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Research Article

Analysis of Deep Learning Methods for Healthcare Sector - Medical Imaging Disease Detection

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Abstract: In this paper, artificial intelligence (AI) and the ideas of machine learning (ML) and deep learning (DL) are introduced gradually. Applying ML techniques like deep neural network (DNN) models has grown in popularity in recent years due to the complexity of healthcare data, which has been increasing. To extract hidden patterns and some other crucial information from the enormous amount of health data, which traditional analytics are unable to locate in a fair amount of time, ML approaches offer cost-effective and productive models for data analysis. We are encouraged to pursue this work because of the quick advancements made in DL approaches. The idea of DL is developing from its theoretical foundations to its applications. Modern ML models that are widely utilized in academia and industry, mostly in image classification and natural language processing, include DNN. Medical imaging technologies, medical healthcare data processing, medical disease diagnostics, and general healthcare all stand to greatly benefit from these developments. We have two goals: first, to conduct a survey on DL techniques for medical pictures, and second, to develop DL-based approaches for image classification. This paper is mainly targeted towards understanding the feasibility and different processes that could be adopted for medical image classification; for this, we perform a systematic literature review. A review of various existing techniques in terms of medical image classification indicates some shortcomings that have an impact on the performance of the whole model. This study aims to explore the existing DL approaches, challenges, brief comparisons, and applicability of different medical image processing are also studied and presented. The adoption of fewer datasets, poor use of temporal information, and reduced classification accuracy all contribute to the lower performance model, which is addressed. The study provides a clear explanation of contemporary developments, cutting-edge learning tools, and platforms for DL techniques.

***Keywords*:** deep learning, deep features, medical image classification, DL techniques, healthcare sector analysis

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1. Introduction

In this age of algorithms, numerous industries, including manufacturing, transportation, and government, have seen significant transformations due to the frameworks of machine learning (ML) and various deep learning (DL) techniques. DL has had a significant impact on many scientific fields in recent years [1]. With respect to the advancements in AI (artificial intelligence) technology, the world is currently growing quickly. The use of AI techniques in healthcare is increasingly common for precise illness diagnosis, patient risk assessment, and clinical research. These approaches vary from ML to DL. AI is concerned with how intelligent robots act to mimic human behavior and use algorithms that can be successfully developed using machine technology. The current models for disease classification in healthcare systems either involve ML or DL.

Since it helps with diagnosis and medication analysis, precise medical picture classification has become increasingly important in the last few years. One of the most crucial concerns in the field of image detection is the classification of images for medical purposes. The main goal is to categorize medical images into different categories to aid clinicians in identifying the precise ailment and use them for further research. Medical picture classification often involves two phases. Getting useful features out of the image is the first step. The next stage is to build models to categorize the clinical data using the features.

Given the complexity of the data, it has become more appealing to apply ML and different techniques of data mining, such as deep neural networks (DNNs), to analyze such data. To develop trustworthy assessment methods utilizing ML models and data-driven techniques, establishing the correlations between all the various patient data formats is a fundamental challenge.

This systematic literature review is intended to supplement existing research by providing the following contributions to the DL approach in medical image data processing. In this review work, we divided DL techniques utilized between 2015 and 2019 into two groups: single DL and hybrid DL. Single-supervised learning refers to techniques that only use DL architecture to create their models. On the other hand, hybrid DL refers to processes that combine DL with other classical ML models. This is how we compare the benefits and drawbacks of DL techniques to models that use both traditional ML algorithms and DL design.

In the last ten years, numerous ML and various AI concepts have been employed to efficiently evaluate the vast amounts of data in the healthcare industry. For instance, a statistical regression-based methodology was proposed to create an automated early detection system for heart disease [2]. Medical imaging has also used ML to automatically identify object attributes [3]. DNN-based techniques are garnering a lot of attention among the many ML models, especially when it comes to the analysis of large datasets. DL approaches, which go through a number of stages in the learning process, are used to filter data through a cascade of layers. DNN models outperform many conventional ML models because, as they process enormous volumes of data, they become more accurate. Processing of natural language and image processing have both shown outstanding performance using DNN-based techniques [4-7].

