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Research Article

Deep Learning Approaches in Healthcare: A Comprehensive Review of Techniques and Applications

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ABSTRACT

Introduction: Deep learning is a method used in artificial intelligence that processes data in a way that is similar to how the human brain does it while also developing decision-making patterns. Deep learning has revolutionized the use of artificial intelligence, and has been deployed in different fields of healthcare applications such as computer vision, natural language processing, and signal processing. Deeply used in various tasks of healthcare.

Objectives: In this paper, we present a comprehensive review and analysis of deep learning techniques used in healthcare applications. This paper explores the diverse range of healthcare domains where deep learning has shown promising results, including medical imaging, electronic health records (EHR), genomics, drug discovery, and disease prediction.

Methods: The paper has discussed the main challenges and opportunities for applying deep learning models in healthcare, such as temporal modeling, interpretability and generalizability. In addition, we highlight recent advances in deep learning architectures, including convolutional neural networks, recurrent neural networks, and generative adversarial networks, and their specific applications in healthcare. Finally, we provide insights on future directions and potential research avenues for advancing deep learning techniques in medicine.

Results: Techniques such as CNNs, RNNs, LSTMs, GANs, autoencoders, and hybrid models have been successfully applied to tasks like medical imaging, EHR analysis, genomics, disease prediction, and drug discovery. The reviewed literature shows that deep learning models often outperform traditional machine learning methods in both accuracy and adaptability. Notable results include high prediction accuracy in diseases such as Alzheimer's, Parkinson's, diabetes, skin cancer, and cardiovascular risks. Despite these advancements, challenges remain in interpretability, generalization, and data availability.

Conclusions: Deep learning has evolved as a transformative technology in healthcare, enabling great advancements in a variety of areas, including medical imaging, honor analysis, genomics, drug discovery, and disease prediction. The ability to model complex patterns across large and diverse data records opened up new opportunities to improve diagnosis, treatment planning, and patient outcomes. Despite its incredible advancements, challenges such as model interpretation, data protection, and model generalization remain active. Latest innovations in deep learning architectures such as CNNS, RNNS, and Goose continue to surpass the limits of what is possible in medical applications. Considering the future, interdisciplinary collaboration and responsible AI practices will be critical to implementing deep learning breakthroughs in reliable, true health solutions.

Keywords: Deep Learning, Healthcare, Convolutional neural networks (CNN), Recurrent neural networks (RNN), Generative adversarial networks (GAN), Interpretability, LSTM, Medical imaging, Electronic health records (EHR)

INTRODUCTION

In over the last few years, Machine Learning (ML), and particularly Deep Learning (DL), has made great strides and has been successfully deployed in many real-world applications such as healthcare, customer care, finance,

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autonomous driving etc. This technology has been revolutionized with the availability of big data and advancements in computing power. It involves the use of algorithms to learn from data, with the goal of improving the accuracy and efficiency of predictions or decisions. Deep learning basically uses neural networks to learn from large datasets.

The amount of research and development in the area of deep learning has significantly increased recently. The growing availability of data and computational power has enabled researchers to develop more advanced algorithms and models, leading to significant breakthroughs in various industries. [1-5]

One of the recent applications of deep learning has been in healthcare. ML/DL techniques have been applied to healthcare in medical imaging, clinical decision making, electronic healthcare records processing etc. [6] Health data analytics is becoming a very important role in personalized medicine. For example, personalized cancer care seeks to provide the right treatment to the right patient by taking into account multiple types of patient data, including genomic variants, environment, imaging genomics, current medications and lifestyle. Over the past decade, modern technologies such as genomics, imaging, and life monitoring technologies have produced vast amounts of complex health data that enable researchers to provide better care to patients. Despite the large amount of information, our understanding of diseases and how to treat patients is still insufficient.

During the past decade, a wide range of Artificial Intelligence (AI) and ML techniques have been used to analyze the massive data in healthcare, effectively [7]. Deep learning approaches in different areas and their rapid continuous methodological improvement are becoming the new and exciting tools to analyze healthcare data. A wide range of initiatives have been conducted using DL models on biomedical and healthcare data. For example, Google's DeepMind and IBM's Watson have developed a computer-based support system to analyze healthcare data [8]. Deep Learning has been successfully used to encode a deformable model's parameters that can facilitate the left ventricle's (LV) segmentation from short-axis cardiac MRI [9]. Another deep learning model based on Restricted Boltzmann Machines (RBM) was applied in medical imaging to identify biomarkers from MRI scans [10].

