accurately. Using AI to decipher subtle discriminative patterns in images suggests these techniques could be useful in other fields of medicine. Before it can be used more widely, significant obstacles must be overcome. It is now necessary to shift the focus of AI research away from the development of models in simulation and toward the design, implementation, and evaluation of applications in the real world, in order to improve healthcare delivery. In the not-too-distant future, ML models will most likely be seen as components of larger AI-enabled solutions that are necessary, but not sufficient on their own. When it comes to the application of AI in healthcare, the delivery science must consider how these systems are created and implemented, and then evaluated to see if they work. Following are the large scale implementation issues with AI technology:

7.1. Point of launch

Intelligent systems are constantly being developed in order to improve reasoning and make better use of collected data. Not only can this be used for retrospective interpretation, but it can also be used for diagnosing purposes. It can also be used to predict the future, giving patients a head start on treatment. However, doctors who could use these systems to their advantage are stuck in the middle of a clinical case and a technical analysis. There is not yet a well-defined launching point from which to approach the application of AI in medicine (Alsuliman et al., 2020). The first step in implementing AI-based solutions is to gather raw material or data. If we want an AI ecosystem with level playing fields, we must address information asymmetry and encourage effective collaboration among the various players. There are the pressing needs of healthcare today, among which are *aging demographic* which is widely acknowledged, *healthcare inequities, rise in cost (drugs, treatments), skill and staff shortages and various pricing models* etc., these are some which have widespread awareness that is actually burdening the healthcare systems to a very serious and concerning degree. To what extent and how can AI actually assist in tackling such issues is the biggest challenge and part of translation puts a sort of discerning eye on this process from technology development to application. Is everything that is the exciting and fancy right thing to put in a healthcare setting is a question to be answered yet.

7.2. Procedure of AI

One of the much-discussed potential applications of AI is in evidence generation (Shah et al., 2019), there is even discussion of AI replacing randomized clinical trials. Randomized clinical trials (RCTs) are very time consuming, very costly and can go on for years which is very much criticized. AI may be able to provide faster and more accurate diagnoses for a larger segment of the population due to its ability to collect and examine a large amount of data. AI may allow those without access to high-quality health care to benefit from that expertise. The cost of healthcare may go down as diagnostics become more advanced and accurate. Even though AI has been thoroughly tested, doctors will still need to use their training and experience to confirm that it is capable of making accurate diagnoses and performing the procedure as planned (Vijai and Wisetsri, 2021), but what happens and what is lost when a research enterprise (AI) with a caring enterprise (Healthcare) collapses? As mentioned in Section 3, there are no specific regulations, this system no longer falls under the supervision that health care has been so careful to and therefore what the implications of this could be is a challenge.

7.3. Trade-offs

It is necessary to interpret the inner workings of artificial neurons, such as in ANNs, so that humans can understand them. In other words, methods with different levels of inherent explainability have a significant benefit in comparison. The only difference is that these methods are more traditional, like linear or logistic regression. Traditional methods, perform worse than modern state-of-the-art methods, such as neural networks (ANNs) in many use cases (Esteva et al., 2019). Clinical decision support system developers face a difficult choice when balancing the need for high performance with the need for easy understanding. However, as Rudin (2019) point out, some believe that this trade-off does not exist in reality and is merely a byproduct of suboptimal modeling approaches. Interpretability is an important goal for AI systems, but getting there is a technical challenge. From traditional expert systems, which are fully explicable but rigid and difficult to use, to deep neural networks (DNN), which are highly effective but virtually impossible to see inside, the explainability of intelligent systems has run the gamut. While it is true that AI/ML interpretability is a difficult problem to solve, that does not mean all AI/ML techniques are equally opaque (Adadi and Berrada, 2020). The truth is, some algorithms are easier to interpret than others, and accuracy is often sacrificed for interpretability.

7.4. Utilization of robotics

Robots have the potential to help the healthcare industry, thanks to recent advances in robotics and AI. Using robotic systems is becoming increasingly common in a variety of healthcare settings, including the hospital, walking assistance and rehabilitation (Kyrarini et al., 2021). When used at home or at work, assistive robots have the potential to provide care and assistance with activities of daily living (ADLs). In healthcare, task shifting is frequently viewed as a way to reduce costs and improve efficiency by transferring responsibility for 'simple' tasks from highly skilled but scarce health workers to those with less expertise but higher pay (Schalkwyk et al., 2020). The concept of task shifting says how to make the decision of which task should be allocated to robotics and which should not. One of the policy questions is that are those task-shifting decisions that are being made are short term, are designed to address a specific problem and a specific context that has arisen or is that a long term solution. Is one going to dispense with training, seeking to train a sufficient healthcare staff/personnel in different areas? What is the trajectory for task shifting to the use of robotics?

