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Review Article

AI in Healthcare

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Abstract

AI has been a powerful emerging tool in the recent years creating revolutionary changes in the field of medicine with the usage of electronic health records, role in drug discovery and interactions. The increasing rise in software application in the field of medicine as well as digitalization of data fuel together the progress of development and usage of AI in medicine. AI applications have proven to be efficient in handling the pressing concerns faced by various health organizations.

This review paper discusses basics of AI-acquired algorithms in the predictions, diagnosis, assessment, clinical management of pathogenesis including a spectrum of various cancers.

Keywords: Artificial Intelligence; AI-led Drug Discovery; Patient Care; Machine Learning; Healthcare

Introduction

With the invention of turning tests in 1950, artificial intelligence in healthcare made its first significant advancement. Eventually, in 1975, the first central AIM workshop at the NIH and the development of the first research tool on computers in medicine underlined the importance of artificial intelligence in healthcare. The introduction of AI in INDIA was through a project completed in 1986 as a part of India's Knowledge-Based Computing Systems effort by H.N. Mahabala and a group at IIT Madras. A knowledge-based programme called Eklavya was created to help community health workers deal with disease symptoms in young children.

The development of AI systems like IBM's Deep Blue and Watson came much later, in the late 1990s. Watson worked at the Memorial Sloan Kettering Cancer Centre in 2013. With the introduction of Deep QA in 2007 and the advancement of deep learning in the 2000s, the use of artificial intelligence in healthcare has increased. Furthermore, the first endoscopy using CAD occurred in 2010, while the first Pharm bot was developed in 2015.

In 2017, the FDA approved the first cloud-based DL application, which also marked the entry of AI into the medical industry. Around 2018 and 2020, a large number of AI experiments in gastroenterology were carried out. The development of AI systems like IBM's Deep Blue and Watson came much later, in the late 1990s. Watson worked at the Memorial Sloan Kettering Cancer Centre in 2013. In 2020, Google DeepMind utilised artificial intelligence to crack the 'protein folding problem,' a long-standing conundrum, and forecast a protein's three-dimensional structure from its amino acid sequence.

Diagnosis and treatment design

Electronic health records (EHR)

A systematic electronic compilation of patient health data, such as a patient's medical history, prescription orders, vital signs, laboratory findings, radiology reports, and doctor and nurse notes, is called an electronic health record (EHR). It automates the ordering procedure for both exams and medications in healthcare facilities, resulting in orders that are uniform, legible, and comprehensive [1].

Benefits

The EHR has the benefit of improving performance. EHRs have the potential to improve clinical outcomes and patient security with the help of a variety of processes. EHR can reduce communication issues by creating a connection between the ordering doctors, the pharmacists who fill the prescriptions, and the nurses who give the patients their medications (even basic ones resulting from handwriting readability). EHRs may also improve the information management process which is crucial for patients with many ailments or those who require intensive monitoring and testing. The diagnosis and treatment of these illnesses both require a sizable volume of medical data. These data may be gathered and organised with the use of EHRs, speeding up and enhancing treatment choices. EHRs are a crucial tool for organising the tasks of healthcare practitioners. Errors can be decreased, unnecessary testing can be avoided, and better care coordination can improve medical judgement.

Features

These systems could be especially useful in situations where patient care calls for a variety of experts or care facility changes. EHR systems have an impact on the effectiveness and cost of healthcare organisations as well as the health system as a whole. For instance, EHRs may provide better documentation of comorbidities to support higher provider payment rates from payers. Better record keeping may enhance charge capture since many insurers pay higher reimbursement rates for individuals with more serious consequences or comorbidities. In this situation, EHRs may increase immediate medical costs but increase long-term effectiveness. In order to receive claims, these systems may also be abused by altering data input or processing data incorrectly.

Large hospitals' EHR systems might cost between $15 million and $30 million (Hufford,1999) [2]. The EHR may lengthen the time required for clinical documentation. Some doctors and nurses may be averse to change and wish to return to the previous paper-based methods (Hufford, 1999) [2]. System issues include sluggish systems, whether brought on by the software or slow networking rates, and system crashes that prevent all clinicians from doing their duties. Systems for redundancy and backup must be created. Security of EHR systems is a significant issue that has to be resolved. Due to the wealth of personal information included in medical records, electronic medical records might become a major target for hackers (Featherly, 2011) [3]. Theft of medical identities is increasing.