DEEP LEARNING TECHNIQUES

When compared to traditional ML techniques, deep learning has a more potent ability to generalize the dynamic relation of enormous amounts of raw data in various healthcare applications. The depths of the various learning models, such as convolutional models, and their various designs, in general, determine the capacity to handle input. Common learning models can easily be over-touched when dealing with a flood of data, but deep learning models can most likely perform better in huge data. Both deep learning and classical machine learning can be divided into two categories: supervised learning and non-supervised learning, which uses labeled and unlabeled data models, respectively.

1. Supervised Learning

A labeled training set incorporates the supervised learning system model. In supervised learning, the backpropagation method is the main technique. [11]

1.1 Convolutional Neural Networks (CNN's)

Convolutional Neural Networks (CNN) are a type of deep learning model that is particularly effective in analyzing visual data such as images and videos [13]. CNNs have revolutionized the field of computer vision and have achieved superior performance in various tasks, including image classification, object detection, and image segmentation. The key concept behind CNNs is the use of convolutional layers, which apply filters to input images in order to capture different features at various spatial resolutions. CNNs typically consist of multiple convolutional layers, followed by pooling layers that reduce the dimensionality of the feature maps, and then fully connected layers that perform the final classification or regression tasks. The combination of these layers allows CNNs to learn hierarchical representations of images, where lower layers capture low-level features like edges and corners, while higher layers capture more complex structures and patterns.

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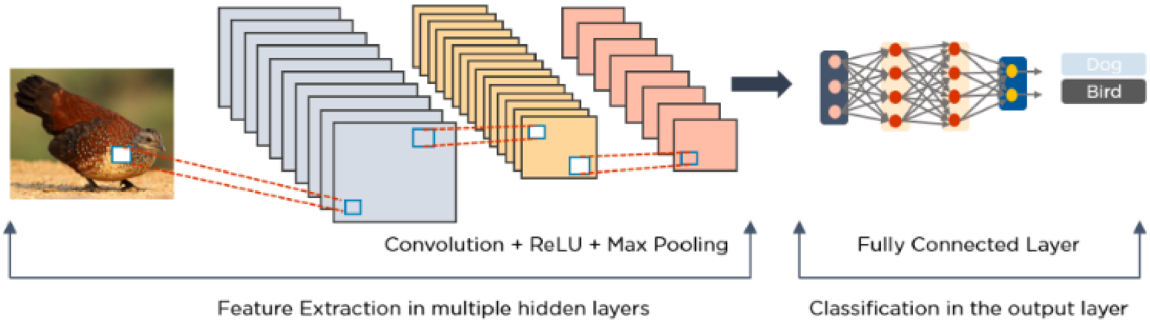

Figure 1 : Image processed via CNN [12]

One of the advantages of CNNs is their ability to automatically learn features instead of relying on handcrafted feature engineering. This makes them highly adaptable to different tasks and domains, as they can learn to recognize relevant patterns directly from raw input data.

1.2 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNN) are a type of artificial neural network specifically designed to process sequential data such as time series data or natural language. Unlike traditional pre-neural networks, RNNs have connections that allow information to flow in a circuit, allowing them to store memory and capture dependencies between elements of the input sequence. RNNs are composed of memory cells, which store and update information based on the current input and previous state. Each memory cell takes as input the current input and the state from the previous time step, and produces an output and an updated state. This process is repeated for each element in the sequential data, allowing the network to capture patterns and relationships across the entire sequence.

