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Healthcare Techniques Through Deep Learning: Issues, Challenges and Opportunities

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ABSTRACT In artificial intelligence, deep learning (DL) is a process that replicates the working mechanism of the human brain in data processing, and it also creates patterns for decision making. Deep learning or neural networks have been deployed in several fields, such as computer vision, natural language processing, and speech recognition. It has been used in many healthcare applications for the diagnosis and treatment of many chronic diseases. These algorithms have the power to avoid outbreaks of illness, recognize and diagnose illnesses, minimize running expenses for hospital management and patients. This paper discusses the deep learning methods used in different healthcare fields, i.e., identifying depression, heart diseases, physiological signals, lymph node metastases from breast cancer, etc. These diseases are categorized into the central nervous system, cardiovascular system, and respiratory system. For each category, after summarizing the studies, comparison tables are laid down using some important factors. Different applications, tools, methods, and data sets used for DL models are leveraged. Finally, research opportunities and challenges being faced for deep learning models are discussed.

INDEX TERMS Deep learning, health care, nervous system, respiratory system, supervised and unsupervised learning.

I. INTRODUCTION

With recent advances in technology, many healthcare technologies proliferate and percolate in every medical diagnosis center, new means of diagnosis of diseases enter our daily routine [1]. Consequently, electronic healthcare has emerged as a new trend in our society [2]. The rampant growth of in-depth learning information is joined with the tendency to assemble things resulting in healthcare techniques. All these techniques are primarily a roadmap to the development in the field of medical diagnosis. According to a report from the Office of the National Coordinator (ONC) for Health Information Technology, almost 84% of hospitals around the world have adopted at least a basic electronic health record (EHR) system [3]. These systems store data, diagnoses, demographic information, laboratory tests and results, prescriptions, radiological images, and clinical notes. By concluding all, it has become essential to collect all the valuable data from healthcare.

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Deep learning is the subcategory of Machine Learning (ML), and its structure consists of many layers used to extract high-level features from the input. These layers transform the input data in the form of images to output the result by detecting the disease [4]. These layers receive input data, transform them with the help of different functions(non-linear), which later pass as an output to the next layer. The first and last layers are called input and output layers, and the middles are hidden layers. Three or more layers (including input and output) can be called "deep" learning [5]. These algorithms do not have a simple buzzword; these sound like you are reading Sartre and listening to a band you have not heard of yet. Each node level trains different resource sets based on the previous level's output in a deep learning network. The more the neural network traverses, the more complex resources they perceive when the nodes merge and recombine the upper-level resources. The deep learning layers include input layers, convolution and fully connected layers, sequence layers, activation layers, normalization dropout, and cropping layers, pooling and un-pooling layers, combination layers, object detection layers, generative adversarial network layers, output layers, etc. Deep learning can take millions of images based on their similarities, making clusters of these images. These images are processed through the deep learning layers that are used to detect different diseases. Somehow, DL replicates artificial intelligence that how the human brain works in data processing and creates a decision-making pattern. Deep learning models such as neural networks, Convolutional Neural Network (CNN), Artificial Neural Network (ANN) are considered the initial steps to automate the systems.

CNN's are the basis of deep learning, the initial work in this field started in the late seventies, and its first application in medical informatics came in 1995 [5]. However, these were considered the initial achievements of CNNs but did not mature CNNs until the powerful new techniques were developed to train the deep networks aptly. The milestone towards establishing momentum in CNNs was ImageNet, also called Alex Net in 2012 [6]. Several improvements have been made in the subsequent years to achieve the maturity level.

Applications in the field of deep learning gained more popularity due to their tremendous growth. In the vast area of medical analysis, it is time to search for every disease's diagnosis separately. This lacuna can be solved by merging the diagnosis techniques of commonly occurring diseases in a combined study. In the last few years, a lot of work has been presented as a lucid summary. In the survey, healthcare techniques are categorized according to the human body systems [7] that focuses on AI methods implemented. This paper intends to list all the computer-aided diagnosis systems invented by using deep learning models. Computer-aided designs (CAD) systems are categorized for diseases specific to the three systems of the human body. Deep learning techniques are widely used these days to help and understand healthcare-related matters [8]. The "vulnerabilities" of the American Recovery and Reinvestment Act (ARRA) have resulted in a steady increase in public health data [5]. For example, the rate of Lung cancer is very high in both men and women. The transience of lung cancer accounts is about 27% of all cancer deaths [9]. If Lung nodules are examined at an early stage, it helps in the patients' survival rates. Alzheimer's disease (AD) is the usual form of dementia, a neurological disorder and deteriorating brain disease, which disturbs problem-solving capabilities, memory issues, and physical activities and affects other necessary daily life activities. Forty-seven million people have dementia, which is mentioned in the World Alzheimer's report in 2016. An increase in number is expected by the year 2030 and 2050, respectively. The 2nd most deadly disease in women is Breast cancer; almost 8% of women got developed breast cancer during their lifespan [10]. Digital mammography (DM) is an influential technique to detect breast cancer. There are some limitations in dense imaging breast; ultrasound imaging (US) is the alternative.

Depression is arising worldwide, a meticulous survey has been performed to determine the existence and risk factors of depression. The estimate is 1 in 13 individuals suffer from depression (world health organization 2017) worldwide. Deep learning methods can be used to find the reasons leading up to the occurrence and symptoms of depression. The commonly known heart disease, myocardial ischemia, is due to less blood supply to the myocardium, which changes electrocardiogram (ECG) signals' morphology. Cardiac arrhythmia are cardiovascular problems such as chest pain, cardiac arrest, or sudden cardiac death. Physiological signals help in disease detection and its treatment. In medical applications, Heart-related diseases and diagnosis of these diseases from ECG are very important. Every heartbeat in the ECG waveform illustrates the time series of the heart's electrical activity. Any vagueness in the heartbeat rate or variation in the morphological pattern is a symptom of an arrhythmia identified by examining a recorded waveform of ECG.

Speech is a primary method of communication, the deep learning methods used for speech recognition are Gaussian Mixture Models (GMMs). The Hidden Markov Models (HMMs) used Gaussian models to represent the sound waves. These models are amateurish for non-linear functions. These models work better for short-time signals, yield better results in deep neural networks. In 2012, the latest Microsoft Audio Video Indexing Service (MAVIS) version was released based on deep learning. Their word error reduces to four major benchmarks by 30%. In the latest heart disease prediction system based on ensemble DL and feature fusion, using sensor data and electronic medical records, EMR combines features to generate records. This system lowers the computation burden and enhances the system performance, with an accuracy of 98.5%. A survey on deep learning for a multi-grade brain tumor covers the DL-based BTG methods, along with achievements and its limitations. In this paper, we discussed the existing applications, research studies, and challenges in healthcare. These approaches focus on biomedical data like imaging, genomes, and EHRs. In this paper, we discussed the recent applications and research studies in healthcare. These approaches focus on biomedical data, i.e., imaging, genomes, and EHRs. We briefly introduce the general deep learning framework and different applications in health care. This paper considers the three most critical human body systems, i.e., central nerve system, cardiovascular system, and respiratory system. We briefly describe the approaches and compare them in the form of tables. We carefully considered the state-of-art surveys in the healthcare sector; to the best of our knowledge, no comprehensive work has been done to categorize system-wise diseases of the human body. This survey's basic motivation is to put together deep learning models for the diagnosis of common diseases in three systems of the human body. In this survey, our contributions are as follows.

- Explanation and Comparison of Machine learning and deep learning briefly.
- Role of deep learning models in common diseases of three human body systems, i.e., central nervous system, cardiovascular system, respiratory system.

- Classification of the studies for each category, i.e., stroke, Alzheimer's, Parkinson's, for the human nervous system.
- Comparison of different studies based on different parameters, i.e., DL models, results, objectives.
- Evaluation of different deep learning models and applications for the diagnose and treatment of the diseases.

The remaining survey is structured as follows. Section II describes the background knowledge of machine learning vs. deep learning and commonly used deep learning models applied to healthcare for diagnosis. Section III comprehensively discusses the DL models used in Healthcare systems. The major portion of the survey discusses the deep learning applications used in healthcare, described in section IV. It also includes related methods/algorithms, data sets, deep learning tools in healthcare. Section V presents the opportunities and challenges of the healthcare field using deep learning and Section VI concludes the paper.

TABLE 1. Abbreviations table.