Drug interactions and discovery

Drug interactions can be dangerous for individuals consuming multiple medications at once, and the danger rises with the number of prescriptions being filled. Although managing all therapeutic effectiveness and the adverse effects they cause can be difficult, artificial intelligence (AI) has enabled algorithms to extract information about drug interactions and probable adverse effects from medical literature. Decades and billions of dollars are spent during the discovery and development of new medications. The process of developing new drugs is significantly accelerated by machine learning techniques. While AI may not be able to support every phase of the drug discovery process, when it can, it can aid with a few of them.

Applications

Lung cancer

Parmar., *et al*. demonstrated that the selection of the classification model for lung cancer assessment was the factor that most affected performance variation (34.21% of the overall variance). They tested 12 different machine learning classifiers on radiomic feature data, including classifiers from the following 12 Bayesian, boosting, decision trees, discriminant analysis, generalised linear models, multiple adaptive regression splines, nearest neighbours, neural networks, partial least squares and principal component regression, random forests, and support vector machines are just a few examples of classifier families. The best strategy for managing radiomic feature instability, according to the researchers, is the random forest method, which also has the highest prognostic performance [4].

The histology and metastasis of lung cancer were predicted using three distinct categorization systems in separate research by Ferreira Junior., *et al*. They tested the effectiveness of the k-nearest neighbours' algorithm, naive Bayes technique and an artificial network based on radial basis functions using up to 100 radiomic features. Even though they aren't now very popular, all of these techniques have a lot of potential for radiomics lung cancer evaluation [5].

Dermatology

Using a very small dataset of clinical data, the topic as to whether machine learning algorithms technology can be used to construct an efficient skin cancer classification system photo was investigated by Fujisawa., *et al*. in an article that was just published (2019). Using a dataset of 4867 clinical pictures collected from 1842 patients with skin cancers at the University of Tsukuba Hospital between 2003 and 2016, they trained a deep convolutional neural network (DCNN). 14 diagnoses were represented by the photos, including both cancerous and benign disorders. Its effectiveness was evaluated in comparison to that of nine dermatology residents and 13 board-certified dermatologists. The trained DCNN's total classification accuracy was 76.5%. The DCNN attained 89.5% specificity and 96.3% sensitivity. Despite the board-certified dermatologists' accuracy in classifying some skin conditions as malignant or benign s was significantly higher than that of dermatology trainees (853% 37% and 74% 68%, P 0 01), the DCNN obtained even more accuracy, reaching 924% 21% (P 0001) [6].

Han., *et al*. have previously investigated the application of Han., *et al*. evaluated the application of a deep learning system to categorize clinical photos of 12 skin disorders, including melanoma, a year earlier in China. When assessed using the confirmation image set, the mean sensitivity and accuracy for all circumstances were 85.1% and 81.3%, respectively, with an area under the receiver operating characteristic (AUROC) of 0.89. The assessed algorithm was shown to function at a level comparable to 16 dermatologists [7].

Cervical cancer

The majority of cervical cancer research focused on predicting and detecting lymph node metastases (LMN), with a few studies focusing on lymph vessel involvement, risk prediction, predicting malignancies vs. non-cancers, and treatment results. Some researches have looked into the robustness of radiomic models as well as the study's reproducibility [8-13].

2008 research on lymph node metastatic evaluation using ultrasound imaging was the first to investigate radiomics for cervical cancer therapy. However, this came after a 10-year hiatus before radiomics was investigated again for cervical cancer therapy in 2018. All additional research has been concentrated in the last two years [8-13].

Radiomic procedures were shown to be a beneficial supplement for diagnosis in all investigations. While manual segmentation was the most often utilized method, six research used techniques for segmentation that are semi-automatic or automated. Most research discovered that more complicated models with more parameters performed better in terms of AUC and accuracy [8-13].

Radiomics was found to perform as well as or better than subjective diagnosis by radiologists.

Ovarian cancer

Al-karawi., *et al*. explored despite just a small percentage of typical radiomic feature sets were examined, researchers have used common computer visual spec sheets to classify ovarian tumours as benign or malignant. Gabor filters were discovered to be the most effective particular characteristic collection [14].