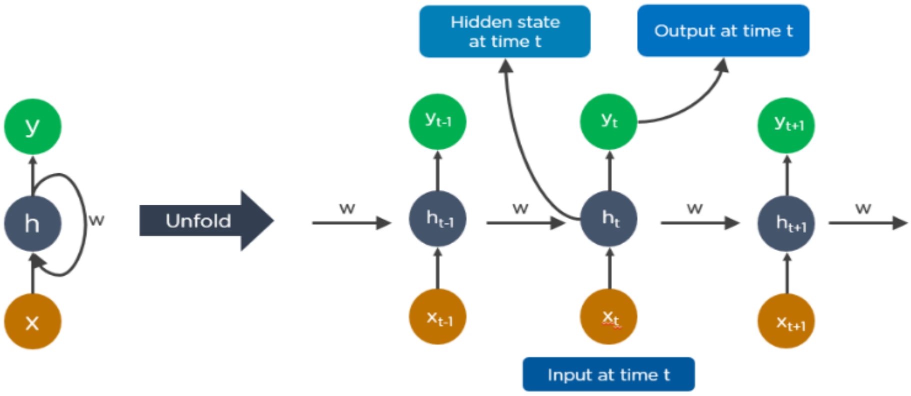

Figure 2 : Unfolded RNN [12]

One of the key advantages of RNNs is their ability to handle variable-length inputs and outputs. This makes them well-suited for tasks such as speech recognition, machine translation, sentiment analysis, and many others. However, due to the prevalence of gradient problems and long-term dependencies, RNNs are limited to only looking back a few steps. New methods have been proposed such as LSTM (long short-term memory)

1.3 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of artificial recurrent neural network (RNN) architecture that is widely used in the field of deep learning. LSTM networks are designed to handle the vanishing gradient problem, which is a common issue with traditional RNNs. The LSTM is discriminative method which can work on time-stamp, sequential and long time-dependent data. The key idea behind LSTM is the inclusion of memory cells within the network. These memory cells can preserve information for long periods of time, allowing the network to learn and remember important patterns and dependencies in sequential data. The LSTM network achieves this by controlling the flow of information through various gates.

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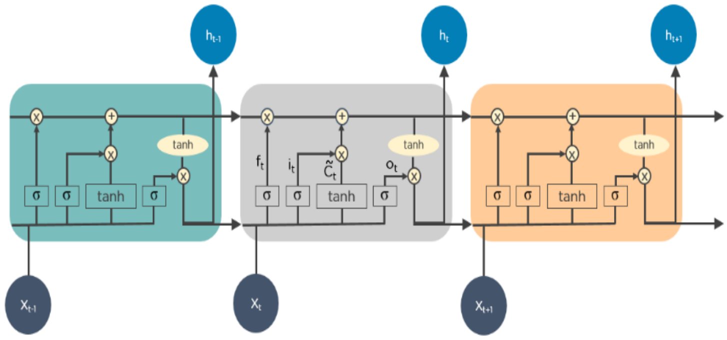

Figure 3 : LSTMs operation [12]

The LSTM architecture has been highly successful in a wide range of applications, such as natural language processing, speech recognition, and time series prediction. It is particularly effective when dealing with long sequences or complex dependencies.

2. Unsupervised Learning

Unsupervised learning should be used as a complement to traditional learning methods to handle large unlabeled data. Training is performed using stacked constrained Boltzmann machines (RBMs) or stacked autoencoders, which can be initialized, reverse cloned, and modified globally [13].

2.1 Autoencoder (AE)

Autoencoder is an unsupervised learning algorithm used to efficiently encode a dataset for dimensionality reduction. It is a type of neural network where the input is the same as the output. Basically, it compresses the input into a lower dimensional code and then reconstructs the output using that representation. A code is a compact way of summarizing or compressing data, also known as a hidden state representation [14]. An autoencoder consists of three components: (1) encoder: this compresses the input; (2) code: this is produced by the encoder; (3) decoder: this reconstructs the input using only the code. To build an autoencoder, the following things are needed: (1) an encoding method, (2) a decoding method, and (3) a loss function to compare the output with the target.

The main function of an autoencoder is to reduce dimensionality (or compress) with the following properties: data specific, lossiness, and no supervision [15].