In light of the success of DL techniques in other disciplines and their swift ongoing improvement in the proposed methodology, these models are quickly emerging as the most innovative and fascinating tools to analyze health records. DL models using biomedical and healthcare data have been used in a wide range of projects. As an illustration, Google DeepMind [8] and IBM Watson [9] have created a computer-based support system that helps analyze healthcare information [10]. The left ventricle (LV) may be segmented using short-axis cardiac magnetic resonance imaging (MRI) with the help of a deformable model, and this model's parameters have been effectively encoded using DL [11]. A separate DL model based on RBM (restricted Boltzmann machines) in medical imaging was utilized to extract biomarkers from MRI data [12].

Here, the overall effectiveness of each method is described in more detail, and mainly the learning curve of the present DL healthcare is again highlighted. Recently, the survey of deep electronic health record (EHR) [13] identified unique deep-gaining knowledge of strategies that can be hired on digital fitness records (EHR). They mentioned the medical packages utilized by unique DL fashions and diagnosed numerous barriers to modern-day DLs consisting of version interpretability, statistical heterogeneity, and the absence of familiar benchmarks. At last, deep EHR concludes the brand-new fashions and diagnosed results for destiny.

In diverse, deep EHR critiques of unique deep gaining knowledge of strategies on digital fitness records, our assessment paper specializes in hybrid deep gaining knowledge of strategies tailor-made to early disorder detection. While our survey indicates a few impediments for single and mixed DLs in the health area, as well as deep EHR, it highlights multiple barriers for DLs using EHR. Our analysis employs the same contemporary categorization measures to highlight the area under the curve (AUC), precision, and responsivity of single-hybrid DL, somehow like deep EHR, and basically points to criteria of DLs including AUC and other accuracy parameters like P (precision), R (recall), and F1 score. This assessment document examines the length of current DL-schooling, health care systems (HCSs) in contrast to deep EHR. While a few research studies have comparable research and assessment metrics, outcomes aren't without delay similar because of the proprietary nature of the data sets.

Personalized treatment is increasingly dependent on the analysis of medical data. For instance, customized cancer treatment aims to give proper care to sick patients by considering a variety of patient-specific factors, including genetic variations, the patient's environment, imaging genetics, current medications, and lifestyle. A vast and complicated amount of health data has been collected in the last ten years by current technologies like genomics, imaging, and lifetime monitoring, enabling researchers to give patients improved therapies. Despite the abundance of data, we still lack a thorough understanding of diseases and effective patient treatments.

For specialized bioinformatics comprehension, Lan et al. [14] provided an overview study on statistics mining and in-depth learning techniques. DL approaches are summarized, along with the advantages and disadvantages of cleaning, segmentation, grouping, and improved neural community structures. Our overview study, in contrast to this effort, deals with more original DL research that is combined with several conventional device learning methodologies. The survey of this paper additionally specializes in unique deep-gaining knowledge of strategies used to become aware of disorder detection. Even the overall performance assessment is not protected, as mentioned in [14]. Overall, the author has specialized in brand-new research that has deep-gaining knowledge of techniques for disorder detection and the evaluation of massive statistics within the subject of healthcare [15, 16]. In this assessment, four deep-gaining knowledge strategies are decided on by means of pointing to the fitness care (HCS) system within the length of the years 2015 to 2019.

Convolutional neural networks (CNNs), deep-belief networks (DBNs), auto-encoders (AEs), and recurrent neural networks (RNNs) are the four architectures under question. The disorder detection software commonly uses these structures [17, 18]. The year-wise growth and research distribution for DL articles in HCS is depicted in Figure 1. The following list can be used to summarize significant contributions are:

- A taxonomy of the most widely utilized DL techniques in the medical field.
- The tremendous insights into the precision and applicability of DL trends in healthcare solutions.
- Discussing the center technology that could reshape deep-gaining knowledge of techniques in healthcare technology.
- Presenting open problems and demanding situations in modern-day deep-gaining knowledge of fashions in healthcare.

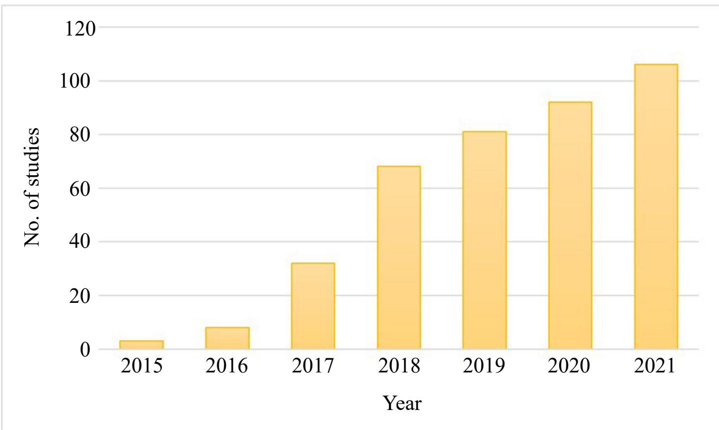

Figure 1. DL approaches for healthcare per year [14]

Table 1 indicates the analysis of different existing methods.