Abbreviation	Explanation
ONC	Office of the National Coordinator for Health Information Technology
EHR	Electronic health record
CAD	Computer-aided designs
ML	Machine learning
DL	Deep learning
AL	Artificial learning
CNN	Convolutional neural networks
ANN	Artificial neural networks
RNN	Recurrent neural networks
FFNN	FeedForward Neural Networks
DCNN	Deep Convolutional Neural Networks
USI	ultrasound imaging
AD	Alzheimer's disease
DM	Digital mammography
GMMs	Gaussian Mixture Models
HMMs	Hidden Markov Models
MAVIS	Microsoft Audio Video Indexing Service
BTG	Brain tumor graphs
MLP	Multi-layer perception
BP	Backpropagation algorithm
GBM	Glioblastoma malignant brain tumor
GEO	Gene Expression Comprehensive Database
SVM	Support vector machines
COPD	Chronic obstructive pulmonary disease
HGP	Human Genome Project
LR	Linear regression
LSTM	Long-short term memory
NHANES	National health organization and nutrition examination survey

II. MACHINE LEARNING VS. DEEP LEARNING

Machine learning and deep learning are subcategories of artificial intelligence. Machine learning is enmeshed in establishing algorithms that can alter themselves without human involvement to generate required output through supplying defined data, shown in Figure 1. While Deep learning is an artificial intelligence subset of machine learning that uses neural networks to learn unsupervised from unstructured or unlabeled data. Machine learning practices algorithms to analyze data, learn from it, and make smart decisions based on the knowledge learned, while deep learning organizes the algorithms into layers to form artificial neural networks that can learn and make intelligent decisions independently [11]. There are several tiers of these processes, each one delivering a precise analysis of data that it feeds on. These types of algorithms are called artificial neural networks. Like their name, their performance is an inspiration, it is an effort to replicate the role of the human neural networks that appear in the human brain [12]. Deep learning replicates how the brain of humans functions in data processing, and it creates patterns for decision making. The stages of machine learning are shown in Figure 1.

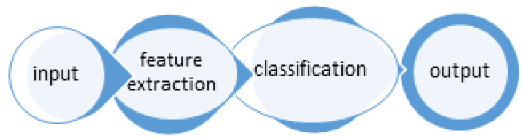

FIGURE 1. Machine learning stages.

The evolution of deep learning started after the invention of neural networks, by adding more neurons and additional hidden layers to neural networks makes deep learning more cultivated. Like machine learning, deep learning is also categorized into two main subcategories, i.e., supervised, and unsupervised. However, unstructured data is so much sophisticated that it takes years for humans to manipulate it. Simple multi-layer model is shown in Figure 2.

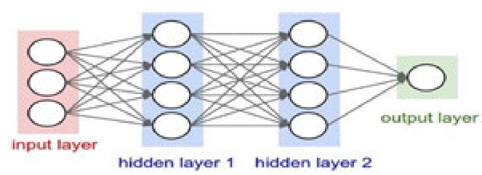

FIGURE 2. Simple multi-layer perception model.

A. SUPERVISED LEARNING MODELS

To extract features from the labeled data set, supervised learning models are used for Multi-layer perception. CNN's, RNNs, deep CNNs are included in supervised learning algorithms. A brief description of all these algorithms is given below.

1) MULTI-LAYER PERCEPTION (MLP)

Multi-layer perception is the extension of neural networks (branch of machine learning) and is considered a first step towards the biological process's mathematical formulation. The human brain processes information, a simulation of every neuron results in potential action. In the biological process, neurons transform themselves, generate new neural connections, and grasp modification according to simulation characteristics. The architecture of MLP consist of 3 layers where the intermediate layer is hidden (may have multiple hidden layers), and the input layer, is connected to the output nodes. It resembles ANN with an objection that MLP consists of multiple hidden layers, and biological processes are performed using the activation function and few assigned weights. Typically, by using this architecture, data flows in one direction because the network is restricted to the specified number of hidden layers.

2) RECURRENT NEURAL NETWORKS (RNN)

When we want to apply deep learning methodologies to the sequentially ordered data, RNNs are considered an appropriate choice as the neural network can analyze all states' data in the network. Traditionally, in RNNs, connections between hidden layers form a directed graph that exhibits temporal behavior. It is useful when the output needs to be dependant on all the previous states, and the trained data have strong interdependencies. For maintaining information about what happened in the previous stages are explained in [13]. Moreover, the working of RNNs, hidden state at the time 't' is sequentially updated not only by the initiation of the current input state at the same time. Also, on the shrouded state at time 't-1', which is revised by the activation of input state at 't-1' and the hidden state at the time 't-2' and so on. To summarize the concept of RNNs, utilize dual sources of inputs, i.e., current and recent back, and we can say that RNNs have memory. A key advantage of using RNNs is that, unlike MLP, RNNs share the same weights in all steps, which results in the reduction of the overall number of parameters required by the network to learn. Practical examples of RNNs includes DNA sequences, text analysis, speech analysis, etc.

3) CONVOLUTIONAL NEURAL NETWORKS (CNN)

Neural network models discussed so far cannot be implemented on multi-dimensional correlated data. For instance, when imagery data is uploaded as training data, the number of nodes and the parameters become very significant and practically impossible. A CNN architecture is proposed [14], which uses the convolutional filter mask. Instead of using predefined kernels, it uses locally connected neurons and data specific kernels for learning. CNN is explicitly proposed for image data analysis, so the filter mask is applied to the whole image repeatedly. The connectivity obtained as a result seems like a sequence of overlapping fields. Many CNN applications are in the field of neurobiology where backpropagation is used, and the architecture has to compensate all the parameters to a particular instance of the mask, which in turn, reduces the links from the architecture.

4) DEEP CONVENTIONAL NEURAL NETWORK

Deep CNN is a typical feedforward neural network, in which the Backpropagation (BP) algorithm is used to reduce the value of the cost function by adjusting network parameters (weights and biases). It is significantly diverse from the traditional BP network in four new designs: the local receptive field, grouping, shared weight, and different layers combination. Deep CNNs are designed to process the data with a network known as topology. It is broadly used to identify objects in images, diagnose patterns in time series data, and classify sensor data [15]. The deep conventional neural networks are a special type of ANNs that uses convolution in at least one of its layers instead of regular matrix multiplication. It has achieved great consideration in the field of noise reduction in images. However, it has two disadvantages.

- The deep CNNs are hard to train for image demonising tasks.
- Most of the deep CNNs faces the issues of performance saturation.

The CNN and deep CNNs are different only in the number of layers. The main difference between CNNs and Deep CNNs is conventional neural networks. In it the hierarchical patch-based conventional networks are used, which reduces cost and abstracts the images on many feature levels. The deep CNNs is a neural network with multiple layers [16]. The pictorial representation of deep learning is elaborated in Figure 3.

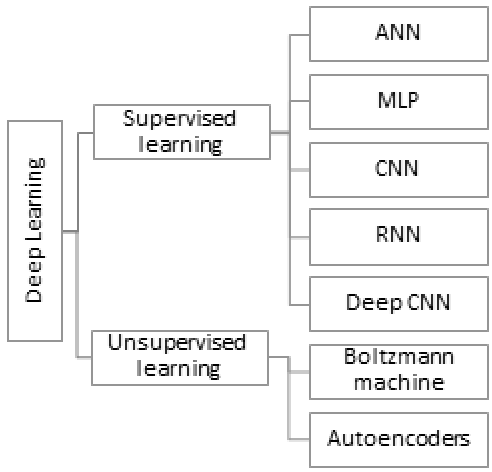

FIGURE 3. Hierarchical representation of deep learning.

B. UNSUPERVISED MODELS

The deep learning models discussed so far are the supervised learning models. But there may be a situation when raw and unstructured data is provided. Some of the unsupervised learning algorithms are proposed like the Boltzmann machine and autoencoders, which are described briefly in the following sections.

1) AUTO-ENCODERS

In auto-encoders, the unsupervised mode is used when a hidden layer reconstructs the input layer. Unlike RNN, which includes weights and bias from the input state to the hidden state, dimensions are assigned. The hidden layer has smaller dimensions than the input layer, and the non-linear transformation function is applied to compute the hidden layer's stimulation. Meanwhile, when the hidden layer dimensions are reduced, a dominant structure appears in the input. The hidden and input layers' dimensions should be kept the same, and no non-linearity function should be added to learn about the identity function [17]. Autoencoders are subdivided into two subcategories. One is the denoising auto-encoder, and the model is proposed to prevent the trivial solution of learning. In this type, the input is reconstructed using the corrupted version of noise. Another type is Stacked auto-encoders, these are built by placing the auto-encoder layers, one above the other. In healthcare applications, each layer is trained individually to predict the output, and the whole network is fine-tuned by using supervised learning algorithms [18].

