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AI in Medical Diagnosis and Prognosis: Current State and Challenges

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Abstract. The COVID-19 pandemic led to physical distancing, thus increasing the use of digital health programs such as artificial intelligence (AI) platforms. Throughout this paper, we will be using AI to describe a system that performs actions that typically require human thinking skills. AI has the potential to transform into a healthcare organization using machine learning, deep learning, and natural language processing. This review will include AI-based diagnostic and prediction tools, and their potential in changing the detection and management of disease in various fields of medicine. AI algorithms are needed to analyze complex medical data, such as X-ray images and heart signals, and often exceed the accuracy of early human detection. Additionally, there are now AI-based wearable devices and supported systems available for real-time detection and personal management, which could also advance a person's capability toward earlier detection and prevention of disease. Of course, data privacy challenges, constant data access issues, and algorithmic inequity are still present. Collaboration in addressing data collection, algorithm design, and constant monitoring or evaluation will be needed across disciplines. As institutions of health care, it is critical to ensure that the data collected, and the algorithm designed are transparent for AI to be applied in the real-world healthcare field.

Keywords: AI, diagnosis, health care, monitoring, algorithm

1. Introduction

AI encompasses a wide range of branches and strategies for building intelligent machines, including machine learning, deep learning, and natural language processing. Machine learning (ML) is a form of technology that teaches data to make future predictions, without being programmed explicitly in advance to do so. While the supervised model is essential to develop predictive models with past data, the unsupervised model aids in the identification of new patterns in diseases or discoveries [1]. The supervised and unsupervised models learn by trial and error to make decisions, but this needs an enormous and consistently updated database.

In machine learning, deep learning (DL) is one of the subsets that neural networks use to study complicated data. A neural network is a computer system that tries to work like the human brain to obtain information. It is comprised of many layers of artificial neurons, which teach how to recognize patterns and improve their processing of data by repetition. In comparison to traditional methods that require people with expertise to specify the main features in the image, for neural

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networks, identifying those features is based on the analysis of sample images [1]. They are especially useful in the analysis of X-rays or nuclear magnetic resonance.

By providing a model that can understand natural language, deep learning has also transformed natural language processing (NLP), enabling computers to learn and understand human language. This technique can be used to extract information from clinical notes or research literature, thus reducing the time spent by medical professionals on repetitive tasks that require less thinking skills [1]. NLP can also identify patterns in patient feedback, automate document tasks, and support diagnostic decision-making, playing an auxiliary role in general medical diagnosis [2]. About 80% of electronic health record data is in unstructured text format, which cannot be processed effectively by traditional analysis methods, but NLP can; therefore, NLP addresses key gaps in health care from its language analysis and understanding skills [3].

All AI models - machine learning, deep learning, and NLP - are trained in the learning mode of large data sets and diagnosing medical conditions [4]. Through continuous trial and error, the model has gradually developed its predictive ability. Then, the model is tested using a method called cross-validation, which divides the data into parts to evaluate the performance of the model on new, unseen data [5]. This method ensures that all independent analysis functions of the model can run effectively and make it more comprehensive. Another technique is called retention verification, that is, intentionally separating a part of the data for post-training testing [4]; this is another method for assessment before the model enters the real world. Using cross-validation and retention validation helps assess the accuracy and specificity of AI, and they can simulate real-world medical situations.

This article introduces the role of AI in disease diagnosis, reviews its application cases, and summarizes its limitations. While some studies concluded that the accuracy of AI may exceed humans, there are challenges of limited data sets in the application of AI algorithms in the real world, privacy issues, and inequity and bias. Regulation and coordinated effort are warranted for the strict evaluation of algorithms and the potential utility of artificial intelligence in health care.

2. AI in diagnosis and prognosis

In medicine, diagnosis refers to determining diseases or symptoms upon clinical evaluation. Prognosis, by contrast, is a prediction about the future course and outcome of a disease. Artificial intelligence algorithms for diagnosis and prognosis can identify patterns in large databases and can make predictions beyond what is possible for humans. For example, they can screen through radiographic images, genetic information, and the medical history of patients to detect cancer at an early stage [6]. In cardiology, AI models forecast the risk of heart attacks and strokes from examining patterns of electrocardiograms and other vital signs [7]. They primarily use deep learning methods, including convolutional neural networks (CNN) and long-term and short-term memory (LSTM) networks. CNN and LSTM analyzed the shape and patterns of electrocardiogram waves, identified abnormal performance, and monitored how the cardiac signal changed over time [3]. Specifically, the deep learning system using the hybrid CNN-LSTM model can predict sleep apnea with about 95% accuracy from the electrocardiogram data, which helps to prevent dangerous sleep and respiratory attacks. Therefore, the system can detect early and subtle signs in cardiac data through a combination of electrocardiograms and other health signals (such as blood pressure, heart rate variability, and oxygen levels). It is reasonable that their efficiency and accuracy in prognosis may be higher than that of humans, because the algorithm continuously and persistently tracks the pattern without tiring. In addition, the key advantage of algorithms is their ability to grow and improve when exposed to new data; at the same time, this requires continuous provision of new data for further experiments and training.