Table 1. Analysis of existing classification methods

Author name	Technique used	Dataset used	Merits	Demerits	Performance (%)
Alshazly et al. [19]	Deep CNN	SARS-CoV-2 and COVID19-CT	High scalability and robustness.	Non-accurate localization of abnormal image regions.	Accuracy- 92.9
Zheng et al. [20]	3D DNN	Real-time data	Storage complexity is reduced.	Inaccurate design, network training and non-utilization of temporal information.	AUC-95.9 PR-97.6
He et al. [21]	2D and 3D CNN	CC-CCII	Effective pre-processing can be carried out.	Limited classification accuracy and increased time complexity.	Accuracy-87.62
Shah et al. [22]	CTnet-10 and VGG-19 model	COVID-CT	Improved detection accuracy can be attained.	Experimentation can be done only on binary classes.	Accuracy-82.1 (CTnet-10) Accuracy- 94.5 (VGG-19)
Purohit et al. [23]	CNN	Public database from GitHub	Discontinuity information can be obtained efficiently.	FPR and testing time is high.	Accuracy-95.38

The medical image classification of these existing methods indicates various constraints that have an impact on the performance of the whole model. Due to growing complexity, poor design, and the training network, some limitations exist, such as improper localization of abnormal picture regions. The adoption of fewer datasets, poor use of temporal information, and reduced classification accuracy all contribute to the lower performance of the model, which is addressed. Moreover, a lengthy processing time is needed for performance estimation, and the likelihood of incorrect forecasts is higher. These difficulties make it impossible to classify computed tomography (CT) scans precisely.

The structure of the current review is described as follows: A variety of research techniques are described in the second section. The definition, framework, algorithm, and architecture of DL techniques are discussed in the third section. The top DL illness detection techniques are presented in the fourth section. Open questions, difficulties, and this paper's findings are offered in the fifth and sixth sections.

2. DL Framework

2.1 *Architecture and algorithms of DL*

An artificial neural network (ANN), a pair or more convolution layers, is the simplest description of a DL architecture that seeks to increase prediction accuracy [24]. In comparison to typical ANNs, DL uses a lot more hidden layers. In a typical DNN, an output is produced by processing a weighted input value with bias correction and a non-linear input vector, such as the SoftMax function. As an output, a DNN's weights are optimized during training in order to reduce the loss function [25]. Figure 2 displays the ontology of popular DL models used to examine HCS data together with a few chosen applications, particularly in illness identification.

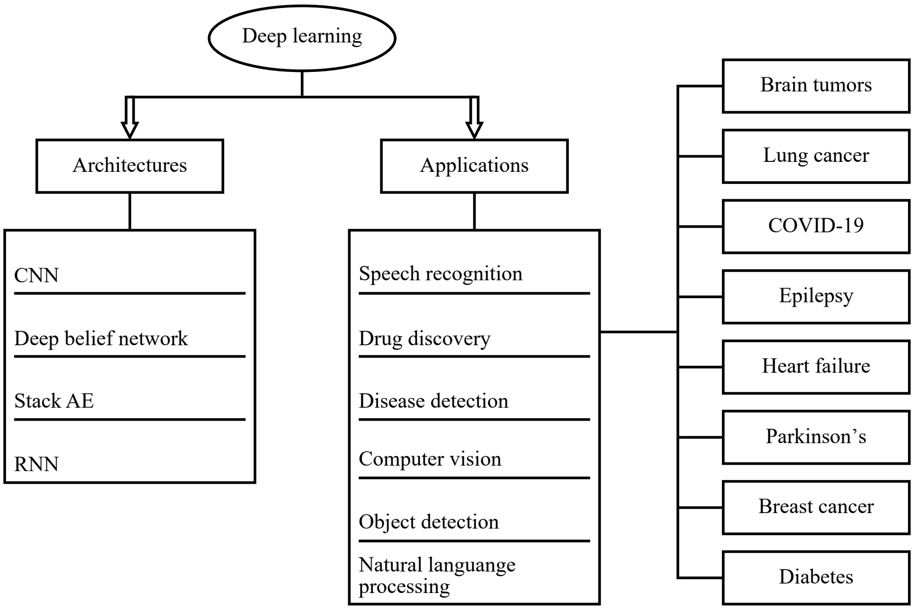

Figure 2. For the analysis of the data in health systems, prominent DL architectures are categorized [20, 21, 24]

2.1.1 *RNN*

Recognition of patterns in sequential or stream data, including voice, writing, and text, is done using RNNs [26].