C. BOLTZMANN MACHINE AND RESTRICTED BOLTZMANN MACHINE

One of the unsupervised learning input data models is a type Markov Random Field known as Restricted Boltzmann machine, which is the Boltzmann machine's variant [19]. It is considered as a kind of stochastic neural network modeled using stochastic nodes and specific Gaussian distribution. The basic purpose is to let the model learn by minimizing the reconstruction error by adjusting the weights using Gibbs or sampling. These networks are referred to as acyclic directed graphs and useful when probabilistic distribution between the input data is required. Another important characteristic of RBMs is the composition of undirected nodes, which implies the propagation of nodes in each direction. An unsupervised learning algorithm, i.e., contrastive divergence [20], is used to train the RBM. Another variant in the family of Boltzmann is the deep Boltzmann machine [21]. Its concept resembles stacked autoencoders, the main difference is the restricted Boltzmann machine which replaces the auto encoder's layer. First, training for the individual layers is performed in an unsupervised manner, and then a linear classifier is included in the topmost layer, leading the training in a supervised direction [22].

III. DEEP LEARNING IN HEALTH CARE SYSTEM

In this section, we present healthcare applications to various diseases that are subcategorized according to the systems of the human body. We highlighted recent deep learning techniques adopted to automatically diagnose specific conditions. The diseases are categorized into three groups: the central nervous system, cardiovascular system, and respiratory system, which are further explained below sections.

A. CENTRAL NERVOUS SYSTEM (CNS)

Study-related to the central nervous system is conducted in the field of biomedical neuroscience. For instance, in the diagnosis of diseases for CNS, computational neuroscience experiments are conducted. It is convenient for radiologists to study the reports and leads the neurologists to treat the patient accordingly. Many different sensual maladies like brain tumors, Alzheimer's, brain strokes, and many others are rapidly increasing. Meanwhile, deep neural networks (DNNs) have been extensively used in different applications to diagnose abnormalities automatically. Deep neural network (DNN) applications for some common neurological disorders are summarized below. With the evolution of AI, different algorithms are used for diagnosis. Earlier from 2008 to 2013, machine learning was considered a hot research area to diagnosis the deadlier diseases. In 2014, machine learning models came into practice to diagnose diseases and to prevent death. The method of region-based contour methodology and segmenting with fuzzy mean algorithm [10] is used. This approach was not fully automated. In [23] a fully automated segmented approach using random forest is proposed. These methods still demand the implementation of engineering techniques for feature extraction. But with the maturity of DNN models, research was molded to deep learning to learn the input parameter and efficiently diagnose the cause of disease. One application that uses the non-linear filters and self-extraction mechanism for the automatic feature extraction is used in 2014 [24]. Eventually, DNN models were used in 2015, 2016 to automate the neural diagnostic systems [25]. These systems still diagnose the brain's state to be abnormal or normal, and no disease was diagnosed using DNNs. From 2017, CNN, deep CNN, and 3D CNN models came into practice to diagnose these diseases. Using CNN and deep CNN models, stroke can be automatically diagnosed, and lesions of the brain can be recognized, which can predict the presence of stroke. As per the world health organization (WHO), the second prominent cause of death is stroke [21]. It is observed that strokes are standard in older age, and their incidence keeps on increasing with age. Strokes are mainly considered of two types, Ischemic stroke, and Hemorrhage stroke. When a blood clot has appeared, or the blood vessels are blocked, ischemic stroke is caused, whereas hemorrhage stroke is caused due to rupturing or bursting of blood vessels, including hypertension r head injury, etc.

One of the mental disabilities of people is seen in the form of Alzheimer's disease, which affects people in many ways, including memory loss, confusion, the problem in speaking and reading, etc. This disease destroys the brain cells that can be cured when diagnosed and treated during its early stages, but it can causes death in older people. Research shows that Alzheimer's disease has three main stages, namely very mild, mild, and moderate. Machine learning methodologies applied to diagnose Alzheimer's disease are at the intermediate stage as multi-class classifiers are not included in this domain. Neurologists also used the mini-mental state examination method, a detailed history, and now, MRI-based data to diagnose Alzheimer's disease accurately. With the evolution of deep neural network (DNN) models, researchers tried to identify how Alzheimer's can be diagnosed and recognized during its early stages. From 2017, different works that used multi-class classifiers and DNN models came for the early diagnosis of AD. In 2019, a lot of work for automatic recognition was also conducted using unsupervised deep learning methods.

Unlike other neurological disorders, special attention towards the diagnosis of Parkinson's during its earlier stages was given. Machine learning is rarely used to Diagnosis Parkinson's, except the decision support. Although

DNN models for measuring dopaminergic neurons are implemented since 2017, little work was done in 2015. Computer-aided diagnosis (CAD) uses the EEG process to diagnose different mental disorders and is widely used in computational neuroscience [26]. Until 2017, CAD systems were used without involving deep learning models, but from 2017, deep learning models, i.e., CNN, deep CNN is applied for automatic feature extraction. Disorder in the brain caused by the deficiency of dopamine-producing neurons results in Parkinsonism disease. In the category of degenerative diseases, Parkinson's is considered to be the second most common disease. The major cause of Parkinsonism is the loss of dopaminergic neurons in the nigral region. As the disease progresses, the pattern for the degeneration of dopaminergic neurons begins from the dorsal striatum and proceeds more to the striatum's central part. The condition is observed in adults, especially in people of age 65 or above [26]. Primary symptoms of the brain include unstable posture, slow movements loss of balance. Cancer in the brain in the form of tumors, that considered a deadlier disease and should also be treated during its early stages by detecting and recognizing the brain's lesion, the tumor's major cause. An accurate and reliable diagnosis is a difficult task as the potential abnormalities and the functional structures lead to a significant surgical plan. Double density discrete wavelet transforms, SVM classifiers, CAD with EEG, were the earlier machine learning methodologies used for lesion detection. Different deep learning methods for such Compositional Pattern Producing, Optimized Convolutional Neural Networks, and hybrid approaches such as Independent Component Analysis are considered. A transfer learning approach can also be very beneficial to detect the tumor. Apart from these, many different models of deep learning are also used for lesion detection and recognition.

Glioblastoma (GBM) is a common malignant brain tumour [27]. Two diseases of the central nervous system and GBM cells release Glutamate and display abnormalities, but the cells behave differently. Therefore, its etiology is not well understood, and it is unclear how central nervous system diseases affect the behavior or growth of GBM. Therefore, using a quantitative analysis framework, the data sets obtained from the Gene Expression Comprehensive Database (GEO) and the Cancer Genome Atlas (TCGA) link central nervous system diseases and GBM diseases with the genes expressing the spoon (DEG). After identifying the DEGs, by identifying the interconnected network of pathological genes and signal transduction pathways and performing the genetic analysis (GA), the focal proteins were identified. The effects of these DEGs were predicted. The chronic neurological disorders, epilepsy is the most common disease. EEG signals were the manual process used so far and record the brain's electrical activities, which in turn misdiagnose the disease. So, automation is also required in this field to diagnose the disease properly. Electrical signals inside the brain are exchanged due to a sudden rush; epilepsy is caused. Many seizure detection works are done, mainly including SVM as a classifier and wavelet transform for feature extraction. The pictorial view of the central nervous system is shown in Figure 4.

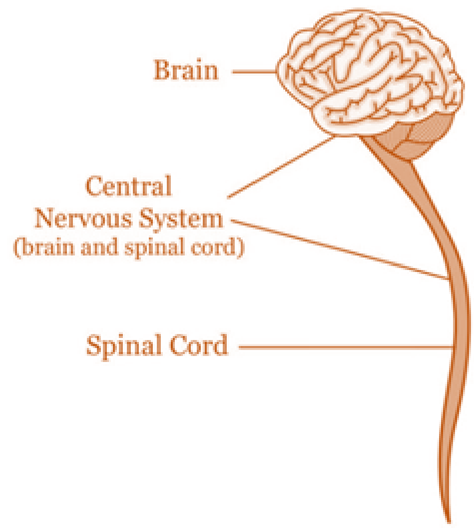

FIGURE 4. Central nerve system.