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For chronic diseases such as diabetes and heart disease, AI-driven wearable devices monitor and analyze data in real time to detect early warning signals [8]. These wearable devices include smart watches or health patches, such as Apple Watch, Oura Ring, and WHOOP. They can alert patients when their blood glucose or heart rate reaches dangerous levels before an emergency occurs. The reason for the creation of wearables was to develop an awareness of personalized patterns over time. They are also able to provide opportunities for personalized lifestyle or medication modifications, such as diet, exercise, and scheduling. This shift of AI algorithms is transitioning health management from a passive role to a more active one that is focused on prevention and early detection.

AI can also impact clinical decision-making directly, rather than just identifying patterns. AI is able to read complex formats of data with high confidence and speed (for example: ECG, MRI scans, or other complex medical records) [9]. In intensive care environments—such as the emergency department (ED) or intensive care unit (ICU) physician decision support systems can be built using AI to support systematic situational awareness in the clinical space. These AI are being used for patient classification and monitoring vital signs and even predicting dangerous measures [8]. AI algorithms are already supporting accurate and timely recommendations while identifying areas for increasing efficiency and quality patient care.

More importantly, the progress of AI in the field of health care represents a shift in the paradigm of understanding and managing health and disease. Unlike other forms of technology or human resources, AI can not only detect patterns, but also learn from continuous clinical, genomic, and behavioral data. As AI is exposed to more cases, it can predict the progression of the disease, identify new subtypes, and predict complications of diabetes and heart disease that are difficult to detect by human analysis alone [9].

3. Case studies and applications

AI diagnostic models have been trained to detect diseases such as cancer, diabetes, and heart disease.

In cancer detection, a case study used DL to analyze mammography for breast cancer detection. Research shows that AI is identifying patterns in mammograms - X-ray examination of breast tissue - indicating cancer growth [1]. This study shows that AI-driven systems are more accurate than traditional methods. Specifically, the AI system shows a decrease in false positives and false negatives, which is an important factor in cancer diagnosis. This progress is significant because it provides evidence that AI technology can improve prognosis and treatment outcomes. In addition, another study in South Korea found that AI-assisted diagnosis (90%) is more sensitive to large-scale diagnosis of breast cancer than radiologists (78%) [10]. In addition, AI is 17% more effective than radiologists at detecting early breast cancer [10]. Considering that well-trained algorithms continue to run at a consistent level, and it is physically impossible for humans to monitor data continuously, this result is reasonable.

Another potential use of AI is diabetes management. AI uses machine learning algorithms to analyze patient data and predict the progression and complications of diabetes. In a study focusing on predicting poor blood glucose control in patients with type 2 diabetes, the highest predictive performance was about 90%, which proved the effectiveness of these models [11]. Another study used a variety of machine learning models to predict eight types of diabetes complications, including nerve damage, hypertension, and vision problems. It analyzed the data of 884 patients with 79 health and population factors [11]. The best models - Random Forest, AdaBoost, and XGBoost - have

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achieved an accurate rate of 97-98%, indicating that machine learning is expected to change the prognosis and diagnosis of diabetes.

Furthermore, the use of AI to predict heart disease is an important step in cardiovascular health care. Artificial intelligence can assess severity and predict when heart disease might happen. A new health care system employs novel DL methods combined with sensors and medical record information to improve the prediction of heart disease. The system selects the most relevant information to improve prediction speed and accuracy. Conditional probability is used to weigh the features, leading to a calculated accuracy of 98.5%, which is a substantial improvement from the previous model [11].

AI tools show greater accuracy and decrease overall costs and time than diagnostic evaluations that lead to a diagnosis. As continued research thrives on ways to use artificial intelligence in medical diagnosis, clinical laboratory tests are a core source of data to train models. Nevertheless, researchers from the National Institutes of Health (NIH) demonstrated that the AI has independently misunderstood descriptions of images and, therefore, also diagnostic interpretation, but ultimately arrives at the correct diagnosis: the process is not an alignment to the result [12]. This finding suggests that there is still an evaluation of multidisciplinary AI technology as it will be introduced formally. As with any ML technology, there is always a measured assessment of risk and understanding the limits of capacity.

These case studies highlight the critical role of AI in promoting interdisciplinary disease detection. As AI continues to develop, it is crucial to address challenges such as data privacy, algorithm transparency, and ensuring the fair use of these technologies.