Every one of the earlier inputs is saved in hidden units of a state vector, and the outputs are computed using these state vectors. RNNs compute the new output by considering both the current and prior inputs. The fundamental issue with RNNs, despite their promising performance, is the diminishing gradient during data training [27]. The structure of RNNs contains a cyclic connection. These hidden unit cyclic connections carry out the recurrent computations for processing the data input sequentially [28].

One method to address this issue is to use Gated Recurrent Units (GRUs) and Long Short-Term Memory networks, which have a long-term capacity for storing sequences [29, 30]. Figure 3 depicts the architectural layout of an RNN. Besides encouraging success using GRU to deal with the issue of vanishing gradients, the success of this strategy is very high because connections between the first two layers are undirected; they are reliant on the input data, whereas connections between all subsequent directed layers [31-33].

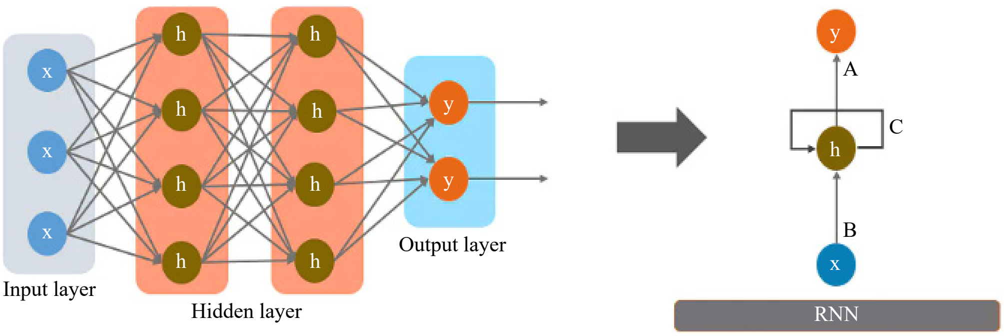

Figure 3. Architecture of RNNs [22]

2.1.2 *CNN*

CNN is an architecture for supervised DL. Applications involving image analysis are its principal use cases [34, 35].

CNN employs three different types of layers: convolutional (the main building block), pooling (to reduce the dimensions of feature maps), and fully connected (which is nothing but output from the other two layers). The input data as the image is processed modifies the convolutional layer with kernels or filters to create different feature maps [36]. Each feature map's size is decreased in the pooling layer to minimize the number of weights. This method is often referred to as subsampling or down-sampling [37]. There are numerous types of pooling techniques, including average, maximum, and global pooling. For the final classification following the layers, the completely linked layer is utilized for one-dimensional vectorization of two-dimensional feature maps [38-40].

Deepr [41] offers an end-to-end solution for extracting essential details from medical records and predicting anomalies. A CNN is used to anticipate unexpected readmissions following discharge by applying it to a series of discrete elements. A DL approach was later used by Gnanasankaran et al. [42] to investigate the temporal aspects of patient EHRs. The convolution operator was applied to the patient EHR matrices' time dimension in the proposed DL's second layer. To incorporate the integration of the EHR's temporal smoothness into learning, early, late, and slow fusion are used as temporal fusion strategies in the model [43].

A CNN design with two convolutional layers is shown in Figure 4. A pooling or subsampling layer came after each fully connected layer. A fully linked layer and a final output layer both receive the output of the final pooling layer.