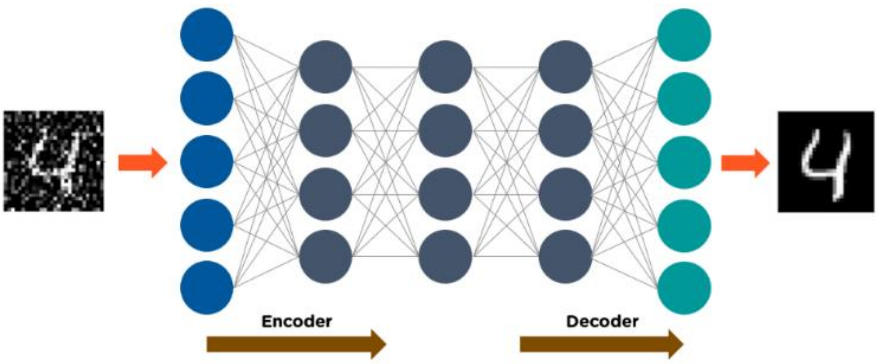

Figure 4 : Autoencoders operation [12]

Autoencoders can be used for various purposes, including dimensionality reduction, feature extraction, and anomaly detection. By training the autoencoder on a specific dataset, it can learn to capture the underlying structure of the data and generate meaningful representations.

2.2 Restricted Boltzmann Machines (RBMs)

RBM is a generative method that can work with different types of data and is suitable for data classification, dimensionality reduction, feature extraction, etc. RBMs are probabilistic graphical models that can be thought of as

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deep stochastic networks [16]. The Boltzmann version of RBM is limited by the fact that neurons can form bipartite diagrams. Symmetric relationships may exist between pairs of nodes in both visible and hidden groups. However, there is no connectivity between nodes in the same group. Additionally, all visible and covert (hidden) neurons are connected to a bias device [13].

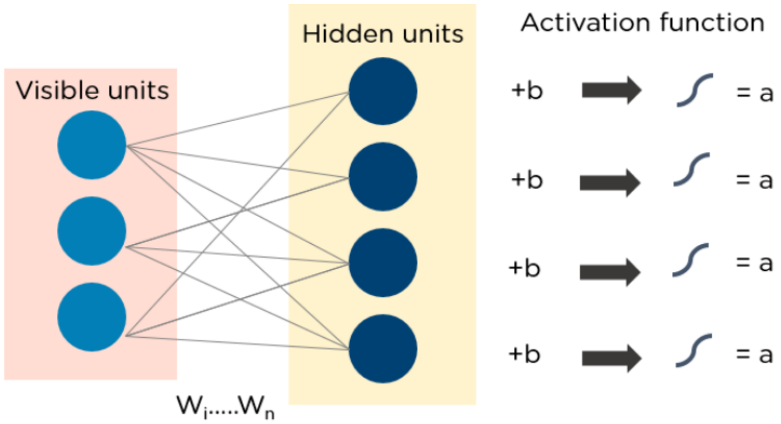

Figure 5 : RBMs function [12]

RBMs are versatile models that can be used for a wide range of tasks, including collaborative filtering, image recognition, text analysis, and recommendation systems.

2.3 Deep Belief Networks (DBNs)

Deep Belief Networks (DBNs) are a type of artificial neural network that consists of multiple layers of interconnected nodes, or neurons. DBNs are commonly used in machine learning and have been successful in various applications, such as image and speech recognition, recommendation systems, and natural language processing. DBNs are "deep" because they typically have more than two hidden layers, allowing them to learn and represent complex patterns and relationships in data. Each layer of neurons processes the output from the previous layer, gradually extracting higher-level features as the information flows through the network.

DBN training is done layer by layer, so each layer can be viewed as an RBM trained on top of a previously trained layer. Therefore, DBN can be fast and efficient in DL methods. The first one is for learning with unlabeled data for data processing and the second one aims to reach an optimal solution by converging the DBN with labeled data [17].

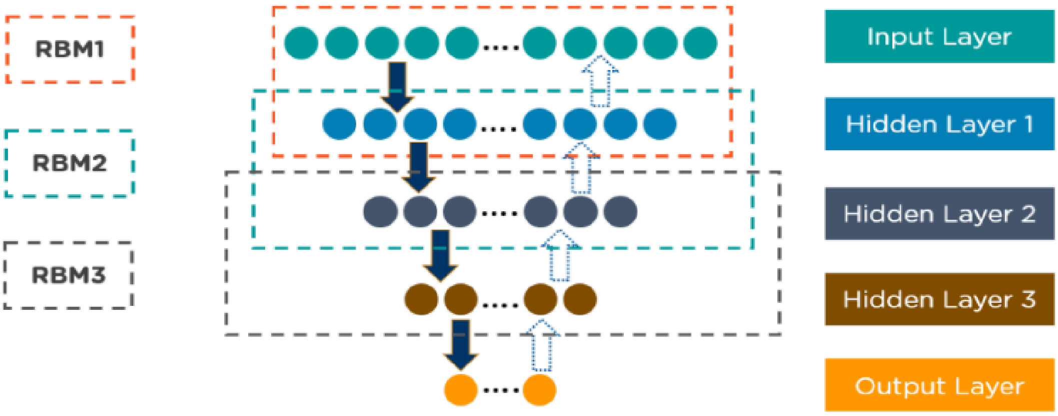

Figure 6 : DBN architecture [12]