B. CARDIOVASCULAR SYSTEM

The circulatory system and vascular are combined to form the cardiovascular system. Organs such as the heart and blood vessels included in cardiovascular systems suffer from significant diseases due to hypertension, which is also listed in CVS disorders. The following table gives an overview of some previous work done about the cardiovascular system's different diseases. It briefly describes the deep learning model used in the studies with their objectives. Medical cardiology has worked a lot to determine the cause of these diseases, but computer-aided systems are proven more efficient. Computational cardiovascular scientists, at the same time, continued their research towards the automatic diagnosis processes.

Due to exponential growth in technology, the smart world is gaining more attention, due to this hypertension is a rapidly occurring disease and affecting human health very seriously. Neither of the methods has been proposed to predict hypertension, nor are any medicines or treatments discovered. Zhang *et al.* [53] proposed a smart system using stacked auto-encoders. First, clinical cases are categorized according to different groups based on the symptoms and use the auto-encoder model. Now, the trend is shifted towards deep learning for automatic arrhythmia detection. ECG, the main technique for predicting arrhythmia, is used by traditional ML methodologies and now with deep learning methods. Auto-encoders, DBN, CNN, and RNN are the major DNN architectures used to predict cardiac arrhythmia. By reviewing the literature, it is predicted that CNN models are used to predict arrhythmia in 2019. Different classes indicate syndrome. The pictorial view of the cardiovascular system is shown in Figure 5 In terms of quality of life and economic costs, the coexistence of chronic diseases affects human health very badly. In most countries in the world, the prevalence

TABLE 2. A brief review of DL models for central nervous system diseases.

Ref. #	Published by	DL model	Results	Objectives
		Stroke		
[28]	IEEE	CNN	More than 90% Accuracy	To develop an early ischemic stroke detection system.
[29]	Springer	Cascade CNN and FCN	Precision = 80.19% and Recall = 82.15%	Identify the types of hemorrhage and to segment the lesion for stroke detection.
[30]	MDPI	DNN model with PCA feature quantile scaling	Accuracy =84.03%	Automatically predict stroke based on medical history and human behavior.
[31]	Frontiers	CNN	Accuracy = 0.34 avg DSC	To segment the ischemic stroke.
		Alzheimer's disease		
[32]	Springer	Deep CNN	Accuracy =73.75%	Multi-class Alzheimer disease detection and classification.
[33]	Elsevier	DNN	Sensitivity =98.9% Accuracy = 99%	Automated classification of Alzheimer and mild cognitive impairments.
[34]	Springer	Shearlet Transform (ST) + KNN feature extractor	Accuracy =98% Precision = 97% Recall = 96%	Development of Computer-Aided brain diagnosis system to determine Alzheimer's disease.
[35]	bioRxiv	Deep CNN	NA	To predict the age of the brain to diagnose Alzheimer's disease.
[36]	Elsevier	Deep Siamese NN	Accuracy = 98%	To detect brain asymmetries to diagnose Alzheimer's disease and mild cognitive impairments.
[37]	Elsevier	DNN	Accuracy = 98.1%	Diagnose as well as monitor Alzheimer's disease.
[38]	Springer	Unsupervised feature learning	Accuracy = 98.7%	Alzheimer disease diagnosis.
[39]	Oxford	(FCN) and (MLP)	Accuracy = 0.968 Sensitivity= 0.957 F1-Scor e= 0.965	Alzheimer disease diagnosis.
[40]	Springer	(CNNs)	NA%	Alzheimer disease diagnosis by using multi-model.
		Parkinson		
[41]	Springer	DNN for deep brain stimulation	N/A	To automatically detect the Parkinson disease
[42]	Springer	Transfer learning with DNN classifier	Accuracy = 98.28%	To improve and automate the diagnosis of Parkinson disease
[43]	Springer	Thirteen-layer CNN architecture	Accuracy =91.77%	Diagnosis of Parkinson disease from EEG signals
[44]	Elsevier	DNN	Accuracy = 98.3%	Automatic system to support the radiological diagnosis of Parkinson disease
[45]	Springer	CNN with Alex Net and DNN	Accuracy = 88.9%	To diagnose Parkinson using MRI images
[45]	Springer	PCA and DNN	Accuracy = 97%	To diagnose Parkinson using MRI images
		Tumor		
[46]	Elsevier	Deep CNN	sensitivity = 88.41% Accuracy = 90.67%	Multi-grade brain tumor classification
[47]	Springer	CNN with SVM classifier	Accuracy =99.8%	To detect brain abnormalities by integrating compositional pattern-producing networks
[48]	Elsevier	Deep transfer learning	Accuracy = 100%	To automate brain abnormalities by transfer learning
[49]	IEEE	Deep autoencoders	F-score= 0.93	To classify the image for brain cancer(tumor) detection
[50]	MDPI	DNN	Accuracy = 96%	To build up a non-contact and name free technique to offer dependable help for the tumor progressively
[51]	ASN	CNN	Accuracy = 94%	To classify genetic mutations in gliomas.
[52]	Wiley	DLM CNN	sensitivity = 95.7% Accuracy = 98%	To classify genetic mutations in gliomas.

of coexisting chronic diseases is increasing. For example, chronic disease type 2 diabetes (T2D) has a major impact worldwide that is the main cause of death and may lead to other diseases, such as cardiovascular disease (CVD). Cardiovascular disease is also associated with increased mortality and disability in patients with type 2 diabetes and may cause more than half of the deaths from type 2 diabetes [54]. Diagnosis and routine monitoring of various diseases require a lot of clinical and economic resources. Recently, the use of network methods and machine learning techniques (random forest (RF), support vector machine (SVM), etc.) to predict the risk of chronic diseases has attracted significant research. The logistic regression and SVM models show an average accuracy of 84.21% and 84.23%, respectively. The DT model shows better performance than Doctor of Veterinary Medicine (DVM) and Random Forest (RF).

TABLE 3. A brief review of DL models for cardiovascular system.

Ref. #	Published by	DL model	Results	Objectives
Arrhythmia				
[55]	ELSEVIER	Deep CNN	Accuracy=98.03%	To detect the standard form of arrhythmia, i.e. premature ventricular contraction
[56]	Nature	CNN	Precision = 0.800 Recall = 0.723 F1 = 0.809	To detect cardiological levels of arrhythmia
[57]	ELSEVIER	CNN	Accoracy=94.9%	CAD system to detect arrhythmias
[58]	IEEE	CNN and LSTM	F-measure= 0.83,0.015	To detect atrial fibrillation to diagnose arrhythmias
[59]	IEEE	CNN with feature-based classifier	F1 = 79%	To improve patient management and reduce healthcare cost for diagnosis of arrhythmias
[60]	Springer	Deep genetic ensemble	accuracy =99.37% F1= 94.62% specificity =99.66%	To develop the hybrid method by applying ensemble learning, evolutionary computation, and deep learning.
[61]	MDPI	2-D CNN	accuracy =99.11%	Classification of Arrhythmia using deep learning.
[62]	IEEE	DNN and GA	accuracy =0.94, F1 Score = 0.953	To improve classification accuracy via a robust feature extraction protocol.
Hypertension				
[63]	IEEE	CNN	Accuracy=92%	To detect intracranial hypertension using the deep learning realm
[64]	IOP	Boltzmann machine	NA	To detect hypertension retinopathy
[65]	Biosensors	CNN	Accuracy =92.55%	To detect hypertension risk stratification
[53]	ELSEVIER	Stacked autoencoders	Accuracy = 70%	To present the model of smart Chinese medicine for hypertension
[66]	IEEE	Convolutional DBN	Accuracy = 84%	To detect hypertension from electronic medical record
[67]	PLOS	CNN and Grad-CAM	Accuracy = 60.94%, specificity = 51.54%, precision = 59.27%, recall = 70.48%	To DL to detect hypertension.
[68]	Elsevier	LSTM, CNN, DNN	Accuracy = 98% precision = 97%, recall = 97%	To detect hypertension from Time Series Classification (TSC).

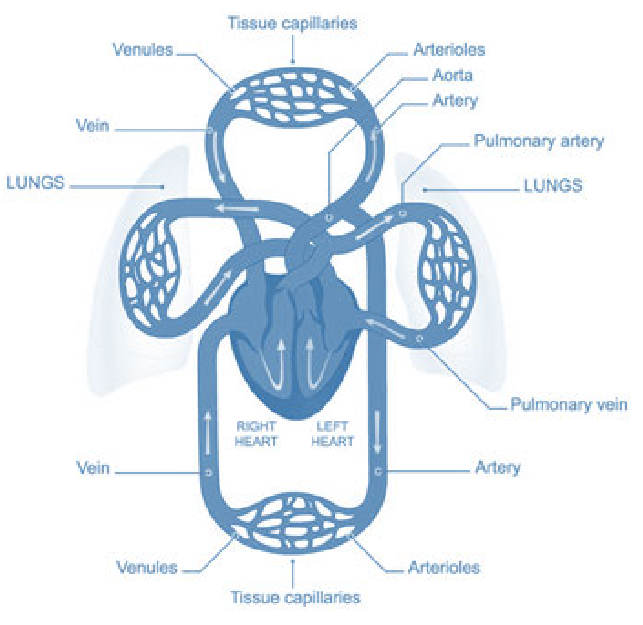

FIGURE 5. Cardiovascular system.