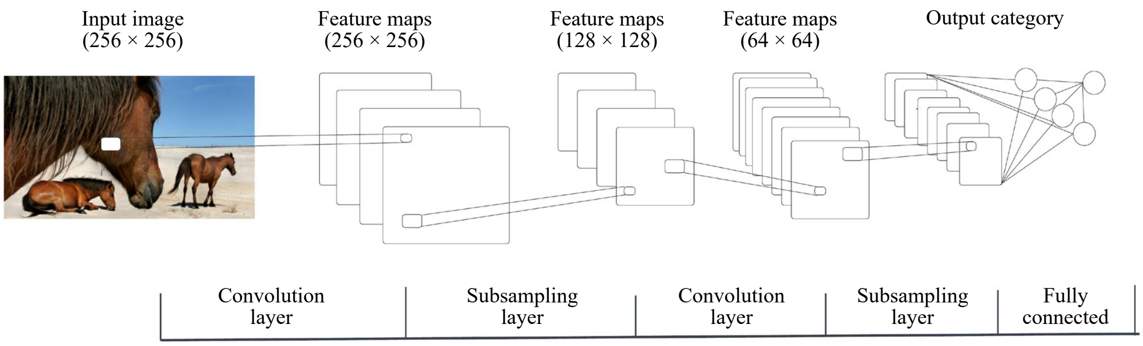

Figure 4. CNN architecture [40]

2.1.3 *The deep belief networks (DBNs)*

The DBNs are capable of learning high-dimensional data manifolds. Directed and undirected connections are seen in DBNs, a multi-layer hybrid network [44]. While all other connections between levels are directed, The upper two layers do not directly connect to one another. DBNs could be thought of as a pile of greedily trained Boltzman machines with restrictions (RBMs) [45]. The RBM layers communicate with one another as well as with earlier and later layers [46-48]. A feed-forward network and multiple RBM layers serve as feature representations in this model [49]. RBM merely contains two layers: a hidden and a visible layer [50]. The structure of the DBN methodology, which was adapted from [51], is shown in Figure 5. In this diagram, "v" represents deep belief mode's stochastic visible variable. The architecture of the DBN technique, which was adapted from [51], is shown in Figure 5, where v is the deep belief model's stochastic visible variable.

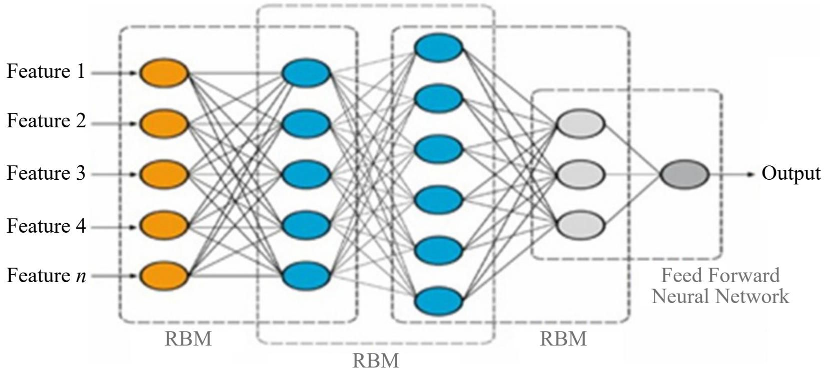

Figure 5. Architecture of DBN [51]

2.1.4 *AE*

An ANN called the AE seeks to efficiently code the data. As a result, it can be applied to network startup or feature reduction. It does this by translating the information through a network of linked neurons to itself. Unsupervised learning is categorized as AE, which encompasses sparse autoencoder (SAE), variational autoencoders (VAE), and denoising auto encoder (DAE) [52]. A neural network called AE with denoising, which was developed from AE, mostly considers collecting features from various noisy and unclear datasets. The DAE has three layers: encoding, decoding, and input layers. DAE may be used to produce advanced features. Stacked Denoising Auto-Encoder (SDAE) is a different DL technique that has always just been applied for reducing dimension, which is nonlinear in nature. The architecture of the DAE approach is shown in Figure 6, according to [53].

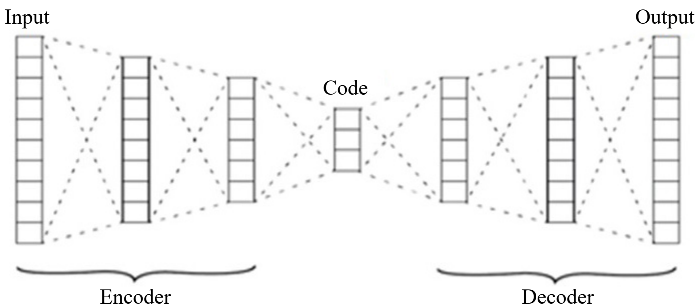

Figure 6. Architecture of AE [53]