Lupean., *et al*. used a texture-based MRI radiomics model to distinguish malignant vs. benign ovarian cyst fluid characteristics. They employed Tex RAD (Tex Rad Ltd., Cambridge, UK) software for feature selection and filtration histogram-based textural analysis. The average pixel intensity variance was found to be a significant predictor of malignancy in ovarian cysts. However, because this was a tiny exploratory study with only 28 individuals and no link with clinical characteristics or cytological fluid analyses, more research is needed [15].

Sepsis

Different sepsis-related acute kidney injury (AKI) clinical features and prognoses exist. In order to enhance care for related patients, AI could be employed to classify features into a variety of sub-phenotypes based on the level of risk [16].

In one study, machine learning algorithms was used to forecast the 28-day mortality and dialysis needs of patients with sepsis-related AKI. To categorize people with sepsis-related AKI and establish three sub phenotypes, the investigators used the K-means algorithm and more than 2,500 feature combinations. The least 28-day mortality rate after AKI (23%) and lowest need for dialysis (4%) were also associated with Subtype 1. The mortality rate for subtype 3 is 1.9 times that of subtype 2 after normalizing [17].

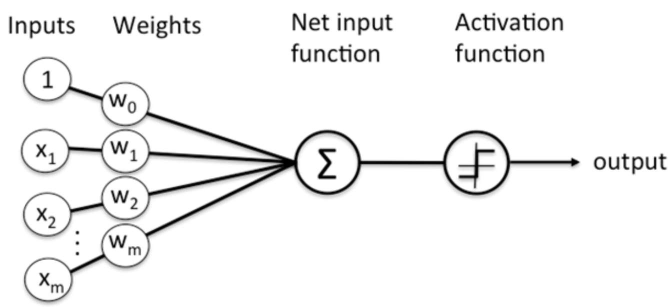

Figure 1: Node diagram [20].

Similar to Ibrahim., *et al*. who employed AI to identify clinically significant sepsis subgroups with various organ failure patterns, organ dysfunction types found in patients with sepsis in the ICU were stratified. SVMs, gradient boost trees, and random forests are all utilised for classification [18].

Research investigated how different AIs classified and predicted death for sepsis patients in the emergency department. Four supervised learning models were compared: C4.5 decision tree, ANN, SVM, and random forest. As a consequence, the best discriminating impact is achieved by SVW and ANN employing physiological variables. It offers promising promise for use in determining the sepsis classification and prognosis. The mortality of patients who are suspected of having an infection in the ED may also be predicted using the deep learning-based method Convolutional Neural Network with SoftMax. The findings demonstrate that our deep learning approach greatly outperforms conventional machine learning algorithms and sepsis scoring systems (SIRS and SOFA) that are often used in clinical practise. Using deep learning critically ill patients were identified [19].

Neural network

By mimicking the functions performed by the human brain, neural networks are a group of systems that find underlying links in a collection of information. The term "neural networks" can also refer to a subset of networks called artificial neural networks, which are the fundamental building blocks of deep learning algorithms. Nodes make up the layers of the neural network. Because it is a region where processing happens and because it is loosely modelled after a neuron in the human brain, it is called a node. A node will provide inputs relevance in reference to the way it is endeavouring to learn by combining input from the data with weights that can either amplify or dampen the input. When input is supplied through the network, a node layer resembles a row of these neuron-like switches that can be either turned on or off. Each layer's output serves as the following layer's input [4].

Convolutional neural network

A synthetic deep neural network is the CNN (Convolutional Neural Network). CNNs are used to classify, segment, and recognise images. The primary functions of CNNs are to classify visual content, recognise items that are provided to it as input, and group the detected objects into clusters. CNNs use subsampling after relying on connections and weights among the units. The core elements of a CNN architecture are a single convolutional layer, a pooling layer, and occasionally fully linked layers for supervised prediction [20].

Input layer

The image's data should be in the CNN's input layer. Images are nothing more than three-dimensional matrices that must first be converted into a single column before being submitted. Each layer's output will be fed into the one below it [20].

Convolutional (convo+ ReLU)

The action begins in the convolutional layer. The ReLu layer is an extension of CNN that identifies an image's features, such as colour, shape, and object elements. This layer increases the nonlinearity of the image. At this layer, improved feature extraction is accomplished.