C. RESPIRATORY SYSTEM

The respiratory system has different organs that take in oxygen from the air and release carbon dioxide. This system's central organ is the lungs, which carry out the exchange process of gases in breathing. The respiratory system organs are the larynx, trachea, lungs, bronchus, alveoli, and bronchiole. Respiratory diseases affect a variety of people and are manifested by symptoms such as asthma and sleep apnea. Due to the large scale and high cost of the monitoring system, continuous monitoring of chronic respiratory diseases is rarely performed outside the intensive care unit. Electrocardiogram (ECG) is a proven method, but ECG monitors' constant use limits its recruitment. In the past few years, due to the widespread use of the built-in Photoplethysmogram (PPG), it has been considered a viable competitor for constant and careful breathing monitoring [69].

Asthma is a chronic disease with an acute attack; that's why constant medical care is needed. Another most common diseases globally are asthma, and clinically, it is defined as a grouping of different respiratory indications and considerable changes in the lungs' functions. The diagnosis of asthma meets international guidelines, and it includes symptoms like shortness of breath, coughing, wheezing. These symptoms are not unique to asthma, so if diagnosed based only on symptoms, 25-30% of asthma patients are misidentified by a doctor. This misidentification can lead to unfair treatment, leading to physical and economic complications. As deep learning neural networks in image classification tasks have been proven successful and these are gradually emerging in medical image analysis. Deep neural networks (DNN)

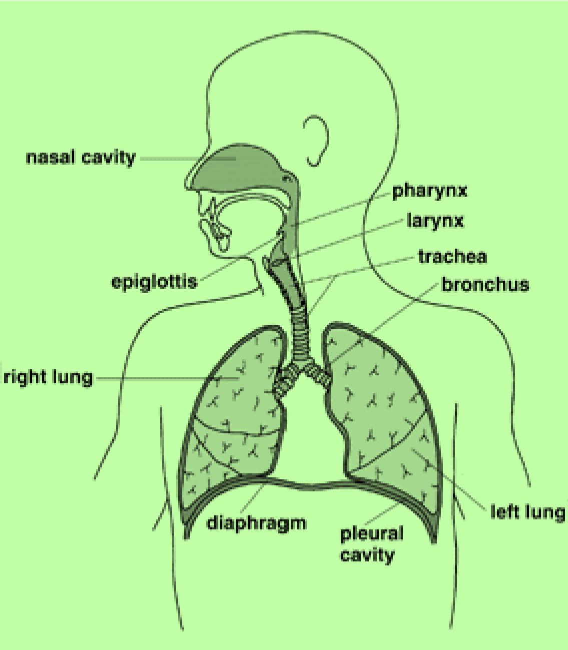

FIGURE 6. Respiratory system.

are used with non-linear regression for image classification. This study aimed to verify DNNs improve the accuracy for asthma diagnosis and compare the predictive performance of various deep learning methods, especially logical analysis and support vector machines (SVM). The pictorial view of the respiratory system is shown in Figure6.

We have also determined whether objective examinations with typical asthma symptoms are most useful in improving asthma diagnosis accuracy. Computer-aided diagnosis (CAD) is a valuable method for improving diagnostic precision, which involves merging expert information with machine learning methods. Machine learning can use complete clinical information to diagnose asthma in adults strongly. Artificial neural network (ANN) may be a more widely used algorithm for classification. Still, it is not expected due to the long parameter setting steps, many architectures of neural networks to choose from, and the large number of algorithms used to train ANN. That is why DNN is a suitable tool to diagnose asthma [44].

Chronic obstructive pulmonary disease (COPD) is a diverse disease categorized by the progression of multiple subtypes and diseases. The deficiency of precise tools for predicting disease progression cannot explain the limited success of reducing COPD's burden and defining the ability to prevent and control the disease [70]. COPD is often categorized by progressive and disruptive airflow and persistent airflow constraint, which improves the chronic inflammatory reply to toxic particles or gases in the air and the lungs. COPD is diagnosed clinically by considering symptoms and known risk factors such as chronic cough, dyspnea, or sputum making [71]. Deep artificial neural networks are used to predict degradation pathways. It is particularly used in Feed-Forward Neural Networks (FFNN) to classify patients in the COPD and Long Short-term memory (LSTM) categories for an early estimate and follow-up examination of COPD deterioration.

Maximum deep learning models need huge data sets to make high-precision predictions. But the FFNN model can reproduce the health status issued by the doctor with an accuracy of 92.86% with only data of 94 patients, indicating that the LSTM model can predict COPD patients' health status. These models' results are helping doctors and nurses to identify patients with acute deterioration and improve patient care and decision-making [72].

Pneumonia is among the leading reasons or diseases that cause death of among children and adults worldwide. It causes inflammation of the air sacs in the lungs. An air sac may be filled with pus or fluid or cause a cough, fever, chills, and shortness of breath. Various organisms, such as bacteria, viruses, and fungi, can lead to pneumonia. Signs and indications of pneumonia contain pain in the chest while breathing or coughing, confusion or altered mental consciousness [73]. Even with the low-contrast peripheral structures obtained by computed tomography (used to detect lymph nodes in clinical diagnostic work), the deep convolutional neural network (CNN) can still achieve significant results. Use deep CNN to classify thoracic and abdominal lymphatic detection problems and interstitial lung disease. Various CNN architectures have been developed with encouraging results at 85% sensitivity with three false positives per patient. CNN methods using data extension have been developed. This method even includes training a small sample of image data obtained from a transparent light microscope. The model was developed to capture high accuracy, and it was used to analyze data obtained by spinal magnetic resonance imaging (MRI). An effective CNN model has been developed to produce spinal magnetic resonance radiographic classification.

Influenza is the leading cause of illness and death, with per year up to 5 million severe infections and 650,000 deaths [WHO, 2018]; therefore, making a precise and appropriate estimate of influenza is an important public health task. The influenza prediction model is built on a deep residual network that predicts influenza's epidemic trend and integrates the spatial, temporal characteristics affecting a particular area. The proposed deep residual model surpasses four basic models, including artificial neural network (ANN), linear regression (LR), spatial temporal based LSTM (ST-LSTM), and long-term memory (LSTM) models, therefore signifying that the efficiency of the proposed prediction model. The deep residual model improves prediction performance a week or two earlier than the other four basic models. The planned deep residual network can integrate influenza's spatial context and predict the impact on the city's finer spatial scale, which can provide vital support for more accurate public health interventions [74]. Since a slide scanner can improve the ability to scan the entire slide image regularly, there has been a concentration on the progress of computer image analysis algorithms that can automatically detect the degree of disease in digital pathological images. Manually specifying lung cancer's presence and extent by a pathologist is essential for patients to manage tumor staging and assess treatment response [75]. Understanding chest radiography is vital for detecting chest diseases such as lung cancer, affecting millions of people every year. CheXNeXt is a deep learning algorithm compared with certified X-ray methods to detect multiple chest lesions on anterior chest X-ray images. These technologies can enhance the delivery of medical services and increase the chances of acquiring chest X-ray knowledge to identify various acute diseases. CheXNeXt uses chest X-rays for the screening, diagnosis, and treatment of lung cancer screening. The CheXNeXt algorithm found pleural consolidation and effusion, the utmost common primary tuberculosis outcome at the radiation level. CheXNeXt has accomplished accuracy in detecting radiation levels for lung cancer and lumps. It is more specific and has the same sensitivity as previously reported computer-aided detection systems. A chest X-ray is the most common chest imaging test and can detect unexpected lung cancer (lumps or lumps), although there is no primary method for examining lung cancer [73].