4. Discussion

4.1. Challenges and limitations

Apart from possible positive results in the experiment, the adoption of AI in health care faces obstacles. AI engines that begin with ML and DL rely on a sizable amount of data so that accurate causal links are established between diseases and outcomes. Nonetheless, health care institutions must ensure the collection and protection of patient data without infringing privacy regulations and ethical considerations [13]. Hence, it is highly challenging to access confidential data about patients. Although this is of ethical importance, it limits the prospective data sharing needed in developing such AI systems. In addition to this, AI should not just have data but also continue getting data for improvement, whereas sharing, in most cases, early in development is inhibited by the fact that most institutions do not enable further data sharing after the first round. Apart from this issue, intrusions into students' data frequently relate to violations of confidentiality regulations, identity theft, and endangering the autonomy and trust of patients in the system [14].

Strict data security protocols must be observed at all stages of the implementation of data-driven AI, from data acquisition to the deployment of algorithms, to address the following issues. Health care institutions should also strive toward data anonymization to curb leakage of sensitive patient data and mitigate privacy risks. Most importantly, health care institutions and practitioners should be transparent to patients regarding their use of artificial intelligence data. They should provide patients with information about the use of data, risks, and how privacy is assured. To do this, an ethical review and a supervision mechanism should be established to evaluate the ethical implications of artificial intelligence projects [15].

At the same time, despite the potential for AI to have access to large databases, the quality of medical records is not necessarily better [13]. They are sometimes messy, inaccurate, or inconsistent,

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and medical records often differ greatly among medical institutions.

This data is usually not standardized, which makes it difficult for artificial intelligence to identify patterns in different regions.

In addition, patient data are often outdated for about 4 months, making it less reliable for future predictions.

Inequality in health care has become a major problem due to the lack of access, infrastructure, and resources in low- and middle-income countries. However, due to the common lack of technology to collect and share data with other parts of the world, low- and middle-income groups often have the same problem with AI modeling - this may mean that AI is trained on data that excludes underrepresented groups, which exacerbates the existing bias [16]. In addition, algorithm deviation may lead to differences in diagnosis, treatment, and results in different patient groups [12]. That is to say, diagnostic algorithms trained mainly based on the data of specific population groups may lead to misdiagnosis when applied to individuals with underrepresentation. Similarly, prediction models that rely on socio-economic factors may inadvertently continue the difference in access to care or resource allocation [11].

In addition to the technical dilemma, if AI makes a mistake, the moral issue of who should be responsible is equally important. There are currently no clear guidelines for the use of ethical AI in health care, so many doctors are not sure how much they can rely on AI advice. Because of these problems, much AI research is carried out in a controlled laboratory environment rather than in a real-world health care environment [17]. This creates a gap in our understanding of the performance of the system in practice.

4.2. Future direction

To reduce the deviation of AI algorithms, it is essential to take coordinated actions in data collection, algorithm design, and model evaluation. First, health care institutions should ensure that the data set used for training algorithms contains data from different groups of people; this means that data contributions from different socio-economic, cultural, and ethnic groups should be fair. This can be accomplished by gathering information regarding previously excluded groups of people, alongside comprehensively engaging with stakeholders as part of advancing inclusive data practices in health care.

Following that, AI module developers should include fair procedures to reduce inconsistent behavior by identifying key distinctions within the algorithm [18]. In this instance, fairness would include improving indicators and changing the algorithmic output to reduce the distance between group differences, as determined in the similarity framework. There are also machine learning systematic procedures developed to identify and explain the inconsistencies created by an algorithm; they can provide researchers with knowledge of what to proceed with next.

Finally, artificial intelligence algorithms must undergo ongoing assessments to minimize inconsistent behavior concerning health care outcomes. Hospitals and other health care institutions must create an ongoing assessment and surveillance plan that uses a diverse team involving clinicians, data scientists, ethicists, and community members as stakeholders to evaluate whether the algorithm is now performing [11]. This widespread, multidisciplinary group of stakeholders is better equipped to help ensure fair evaluation standards.

As bias improves and transparency advances, patients might eventually be more comfortable with AI in health care and build trust in the algorithms.

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5. Conclusion

The healthcare industry is being revolutionized by AI technologies, including ML, DL, and NLP, that can reduce errors in determining and diagnosing medical conditions, identify and track patients in real-time, and generate and deliver treatments based on patient preferences. Some reports have indicated that the use of AI in assisting diagnosis for diseases such as cancer, diabetes, and heart disease has substantial potential, but a significant amount of work is required. AI relies on experimentation with large datasets, which exposes risks to data privacy and algorithmic bias because datasets are not historically distributed across demographic groups. In this paper, we elaborated on the promise of AI for health care and provided some of the challenges that will need to be addressed before large-scale clinical implementation. Ongoing, multidisciplinary collaboration and experimentation among clinicians, data scientists, and community members must support the evaluation and monitoring of AI applications for health care reliability and safety.

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