Accumulating layer after passing through the convolutional layer, the pooling layer lowers the spatial volume of the input image [20].

Fully connected layer

Weights, neurons, and biases are all present in this layer. Using completely connected layers, neurons in one layer are connected to neurons in another layer. At this layer, categories are created for images using training data [20].

Soft max layer and output layer

These are CNN's last layers. The FC layer is just below the Soft max layer, which is utilised for binary classification. Additionally, the final output label of the input image fed into the input layer will be provided by the output layer [20].

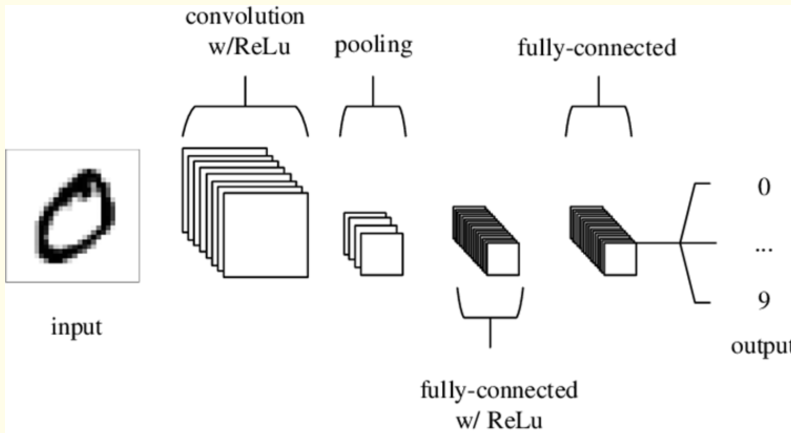

Figure 2: Architecture of a simple CNN [20].

Recurrent neural network (RNN)

A type of neural network called a recurrent neural network repeats itself over time. By permitting self-loop connections, RNN generally share various parameters at different steps. From a feed forward neural network, RNNs are derived. While a feedforward network maps an input vector into an output vector, an RNN maps a series into another series. Since RNNs were first announced in 1980, other RNN variants have been proposed. Basic recurrent neural networks are shown in Figure 3.

Some of the variants of RNNs are:

- One type of RNN with a sparsely connected random hidden layer is the echo state network. The output neuron's weights are the sole component of the network that can be taught. Another type of RNN is the independently operated RNN. The classic fully connected RNN's issues with gradient disappearing and exploding problems are addressed by this RNN [20].
- Another kind of RNN is the recursive neural network, which is built by applying a similar set of weights repeatedly across a differentiable graphs like structures, traversing them one after the other in topological order [20].
- Long short-term memory is a form of RNN and a deep learning system that circumvents the vanishing gradient problem. The LSTM is enhanced by recurrent gates known as forget gates. LSTM prevents backpropagated mistakes from dissipating or erupting. The LSTM can handle signals that combine high and low frequency components even when there are significant time gaps between events [20].
- Recurrent neural networks use gated recurrent units (GRUs) as their gating mechanism. They perform similarly to long short-term memories (LSTMs) and have fewer parameters than LSTM [20].
- Continuous temporal recurrent neural networks are yet another variety of RNNs that employ a set of ordinary differential equations to simulate the effects of an incoming spike train on a neuron.

The rate of change of activation for a neuron with activation yi is given by:

$$Tiyi = -yi + \sum_j^n \omega_{ji}\sigma(y_j - \theta_j) + I_j(t)$$

Where Ti is the postsynaptic node time constant Yi are postsynaptic node activation

yi are presynaptic node activation.

w_{ji} It is the weight connection from pre node to postsynaptic node

$I_j(t)$ is the input node

θ_j Bias of presynaptic node

σ(x): this means sigmoid of x (the value of x could be anything here x is taken as reference).