Acute bronchitis is the tenderness of the pulmonary airways. It is a common clinical manifestation in the emergency department doctor's office. Around 5% of grown-ups experience acute bronchitis attacks every year. Acute bronchitis is generally self-limiting and is usually produced by a viral infection. Bacterial infections are rare [76]. Medical X-rays are imageries commonly used to diagnose sensitive parts of the human body, such as the chest, bones, skull, and teeth. For decades, medical experts have used to investigate and visualize fractures or abnormalities. It is a handy analytical tool used to clarify pathological changes and non-invasive features and economic considerations. Chest diseases can be irradiated with pleurisy stroke by analyzing cavitation, fusion, infiltration, and insensitive X-rays. X-rays can diagnose different diseases like pneumonia, bronchitis, infiltration, lumps, pericarditis, cardiac, fractures, and many more. A deep convolutional neural network (CNN) is used to achieve the smallest square error of accuracy to improve chest disease diagnostic performance. To this, existing deep learning networks are used to classify the most common chest diseases and provide comparative results. Back Propagation Neural Network (BPNN), convolutional neural network (CNN), and competitive neural network (CNN) is checked to categorize the common diseases seen on chest X-rays, one of which is bronchitis [76]. Emphysema is an enduring lung disease caused by shortness of breath because of excessive swelling of the alveoli. In people with emphysema, the lung tissues are weakened or destroyed; they are involved in gas exchange in the human body. Emphysema is also in a category of diseases category called chronic obstructive pulmonary disease [77]. Artificial neural networks (ANN) for medical image recognition have been effective for some time. But, due to the deficiency of ANN algorithms' growth, the recognition precision of complex medical images is not very high. Therefore, to calculate a feature amount of a medical image like SIFT, a conventional image processing technique is adopted. Deep learning methods using deep Convolutional Neural Networks (DCNN) for deep recognition and also image recognition tasks have been resolved with the same structures. DCNN learn region classification and organ extraction from accurate CT scan images taken from the entire body [78]. Cystic fibrosis is a genital illness that is likely to occur early in life, along with physical abnormalities in the lungs' tissues. The patients with the problem of cystic fibrosis have commonly had chronic rhinosinusitis. This can result in many problems in patients and can be life-threatening sicknesses. Texture classification is used to detect these types of abnormalities. This method is a cataract of a two convolutional neural network. The first network is used to figure out the presence of abnormal tissue. The second type of network is used to identify network structure abnormalities such as bronchiectasis and mucus obstruction. The proposed network of anomalous maps by learning only from patch annotations [79]. Deep learning (DL) solutions are proposed to explain various imaging modalities, including radiography, magnetic resonance imaging, and computed tomography. For chest X-rays, the DL algorithm has successfully evaluated deformities such as pulmonary nodules, cystic fibrosis, tuberculosis, pneumoconiosis, and the assessment of change or stability in sequential discovery radiographs. Chest X-rays are the most widespread radiological inspection and include many clinical signs that are absent and emerging. The objective was to assess the extent of the deep learning algorithm (DL) and to assess the stability of changes in a series of radiological imaging findings that detect conventional frontal chest X-ray (CXR) abnormalities [80].

Pleural effusion is an excessive fluid collected in the pleural cavity, which is filled with fluid surrounding the lungs. This surplus of fluid can damage breathing and limit lung expansion. The pleural disease's clinical treatment can be subdivided into respiratory chest surgeons, intensive care physicians, oncologists, cardiologists, and other infectious disease physicians. Thus, it is tough to standardize care, and the treatment of pleural effusion may be very different [81]. If the patient has a malignant effusion, he may take multiple treatments. The use of an indwelling pleural catheter (IPC) has revolutionized the management of pleural effusion. The case has been confirmed by radiation chest computed tomography (CT), pleural biopsy, pathology, pleural smear, and fiberoptic bronchoscopy. The normality of the variables is tested using the Shapiro-Wilk normality test. Median and quartile ranges are used to represent the distribution of pleural effusion. Because the variables were not normally distributed in the comparison between groups, the categorical variables used the chi-square test. Fisher's exact test applied the non-parametric Kruskal-Wallis test for constant variables [82].

Furthermore, Chen *et al.* put forward an approach that applies a neural network ensemble (NNE) method to diagnose lung cancer. This has an accuracy of 78.7%, which is more efficient than the LVQNN: 68.1%. Kuruvilla and Gunavathi proposed an approach that a texture feature using artificial neural networks (AAN), with a precision of 93.30% [83].

TABLE 4. Comparison of DL models for respiratory system.

Ref.	Published in	DL model	Results	Objective
		Asthma		
[69]	ICPRAM	MLP neural network	recision =0.72 Accuracy =80% F =0.747	To find the early stage of syndromic surveillance for asthma or difficulty breathing
[44]	Elsevier	DNN, CNN, and CAD	Accuracy = 98%	To determine whether objective examinations with typical asthma symptoms are most useful in improving asthma diagnosis accuracy.
[92]	Taylor & Francis	DNN, CNN, and LSTM	Accuracy = 0.951%	to predict sleep disorder in an asthma cohort.
		Chronic obstructive pulmonary		
[70]	ATS Journals	Deep learning CNN	Accuracy = 75%	To personalize disease prevention and management.
[71]	Cochrane library	DNN, RCTs	Accuracy = 95%	Compare the effects of short-term systemic corticosteroids and conventional long-term corticosteroids on the acute exacerbation of COPD in adults.
[72]	Springer	FFNN	Accuracy = 92.86%	To identify patients with acute deterioration and improve patient care and decision-making.
		Pneumonia		
[93]	arXiv	CNN	Accuracy = 95%	To detect pneumonia from chest X-rays.
[73]	arXiv	CNN	Accuracy = 95%	Developed to produce spinal magnetic resonance radiographic classification.
[94]	Springer	DL Algorithms	Accuracy = 95% sensitivity = 0.96	to detect abnormalities in chest CT images from COVID-19 patients.
		Influenza		
[74]	ACM	DL DSM, ANN	NA	To provide vital support for more accurate public health interventions.
[75]	Hindawi	DNN	Accuracy = 81%	To evaluate the clinical characteristics and consequences in incidentally detected lung cancer and in symptomatic lung cancer.
[95]	PLoS	Deep learning CheXNeXt algorithm	Accuracy = 95%	To understand chest radiography is important for detecting chest diseases such as lung cancer.
		Acute bronchitis		
[96]	Taylor & Francis	DNN	Accuracy = 90%	To examine areas of quality improvement.
[76]	ELSEVIER	CNN	NA	To diagnose and for treatment of cough due to acute bronchitis.
		Emphysema and Cystic fibrosis		
[77]	IEEE	CNN	Accuracy = 90.73% sensitivity of 85.65%	For diagnosis and management of patients with COPD.
[78]	Scientific research	DCNN	Accuracy = 99%	For region classification and organ extraction from accurate CT scan images taken from the entire body.
[79]	arXiv	CNN	NA	Identify network structure abnormalities such as bronchiectasis and mucus obstruction.
[80]	PLoS	Deep learning algorithm	Accuracy = 75.8%	To describe numerous imaging modalities, containing radiography, magnetic resonance imaging, and computed tomography.
		Pleural effusion		
[81]	SSRN	Deep learning and entropy weight method	Accuracy = 71 to 78%	Automate the diagnosis and treatment of pleural effusion.
[82]	AME	IPCs	Accuracy = 90%	Revolutionized the management of pleural effusion.
[97]	SPIE	CNNs	DSC = 0.690	segmentation of malignant pleural mesothelioma tumor.

In [84] a methodology of applying the stacked autoencoder (SAE) with an accuracy of 75.01%. Shen *et al.* diagnosed lung cancer on the LIDC database by using 2-layer CNN with an accuracy of 86.84% [85]. For dementia, grey level co-occurrence Matrix (GLCM) and SVM based classification is used. In this effort, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to pre-process raw imagery before extracting the feature. In AD, 3 phases were performed, i.e., landmark definition, detection, and classification between AD and HC (healthy control). AD classification uses only one layer of CNN and proposed a modified Alex Net architecture [86]. Shinohara [87] gave an overview of deep neural networks that assimilate various hidden layers trained by utilizing some of the new methods that transcend GMMs - HMMs on speech recognition benchmarks. Deng *et al.* [88] gave an overview on the summaries of the papers that were part of the session at ICASSP- 2013, named as "New Types of Deep Neural Network Learning for Speech Recognition and Related Applications'. Acoustic models can likewise be appropriate and improve execution in another sign handling applications. It reviewed Microsoft's effort since the year 2009, showing that improvements should be made on acoustic measurements' features [89]. For computational-phonological outlook, Li *et al.* [90] put forward the basics solutions for automatic spoken language recognition and modern noise-robust practices for automatic speech recognition. It differentiates amongst the various noise-robust methods. It also provides inclusive insight into the working complex back-and-forth. Respiratory diseases and disorders that represent major global health problems account for more than 10% of all disability-adjusted life years (DALY). The scale is used to analyse health and public health impacts and predict healthy life span due to diseases—medical, disabled, or untimely. Cardiovascular disease is the second leading cause of death from respiratory diseases, and the incidence of disability affects the global economy and medical costs. Chronic obstructive pulmonary disease (COPD) and asthma will increase the burden in more cases of respiratory diseases. Three random forest classifications are used, including individual, generic classifier and adaptive weight classifier, and radio data from subjects are processed in four modes. The results show that the breathing action is individual and depends on the environment. The posture classification accuracy of generic classification reaches 21.9±1.7%, but the weighted adaptive classification and individual classifier show very high scores, reaching 98.8±0.6% and 98.9±0.6%, respectively. After the occurrence of respiratory diseases or respiratory diseases such as chronic obstructive respiratory disease (COPD), asthma, and apnea, respiratory behaviour can be managed accurately and objectively [91].