2.4 Generative Adversarial Networks (GANs)

GANs in their most common form are a type of unsupervised learning because the data we start with is unlabelled. This is commonly a collection of images, video or binary files. The goal of the GAN is to learn about the structure of the data. It is a type of neural network architecture that consists of two components: a generator and a discriminator.

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The generator's role in a GAN is to create new data instances, such as images or text, that resemble the training data it was trained on. On the other hand, the discriminator's job is to distinguish between the generated data and real data. The two components are pitted against each other in a training process known as adversarial training.

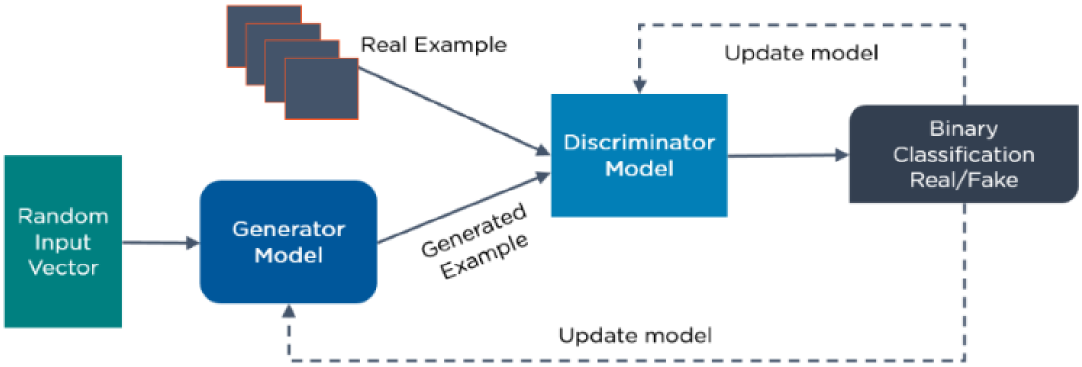

Figure 7 : GANs operation [12]

GANs offer a unique approach to understanding, generating, and manipulating complex data distributions, making them a valuable tool across various domains.

LITERATURE REVIEW

Machine learning and deep learning are two areas of artificial intelligence that have received a lot of attention in recent years. Machine learning is a data analysis technique that automates the creation of analytical models. This allows computers to automatically learn and improve from experience without being explicitly programmed. Deep learning, on the other hand, is a subset of machine learning that uses neural networks to solve complex problems. Deep learning models are inspired by the structure and function of the human brain and can learn from unstructured and unlabeled data.

The authors prepared a model for early detection of Alzheimer's disease (AD) stage by use of deep learning to integrally analyze imaging (magnetic resonance imaging (MRI)), genetic (single nucleotide polymorphisms (SNPs)), and clinical test data to classify patients into AD, MCI, and controls (CN). They use stacked denoising auto-encoders to extract features from clinical and genetic data, and use 3D-convolutional neural networks for imaging data. The networks are separately trained for each data modality, then combine them using different classification layers, including decision trees, random forests, support vectors machines (SVM), and k-nearest neighbors (kNN). Their overall analysis shows that - For single-modality data (clinical, and imaging), the performances of DL models are always better than those of shallow models; and When using DL models, predictions by multi-modality data is better than those by single-modality data. The three best fusion set ups are: EHR + SNP, EHR + Imaging + SNP, and EHR + Imaging [18].