Limitations and drawbacks of ai in health care

Due to privacy concerns, patients rarely engage in providing data in the healthcare industry. Additionally, determining how each person's condition varies from another is significantly more difficult than it is in other AI domains. In contrast to other fields like software, applying AI to the healthcare industry is a little more

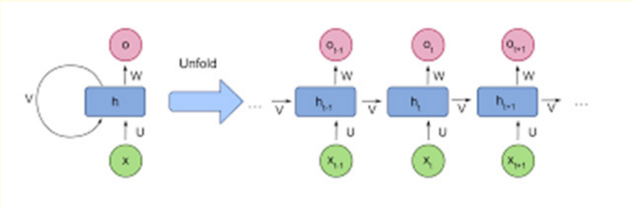

Figure 3: Recurrent neural network [20].

challenging because to the unclear, noisy, and partial nature of the data. There needs to be improvement in the way that clinicians were trained to adopt to technological advances and their use in healthcare. Future research that is more in-depth is needed. The analysis will frequently become outdated when new research studies are published because this is a developing field of study.

Future research that is more in-depth is needed. It needs to be overseen by people. Depending on each individual's circumstances, a final decision about whether to accept or reject AI's suggestions and presentations still needs to be made. As healthcare AI relies on algorithms that may find it more convenient to the majority, it could lead to social prejudices (i.e., nearest possible clinic or hospital for a patient). Because AI can perform most of the laborious and menial work currently performed by humans in healthcare, there is a possibility that certain hospital staff may eventually no longer be required because AI may be able to perform their duties.

The most glaring and direct drawback of AI in healthcare is the potential for data privacy security breaches. It is vulnerable to information gathering being misused and taken by the wrong hands because it develops and expands dependent on information obtained. Due to privacy concerns, patients are frequently reluctant to disclose data in the healthcare industry.

Additionally, compared to other fields of AI, comprehending the diversity of each person's sickness is significantly more difficult. In comparison to other industries, like software, applying AI to medicine is comparatively challenging due to the fuzziness, noise, and incompleteness of medical data. There needs to be improvement in how clinicians are trained to adapt to technological advancements and medicinal applications. Future research will be required. The analysis will constantly be out of current when some fresh research investigations are published because this is a new research area. Future research will be required. Human oversight is necessary to decide on whether to accept or reject the cases [20].

Challenges faced by ai in health care

Ethical difficulties

Although there is much promise for improvement through the application of AI in therapeutic settings, there are also ethical issues that we now address.

Informed consent of use

The patient-physician interaction will change as a result of health AI applications in areas like imaging, diagnosis, and surgery. It is necessary to investigate when (if ever) the informed consent principles should be used in the context of clinical AI, much of a duty do clinicians have to inform patients about the intricacies of AI, such as the type(s) of ML employed by the system, the type of collected data, and the potential for biases or other flaws in the data being used.

AI health platforms and chatbots are also being used more and more, with applications ranging from food advice to health evaluations to improving treatment adherence and data processing from wearable sensors. Bioethicists may have concerns regarding the user agreements in these apps and how they relate to informed consent. A user agreement, as opposed to the standard informed consent procedure, is a contract that a person accepts without having a face-to-face discussion. Most people habitually disregard user terms because they don't take the time to study them. Furthermore, many find it increasingly challenging to adhere to the terms of service they have accepted due to the software's constant modifications [21].

Safety and transparency

One of the main obstacles for AI in healthcare is safety. One well-known instance of this is IBM Watson for Oncology, which use AI algorithms to analyse data from patient medical records and assist physicians in considering cancer treatment options for their patients. It has recently drawn criticism though, as it is said to have made "unsafe and inaccurate" suggestions for cancer therapies. Watson for Oncology appears to have a difficulty since, rather than learning from actual patient records, it was only taught using a small sample of "synthetic" cancer cases, which were created by Memorial Sloan Kettering (MSK) Cancer Centre physicians. According to MSK, mistakes only happened during system testing, and no wrong treatment recommendation was ever delivered to a real patient.

Future of artificial intelligence

Doctors and patients in the healthcare sector benefit from AI's capacity to gather and analyse enormous volumes of medical data, which leads to faster and more accurate diagnoses for a large section of the population. So, if there is a group of people who cannot access specialised medical treatment, they could be able to benefit from artificial intelligence. Another important forecast is the continued decrease in healthcare expenses as a result of increasingly accurate diagnoses. The use of AI in healthcare will increase, and as a result, clinicians' patient care methods will change, making it more likely that diseases can be predicted and treated. As a result, healthcare expenses will be reduced, and it will be easier to develop medical care in isolated areas with little access.

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