IV. APPLICATIONS, METHODS AND DATA SETS USED IN HEALTHCARE

This Section discuss different applications, Data sets, Methods or tools, etc. used in healthcare systems using deep learning models.

A. APPLICATIONS OF DL IN HEALTHCARE

1) TRANSLATIONAL BIOINFORMATICS

The objective of the study of Bioinformatics is to understand biological procedures at the molecular level. The Human Genome Project (HGP) provides a huge number of unmapped data and allows new hypotheses about the interaction of genes with environmental aspects to generate proteins. Other developments in biotechnology helped decrease the price of genome sequencing and concentrate on disease diagnosis, prognostic, and treatment by evaluating genes and proteins [6]. Further studies can be applied to bioinformatics and are categorized into 3 parts: diagnosis of biological causes, disease prevention, and personal treatment. Genetics examines the functions and structure of information encoded in living cell DNA. We can also say that alleles expressing genotypes and phenotypes are analyzed. Genomics aims to classify genes and alleles of habitat that contribute to ailments such as cancer. By identifying these types of genes, it allows the design of targeted therapies [98].

2) MEDICAL IMAGING

In modern medicine, automatic medical image evaluation is very critical. The diagnosis, which is based on the scanned image, can be very subjective. The Computer-Aided Diagnosis (CAD) comes up with an actual assessment of the current primary disease process. In many neurological conditions, disease modeling is common, like strokes, multiple sclerosis, and Alzheimer's. Using multi-modal statistics, the brain's thorough areas and an examination of the brain scan can be done, which is needed in these types of diseases [99]. In recent years, for medical imaging research, CNNs have been adapted very fast due to their remarkable functioning and capability to parallelize with GPUs. In the latest study, CNN methods in brain pathology segmentation and neural networks in computer-aided design, shape evaluation, segmentation, have generated encouraging results in health informatics and biomedical [100]. Also, Speech recognition can produce documents in less time as compared to typing. Persuasive sensing for health care Implantable, wearable ambient sensors in persuasive sensing permit a constant supervising of health and safety. To tackle flabbiness, the precise estimate of food consumption and energy outflow during the day can be used. The ambient sensors and wearable can be used for older patients with persistent diseases. They can enhance the value of care by allowing patients to residing freely in their homes. Wearable, human activity recognition, and implantable devices have also improved the care for patients with disabilities and those undergoing rehabilitation. The consistent observation of crucial indications, such as respiration rate, blood pressure, and body temperature, is crucial for patients in critical care; these are essential for getting better results by closely examining the patient's condition.

3) MEDICAL INFORMATICS

Medical Informatics concentrates on the evaluation of huge collected statistics in healthcare, with the purpose to improve and build clinical assessment support systems. It can measure medical records both for quality guarantee and availability of health care facilities. Electronic Health Records (EHRs) are a deep source of patient information, including comprehensive medical histories, such as diagnostics, diagnostic tests, current treatment and plans, allergies, immunization records, radiological imaging, and multivariate time series sensors laboratory and its test results. Effective big data extraction provides useful insights into disease management [101], [102]. However, this is not insignificant for numerous reasons: The complexity of the data due to the variable lengths, improper sampling, the missing data, and the absence of structured reports. The worth of reports differs significantly among people and agencies. More than a few petabytes of modal databases containing medical images, lab results, sensor data, and unstructured text reports a Long-term dependency among clinical events and the identification and medication of disease that makes learning complicated. The accomplishment of DNNs depends on the ability to learn new features/patterns to identify the representation of data both in a supervised hierarchical and unsupervised way. The DNN has been shown to effectively manage multi-modal data as it can merge numerous DNN architectural components

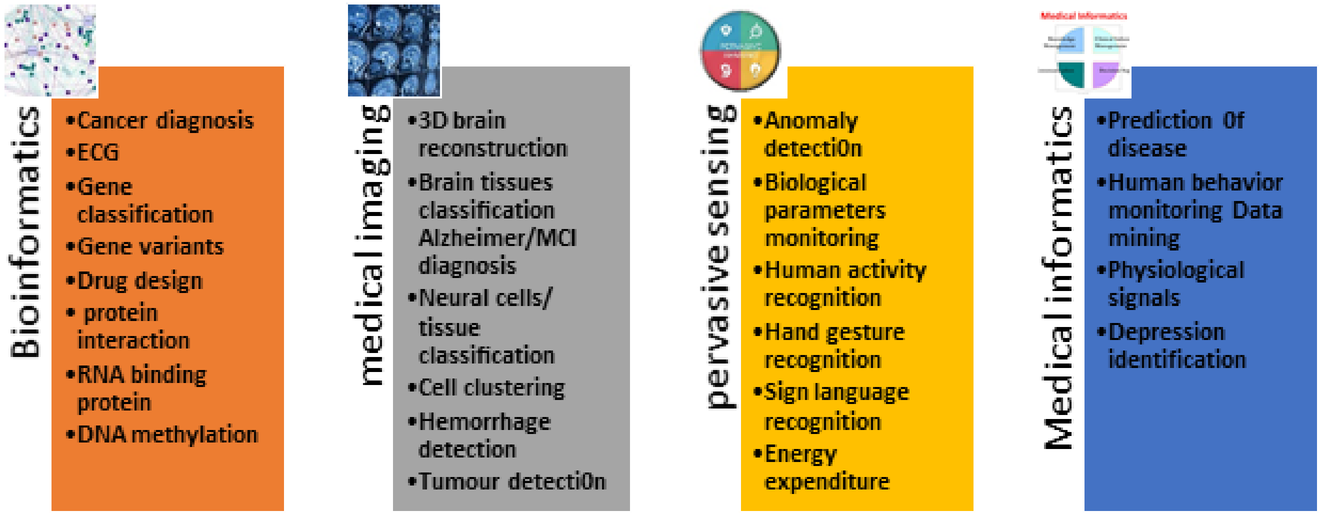

FIGURE 7. Deep learning application.

simultaneously [66]. Figure 7 represents different applications of deep learning that show various medical fields.

B. DL BASED METHODS USED IN HEALTHCARE

The computer models learn to perform the classification task directly from the data set in deep learning. To train the computers, it needs different deep learning methods. This section provides information about the different algorithms used to prepare the computer system in health care.

1) ANN ALGORITHM

The ANN algorithm is used in a biological brain to prototype the functionality. The model is made with a structure consisting of input, hidden, and output levels. Each nerve cell or neuron is associated with each neuron in the following layer via a link. A nerve cell consists of dendrites (input), axon (output), core (activation function), node (sum), and synapses (weight). Unfortunately, the ANN structure is sensitive to conversion and modification, which can negatively influence classification performance. To remove these flaws in ANN, a convolution neural network (CNN) architecture guarantees transformation and modifies invariance.

2) CONVOLUTION NEURAL NETWORKS (CNNs)

In the 1960s, a proposal was given for CNN, which is a multi-layered neural network; it consists of layers and is monitored by fully connected layers afterward. As the basic features, Local perception helps in finding out some local features of the data, which is an effective identification method. CNN's are simpler to train and have many fewer limitations than fully connected networks having the equivalent number of hidden units. Two types of layers are usually used in CNN, i.e., the Convolution layer and the pooling layer [103]. The pooling layer operation includes 2 types of pooling, which are mean pooling and max pooling. The function of mean pooling is to analyze the median region within the feature points. Altogether, max-pooling calculates the neighborhood within a maximum of feature points. The neighborhood's size is controlled by the estimated variance (EV) and convolution layer parameter, whereas the approximate inaccuracy is occurred by the mean deviation (MD). Mean pooling cutbacks, the EV maintains information of image background.