One approach that has shown promise is the use of convolutional neural networks (CNNs) for diagnosing Parkinson's disease. Parkinson's disease is a progressive neurological disorder that affects movement and can cause tremors, stiffness, and difficulty with coordination. Traditional diagnostic methods often involve clinical evaluation by experts, which can be subjective and time-consuming. Deep learning techniques, such as CNNs, offer an alternative approach by analyzing large amounts of data to automatically learn patterns and make accurate predictions. In the context of Parkinson's disease, CNNs are trained using various input data, such as MRI or PET scans, voice recordings, and handwriting samples, which are representative of the disease. The network learns to extract relevant features from the input data and maps them to a diagnosis. By training on a diverse dataset of Parkinson's disease cases, the CNN can learn to identify subtle patterns or markers that may be indicative of the disease. Once trained, the CNN can be used to predict the presence or severity of Parkinson's disease in new, unseen cases. It takes advantage of the network's learned knowledge to classify input data accurately. This has the potential to aid healthcare professionals in early detection and accurate diagnosis, enabling timely interventions and personalized treatment plans for

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individuals with Parkinson's disease. An accuracy of 88.9% is achieved with that system by authors [19]. By using CNN other authors present Deepr, new end-to-end deep learning system that learns to extract features from medical records and predicts future risk automatically. This advanced model uses deep learning techniques to analyze and interpret large amounts of medical data, extracting meaningful patterns and insights. With its convolutional architecture, Deepr can effectively capture complex relationships and dependencies within medical records, making it ideal for tasks such as diagnosis prediction, disease classification, and treatment recommendation.CNN is used to validate Deepr on hospital data to predict unplanned readmission after discharge [23]. By experimenting different DL algorithms authors developed a novel diabetes classifying model based on Convolutional Long Short-term Memory (Conv-LSTM). Authors combines the power of convolutional neural networks (CNNs) and LSTM models to effectively analyze medical data related to diabetes. The CNN component helps in extracting relevant features from input data, such as medical images or time series records, by applying filters and detecting patterns. These patterns can be indicative of diabetes-related abnormalities or symptoms. The LSTM component, known for its ability to process sequential data and capture long-term dependencies, is integrated within the CNN architecture. This allows the model to learn and remember relationships between different time steps or image frames in the input data. In the context of diabetes detection, this enables the model to capture temporal patterns or changes that may be crucial in identifying the presence of the disease. They used Pima Indians Diabetes Database (PIDD) as a dataset and identified that Conv-LSTM model achieved the highest accuracy of 97.26 % [20].

The Authors demonstrate classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs. They train a CNN using a dataset of 129,450 clinical images. And test its performance against 21 board-certified dermatologists on biopsy-proven clinical images with two critical binary classification use cases. The first case represents the identification of the most common cancers, the second represents the identification of the deadliest skin cancer [21]. Authors introduces a deep dynamic memory model for predictive medicine. The aim of this model is to accurately predict patient outcomes and provide personalized care plans using longitudinal electronic health records (EHRs). The paper addresses the challenge of effectively leveraging the temporal nature of EHR data and incorporates both static and dynamic features into the model. In the DeepCare model authors combines a deep learning framework with a memory network that can adapt and update its knowledge based on new patient information. The model takes into account various patient-specific factors such as demographics, lab results, medications, and diagnoses. It also considers temporal patterns by incorporating time-sensitive information, such as the sequence of medical events. To evaluate the model's performance, the researchers conducted experiments on a large dataset of real-world EHRs. The results showed that DeepCare outperformed several baseline models in predicting different clinical outcomes, including mortality and readmission rates [22]. The systematic review done by authors to analyze and evaluate the use of artificial intelligence (AI) techniques in the detection and classification of COVID-19 medical images. The paper focuses on providing a taxonomy analysis, addressing the challenges faced in this field, proposing future solutions, and highlighting important methodological aspects. The review begins by discussing the taxonomy of AI techniques used in COVID-19 image analysis, such as machine learning algorithms, deep learning methods, and ensemble models. It explores how these techniques have been applied to various types of medical images, including X-rays, CT scans, and ultrasound images. Authors highlights the need for standardized evaluation and benchmarking frameworks for AI models in COVID-19 image analysis. It emphasizes the importance of establishing reliable performance metrics and validation procedures to ensure the accuracy, reliability, and comparability of the AI models [24].