8. Future research directions

In the healthcare industry, AI has already had an impact. However, there are numerous details and future prospects that need to be addressed before it can be implemented in clinical practice. Before incorporating AI and ML into clinical practice, following are a few things to be looked into:

8.1. Internet of Things

The Internet of Things will be essential to the provision of a great deal of future healthcare services, procedures, and products. A significant portion of the underlying infrastructure can be compromised by both cyber and physical assaults. Worms, viruses, and trojan horses are all types of malicious software that can put patients' health and privacy at risk. They are getting better at threatening, harming, or interrupting essential (medical) services. Researchers must look into ways to prevent this in the healthcare industry. The emerging Internet of Things (IoT) devices will likely revolve around the 5G and 6G mobile networks that are currently in development. 5G has the potential to solve the problems plaguing the telecommunications industry at the same time that its use is expanding into new areas like cloud computing and smart devices. Integration of 5G and health monitoring is on the rise, but the security implications of this trend need more analysis.

8.2. Data sharing & efficiency

Large-scale AI implementation in healthcare requires more data sharing. Some stakeholders are hesitant to share their data with other parties for a variety of reasons, including worries about the safety of sensitive personal information or sensitive commercial data. As a result, healthcare competition and antitrust law will need to evolve to better understand big data and AI. When applied to a significant issue, AI-based models can be extremely helpful in the healthcare industry. Some problems can be solved without resorting to AI techniques at all, as alternative approaches already exist. If the dataset is very large, if some or all of the parameters are difficult to predict, if it takes too long to infer the right results, or if conventional approaches are ineffective, then these methods are required. As a result, researchers need to employ cutting-edge, genuine AI methods.

8.3. Multidisciplinary research workforce

The healthcare industry stands to benefit greatly from the developments in ML/DL methods. Nonetheless, obstacles like ethical concerns must be effectively addressed if society is to reap the full benefits of these innovations. Some research in this area has proposed including a wide range of interested parties—clinicians, policymakers, data scientists, ML researchers, hospital staff, and so on—in the process of creating new ML/DL methods. By bringing together clinicians and AI researchers, for example, healthcare service providers will be able to pool their knowledge for the greater good of patient care.

8.4. Dataset labeling

One obvious way to boost ML/DL model performance is to amass more labeled training data. This necessitates the use of precious radiologists' and other medical professionals' time to manually annotate medical data such as medical images, signals, and reports. Creating authentic validation sets to test ML/DL models' efficacy and reveal their shortcomings is also crucial. As a result, it is a messy, expensive, and time-consuming process to manually annotate samples into their appropriate categories. To solve this problem automatically, we need to create methods like active learning, which can annotate unlabeled data samples.

8.5. Public awareness

It is not yet known what the optimal level of trust should be between clinicians and AI systems in order to make clinical decisions that are the most accurate and reliable. Another unknown is how to link optimal AI system trust to design attributes. People-specific issues like large variability associated with aleatory processes and changing AI capabilities should be considered in the problem analysis (AI). Ethical considerations of applying AI to health care may benefit from hearing different perspectives from around the world and across cultures. Researchers may be able to gain access to literature that would otherwise be inaccessible by collaborating with global partner organizations like regional offices of the WHO. A study in this subject area could be conducted in the future.

8.6. Preparation for potential pandemics

Initial coronavirus pandemic research looked into ML, IoT, and blockchain. Real-world applications were less common and the work was primarily done at the development and research levels. Researchers would benefit greatly from the creation of large, publicly available databases containing domestic or international clinical data. AI-based tools should be developed to enable the design of multiple synopses to aid in the making of better decisions regarding the distribution of expensive rare devices and types of equipment like ventilators, elderly patient monitoring, school, and university education, to name a few.

9. Conclusion

An increasing number of medical tasks are benefiting from AI. The rate at which AI applications can co-evolve with a healthcare system will determine the extent to which this performance will have an impact on the landscape of medical practice, including the detection and treatment of disease. It is the responsibility of the education system in the medical field to provide the physicians of the future with the resources and strategies that will enable them to adapt to their new roles as information integrators, interpreters, and patient advocates. Rather than focusing on how to put our faith in AI technologies, this paper argues that we should instead focus on whether or not we can actually rely on them. In this paper, the current state of AI technologies and various applications, the difficulties of integrating AI at a large scale into healthcare, as well as the ethical, legal, trust-building, and future implications of AI in health care is discussed in details that will benefit the research community to build AI systems around healthcare while considering all the key aspects of it. Trust in other humans, objects, and AI, in addition to the one-of-a-kind technological characteristics of AI, is influenced by human and environmental characteristics. The AI's performance and purpose will be critical in establishing long-term trust. We are not yet in a position to regulate the responsible design, development, and use of AI for health, as the field is expanding faster than we are. Whether or not this course of action is ethical in every situation, we still have a responsibility to carefully consider the ethical implications of implementing AI and to provide appropriate responses.

Since it is unclear who will ultimately be in charge of overseeing, certifying, or profiting from the use of AI, finding the right balance between regulatory safeguards and market forces is a top priority for everyone involved.

CRediT authorship contribution statement

Pranjal Kumar: Conceptualization, Methodology, Writing – original draft. **Siddhartha Chauhan:** Supervision. **Lalit Kumar Awasthi:** Supervision.

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.

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