3) DEEP NEURAL NETWORK (DNN)

In a Deep Neural Network, the number of hidden nodes is increased in a simple neural network. The neural network executes more complicated input calculations, as each obscure layer can be the nonlinear conversion of the output. The notation f(x) is used; when the activation function is linear, it is matched with the particular hidden layer neural network. The intensity of the hidden layer does not improve the capacity to express. Various network layers are applied to obtain the attributes of the pulmonary nodules concerning diverse sizes. In the training process, to save a significant amount of comprehensive information of the image, the original image is utilized as the input layer parameters. These parameters are too susceptible for overfitting, fine-tuning, increased data volume, and regularization required for solving.

4) STACKED AUTO-ENCODER (SAE)

SAE neural network is a multi-tier auto-encoder, which is an unsupervised learning algorithm. This network is categorized into three layers: the input layer, hidden layer, output layer, and the coding stage and decoding stage. The quantity of neurons in the input and output layers is equivalent. The coding stage is the planning of the input layer to the output layer, and the interpreting stage is the planning of the concealed layer to the yield layer. The analysis of lung knobs has a place with the issue of picture order for which each SAE erases the translate layer and legitimately utilizes the encoding cycle for the following SAE preparing of the yield. In table 5 compares different DL model.

TABLE 5. Outcomes for all architectures.

Models	Accuracy	Sensitivity	Specificity
CNN model	80-85%	80-83%	80-85%
DNN model	80-84%	78-80%	80-85%
SEA model	80-85%	80-83%	79-80%

5) MULTILAYER PERCEPTRON (MLP)

MLP consists of nodes of 3 layers: an input layer, hidden layer, and output layer. Each input node uses a nonlinear activation function. It uses the backpropagation technique for training. This function maps the weighted inputs to the output of each neuron. It helps in distinguishing data that is not linearly separable. MLP is one of the most comfortable models; other designs often integrate fully linked neurons in their last layers. Long-Short Term Memory LSTM contains the knowledge of previous stages and can be used for memory or stage awareness. It consists of memory cell blocks along with gates. These gates control the storing, reading, and writing of the cell. This LSTM keeps long-term dependencies that is why they are great for learning purposes.

C. DATASETS

Datasets are a collection of instances that all share a common attribute. Once you feed these training and validation sets into the system, subsequent datasets can then be used to sculpt your machine learning model in the future. The more data you provide to the ML system, the faster that model can learn and improve. Datasets are fundamental to foster the development of several computational fields, giving scope, robustness, and confidence to results. Datasets became popular with the advancement of artificial intelligence, machine learning, and deep learning. The National health organization and nutrition examination survey datasets for the United States (NHANES) [104] and South Korea (K-NHANES) are utilized for training the machine learning classifiers and deep learning algorithms. NHANES is a wide-ranging analysis to evaluate the health and nutritional significance of the USA's overall inhabitants. It comprises nutritional, demographics, and many other survey data and medical research, and several laboratory examinations. NHANESA and K-NHANES both used certified tools to test the depression for the overall population. Between 1999 and 2004, NHANESA utilized the computerized version of the world health organization, i.e., CIDI-Auto 2.1, which was created to evaluate psychological syndromes, and it is specifically appropriate for significant populations (Andrews and peters, 1998). From 2005 to 2014, a new certified diagnosis device for depression, i.e., PHQ-9, replaced the previous CIDI-Auto 2.1 for NHANES. PHQ-9 comprises "depression from a diagnostic and statistical manual of mental disorders IV" (DSM-IV) (Kroenke and spitzer). This tool is consistent and valid in measurement for diagnosing depression. Table 6 provides the summarized facts of all DL methods.

TABLE 6. Summary of deep learning models.

Model	Applications used in Healthcare	Advantages of models	Limitations in the models
CNN model	Abnormal Heart Sound Detection [105] Myocardial Infarction Detection [106]	Performance is better for 2D data. Model learning is quick.	Categorized data is required for grouping.
RNN model	Heart malfunction recognition onset [69], categorization of lung malformations [107]	Study sequential events and model time dependencies. Require better precision for speech & character recognition and also for NLP associated tasks.	Large datasets required and it has several problems because of gradient vanishing.
DBN model	Foresee Drug combination [108], recognition of type 1 diabetes	Reinforces supervised and unsupervised learning models.	Expensive training procedure.
DNN model	Heart Sound Recognition [109], Phono-cardiography [110]	Better accuracy	The training process is not a trivial and too slow learning process.
GAN model	Producing synthetic brain CTs [111], Reforming natural illustrations from brain movement [112], Medical imaging platform [113]	Decent process for training classifiers	Learning for generating and training discrete data is challenging.

TABLE 7. Tools used for deep learning.

Tools	Ranked
Tensor flow	1
Torch/PyTorch	2
Sonnet	3
Keras	4
MXnet	5
Gluon	6
Swift	7
Chainer	8
DL4J	9
ONNX	10

D. DEEP LEARNING TOOLS

Tools and algorithms are the major parts of any system. In deep learning, tools are used to convert data into actionable info. The top 10 tools ranked in 2019 are in the table 7.

V. RESEARCH OPPORTUNITIES AND CHALLENGES

In this section, we discuss the challenges and opportunities related to deep learning in healthcare. Despite promising results received in the given field, some challenges still need to be resolved.

A. DATA COLLECTION

Deep learning implies a set of extremely intensive computational models. A fully connected multilayer neural network is its typical example. The network needs to correctly estimate a large number of network parameters [114]. A large number of data is the basis for fulfilling the given goal. Generally, there are not any guidelines fixed about the minimum number of data set or training documents. A general rule is to have at least 10x as a sample of parameters to be available in the network, that's why deep learning is more successful where there is a large amount of available data. Though healthcare is a distinct domain, and there is not any standard data collection procedure. Different data sources have been used in various studies and research papers, which results in difficulty in fairly comparing the results among other datasets. Moreover, it is challenging to acquire high-quality data and annotate many recent works using the old dataset [115]. The most current database used is physio Net computing in cardiology challenge 2017 and china physiological signal challenge 12 lead 2018 both used high-quality data. Still, it only focuses on short-term ECG recordings [116]. Research opportunities are available in the long term, high-quality ECG datasets with observations, such type of dataset would motivate new studies.

B. DOMAIN COMPLEXITY

The issues in healthcare and biomedicine are more complex, unlike other domains. The diseases are extremely diverse, and there is still significantly less knowledge about their causes, how they spread, and the cure for them for many diseases. Sometimes, the number of patients is very limited, so we can't acquire enough datasets. But this challenge can be solved in the future. Due to the small number of patients, we should capture every patient's possible information and find a novel method to process all acquired data and include these data sources. Moreover, we can exploit the tiered nature of deep learning. We can separately process every dataset with an appropriate method of deep learning and put the representation of the result into a general model (e.g., deep Bayesian approach or layers of advanced encryption standard) to extract patient data as a whole [114].

C. INTERPRETABILITY

Deep learning models are generally contemplated as black-box models. They usually have several model parameters or complicated model architectures. It becomes difficult to understand the results in generating such models. In the medical and medicine field, the quantitative algorithm's performance is important, and why and how the algorithm work is also important. Since medical experts do not accept unexplainable diagnoses, the problem is even more serious in the medical field. The ability of both models to explain performance and interpretability is important for health issues. Doctors are unlikely to use an incomprehensible system. Deep learning models are known for their outstanding performance. However, it is important to explain and understand the results obtained using this model when describing a stable system. For this issue, it is needed to involve the algorithm to explain the deep learning models and methods used to support the existing tools that explain the given data-driven system [117].

VI. CONCLUSION

This paper elaborated the deep learning models applied to healthcare to diagnose the diseases of three major human body system. The deep learning models are categorized according to supervised and unsupervised learning techniques. Due to these algorithms' significant importance, medical devices should be built over time based on these models, such as the microscope, phonendoscope, and electrocardiogram, accommodating physicians' perceptive capability limitations. In processing and forecasting from large datasets, deep learning is playing a critical role. Many researchers used deep learning with EHR data because it provides a solid predictive outcome. We compared different diseases based on different factors and parameters. Different DL applications and algorithms, tools and data sets are also compared and laid down research opportunities and challenges. Concluding all, research on deep learning models in healthcare is extensive, and still, many challenges are laid forward. We hope that our survey may be a new step towards the invention techniques applied in healthcare and may lead to more intelligent systems.

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