Parkinson's disease (PD) is a neurological disorder that affects millions of people worldwide. Diagnosing this condition can be challenging, as it requires accurate identification of subtle symptoms and distinguishing them from other similar disorders. To address this issue, researchers have implemented deep transfer learning techniques to refine the process of Parkinson's disease identification. Deep transfer learning is a branch of artificial intelligence that leverages pre-trained neural networks to extract meaningful features from raw data. By training these networks on large datasets, they can learn to recognize patterns and make accurate predictions. In the case of Parkinson's disease, deep transfer learning models can be trained on existing datasets containing information on various neurological disorders. By fine-tuning these pre-trained models, researchers can optimize their performance specifically for Parkinson's disease recognition. This involves retraining the models on smaller, carefully curated datasets of individuals with confirmed Parkinson's disease, allowing the models to focus on the specific

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characteristics and biomarkers associated with this disorder. PD identification is realized with help of handwriting images that help as one of the earliest indicators for PD. Authors achieved 98.28% accuracy using fine-tuning-based approach [25]. Another attempt made by authors to classify brain MRI images for cancer detection. The authors utilize a combination of deep wavelet autoencoder (DWA) and deep neural network (DNN) techniques to achieve accurate and efficient classification. The deep wavelet autoencoder is employed as a feature extractor, which effectively enhances the representation of the MRI images. This technique leverages the ability of wavelet transforms to capture both spatial and frequency components of the images, allowing for more comprehensive feature extraction. The deep neural network is then utilized to learn and classify the extracted features. This network is trained on a large dataset of brain MRI images, enabling it to accurately distinguish between cancerous and non-cancerous images. The authors use state-of-the-art deep learning techniques, such as convolutional layers and pooling layers, to build a robust and accurate classifier. To evaluate the performance of the proposed method, the authors conduct experiments on a publicly available brain MRI dataset. The results demonstrate that the deep wavelet autoencoder based deep neural network achieves high accuracy in classifying brain MRI images for cancer detection [26]. Another research conducted by authors to presents a hybrid ECG-based deep network that aims to identify high-risk hypertension patients who are prone to experiencing major cardiovascular events in the early stages. The proposed deep network combines electrocardiogram (ECG) data with advanced deep learning techniques to improve the accuracy of risk prediction. By analyzing the ECG signals of hypertension patients, the deep network extracts relevant features and learns patterns associated with cardiovascular events. The deep network consists of multiple layers that perform both feature extraction and classification tasks. The hybrid approach incorporates both convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. CNNs are used to extract spatial features from the ECG signals, while LSTM networks capture temporal dependencies in the data. The authors trained and evaluated the deep network using a dataset consisting of ECG recordings from a large number of hypertension patients. The performance of the hybrid deep network was compared with other existing methods for risk prediction. The results of the study indicate that the proposed hybrid ECG-based deep network outperforms other methods in accurately identifying high-risk patients for major cardiovascular events. Its ability to capture both spatial and temporal features from ECG signals improves the accuracy and reliability of risk prediction [27].

TABLE-1 LITERATURE SUMMARY

Model for	Methods/ Classifier	Year	Advantages	Challenges
Alzheimer's disease	Auto-encoder+CNN [citation]	2021	Classification of pateints into CN, MCI, and AD groups by using DL model for data fusion of ADNI dataset	Limited dataset & low acciuracy achiveded
Parkinson's disease	CNN	2019	CNN architecture AlexNet is used to refine the diagnosis of PD. An accuracy of 88.9% is achieved on PPMI public domain database.	Limited dataset size & time factor is not included for early detection of Parkinson's disease.
Diabetes	Convo-LSTM	2020	Conv-LSTM is porposed over the Pima Indians Diabetes Database (PIDD). Model achieved the highest accuracy of 97.26 %.	Imbalanced dataset, also how the model makes predictions or detects diabetes can be difficult, which can limit its interpretability and explainability
Skin cancer	CNN	2017	CNN trained by using a dataset of 129,450 clinical images. High accuracy is acvhived.	Limited generalization, interpretability & explainability

Medicine prediciton	LSTM	2016	LSTM is used to handle irregular timing. Also capture and model temporal dependencies in medical data.	Data Quality and Availability, Interpretability and Explainability
Readmission after discharge	CNN	2017	CNNs offer interpretability at the feature level also p redictive performance is improved.	Data Quality and Heterogeneity, Limited Interpretability
COVID-19	All AI techniques	2020	Comprehensive analysis & comparative study for various classifier to identify best classifier	Heterogeneity of Studies, Interpretability and Explainability, Lack of Standardization
Parkinson's neurological disorder	Deep CNN	2019	Deep CNN classifier to with transfer learning and data augmentation techniques . An accuracy of 98.28% is achieved.	Limited Availability of Labeled Data, Not suitable for time-series data.
Cancer Detection	DWA-DNN	2019	Accurate Cancer Detection, An overall accuracy of 96% is achived using DWA-DNN over RIDER dataset.	Limited dataset, Complexity of model is high.
Hypertension	LSTM+ CNN+DNN	2021	Hybrid approach increase accuracy of early Identification of High-Risk patients over ECG data.	Lack of interpretability and explainability.

RESEARCH GAP

Deep learning has made significant strides in healthcare, but there are still several challenges that need to be addressed. Temporal modeling & Interpretable modeling are very important factors for healthcare related problems. Temporal modeling involves "time factor" which provides progression of disease over time and Interpretable modelling involve "explanation & understanding" which provides the reason of predicated disease. Recent works in prediction and classification tasks shows that deep learning approach perform better than the traditional approach. But all approach used CNN, RNN, LSTM as an individual method and only detect disease on early basis.

Early detection of any disease only focuses on present situation of patient. So technically existing system only work for short-term approach which is not suitable for solving healthcare problems like cancer, Parkinson disease etc. as they need timely treatment.

FUTURE DIRECTIONS

Deep learning has already made significant contributions to medical imaging analysis, clinical decision support systems, drug discovery, genomics, and electronic health records. However, there are still numerous emerging applications that need exploration, as follow.

Generation of medical dataset with proper quantity and quality must be required for the deep learning-based system. It will be difficult to use patients' data for the research and development of the system. Here, the patient consent and asscurity will be required for the medical research. The available medical data suffers for class imbalance problem, which provides poor performance of the model.

Interpretation of medical reports/MRI/CT scan/X-ray for patient diseases is one of the challenging tasks due to complex structure of human body. The manual process of the interpretation of these reports is time consuming and

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requires superspecial medical expert for the correct diagnosis. To develop deep learning based system to automate this process and correctly predict the diseases in real-time environment.

Primary treatment recommendation is also one of the challenging tasks for the people of Rural Area or poor people. Deep learning based system will suggest primary medicine for the intial level of the diseases. If there is a need then system will recommend medical expert to the patient.

Remote monitoring and anlysis of the patient reports and diagnosis prediction will be developed for the medical experts as well as to patients from their home. With the help of deep learning, we can enhance telemedicine by enabling remote analysis and diagnosis. For example, a deep learning model can analyze patient symptoms and provide preliminary diagnoses, allowing healthcare professionals to make informed decisions even from a distance.

Deep learning-based system will be significantly useful for the process of the drug development, drug analysis and understading of chemical structure in clinical process.

Automatically extracting useful information from electronic medical records/text records along with disease diagnosis is one of the challenging tasks in medical domain. Chronic diseases are a major global health problem associated with high number of people. So, diagnosis of chronic diseases is very important in the medical field as they persist for a long time.

The black-box nature of deep learning models raises concerns regarding their interpretability and explainability. Future research can focus on developing methods to provide insights into model predictions, enabling clinicians and patients to understand why particular decisions were made. Exploring interpretability techniques like attention mechanisms, saliency maps, or surrogate models could be an interesting area to investigate.

CONCLUSION

Deep learning techniques have become powerful tools in healthcare and offer significant opportunities to improve medical diagnosis, treatment and research. This review provided a comprehensive analysis of deep learning techniques in healthcare and highlights their impact in various fields such as medical imaging, e-health, genomics, drug development and disease prediction. It has also examined the recent advancements in deep learning architectures, including convolutional neural networks, recurrent neural networks, and generative adversarial networks, showcasing their specific applications in healthcare. These architectures have enabled accurate medical image analysis, improved patient risk stratification, and enhanced drug development processes. Looking ahead, the future research should concentrate on solving the remaining problems and improving deep learning methods to allow for easy integration into clinical practice. In conclusion, deep learning methods have shown enormous promise in the medical field and have the potential to greatly enhance patient outcomes, treatment efficacy, and diagnostic accuracy.

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