Table 2. Review of the study on how DL designs utilized in the health system sector are influenced by neural networks

Architecture	Summary
RNN	RNNs are helpful for processing data streams [53]. The value of every output depends on the preceding iterations, and they are made up of a single network that completes the identical task for each sequence element. Due to vanishing and expanding gradient issues, RNNs could only go back a few steps in the original formulation. By modeling the obscured state, which contains cells that decide what information to keep in memory based on the input value, the current memory, and the prior state. In applications involving natural language processing, these modifications achieved excellent results [54] and are effective at capturing long-term interdependence.
CNN	CNNs were designed using the visual brain anatomy of cats [55, 56]. CNNs use feature merging after local contacts and associated weights across the units to get translation-invariant descriptors. The basic CNN design consists of one pooling and convolutional layer, optionally continued by a completely connected layer for monitored prediction. To model the input space more accurately, Over ten convolutional and pooling layers are frequently used in CNN architectures. The best applications of CNNs have been created by computer vision [57]. CNNs often require a large data collection of labeled documents in order to be properly trained.
AE	An AE is a model of unsupervised learning in which the input and target values are identical [58]. A decoder that maps the input into a low-dimensional representation and reconstructs the input value from this low-dimensional representation that makes up an AE is nothing but a decoder. The goal of AE training is to reduce reconstruction errors. It is possible to find important patterns in the data by requiring the implicit representation's dimension to vary again from the input. AEs are frequently regularized by including noise in the original data and are mostly utilized for learning low-dimensional representation.
Deep Boltzmann machines (DBMs)	Using data from the input space, a DBM is a stochastic model that is generative and adopts a posterior probability [52, 53]. confined to the requirement that its neurons form a bipartite graph; Boltzmann machines are known as DBMs. There are only symmetric interactions between pairs of nodes in each of the two categories; there aren't any interactions among nodes within a group. In comparison, Boltzmann machines have a general class, which permits hidden unit connections; this constraint enables more effective training techniques.

3. DL: Medical imaging and detection of disease

This section comprises a variety of DL algorithms used in the medical field to distinguish between healthy and unwell people. Finally, here, some of the effectiveness of DL is highlighted for differentiating between infectious and healthy individuals.

3.1 *Medical imagery*

In image processing, namely in the analysis of central nervous system MRI scanning to forecast Alzheimer's disease and its variants, DL was first applied to clinical data [54]. CNNs have been used for the automated segmentation of cartilage and the prognostication of osteoarthritis in low-field knee MRI data in other medical fields. Despite using 2D photos, this method outperformed a cutting-edge technique that used manually chosen characteristics with a 3D multiscale. Additionally, supervised learning was used for the evaluation of patients with benign versus malignant breast masses from CT and to segment chronic regions in multi-channel 3D MRI [55].

In a more recent study, Yin and Zhang [56] employed CNNs, which help to recognize the various retinal fundus, diabetic retinopathy, achieving more specificity and sensitivity across around nine to 10,000 different test photos in comparison for certifying the ophthalmologist's annotations. On a huge data set for a variety of skin cancers, CNN also produced categorization results that were on par with those of 21 board-certified dermatologists.

3.2 *Disease categories*

Here, we examine various approaches based on different categories of disease. This section focused on the significant DL techniques, along with performance variations and applications in various categories of disease.

First, those that have received extensive DL model research. Second, those who used DL models to address problems or produce encouraging outcomes.

The DL approaches utilized to combat these diseases are covered in full below.

3.2.1 *Breast cancer*

After that, [59] presented DL architecture with two layers to classify benign and malignant breast cancers using shear wave elastography, which contains a Boltzmann machine that is confined and also one that is point-wise gated. The method's accuracy, specificity, AUC, and sensitivity were compared to statistical parameters that characterize image intensity and texture. A computer-aided disease diagnosis machine using DL techniques to identify, divide, and categorize masses in mammograms was introduced by the authors in [57, 58]. They thought about three steps — detection, segmentation, and classification — to do this:

For mass detection, a series of DL-process including convolutional, deep belief, and conditional random field (CRF) was suggested. To boost the performance of handcrafted features, it was suggested to use a DL classifier for mass recognition and a deep structure output for mass separation. CNN received training to divide the mass into two categories. The handcrafted features were used to estimate a regressor in the first phase, and the CNN model was tweaked in the second phase. Figure 7 illustrates the method's architectural layout.

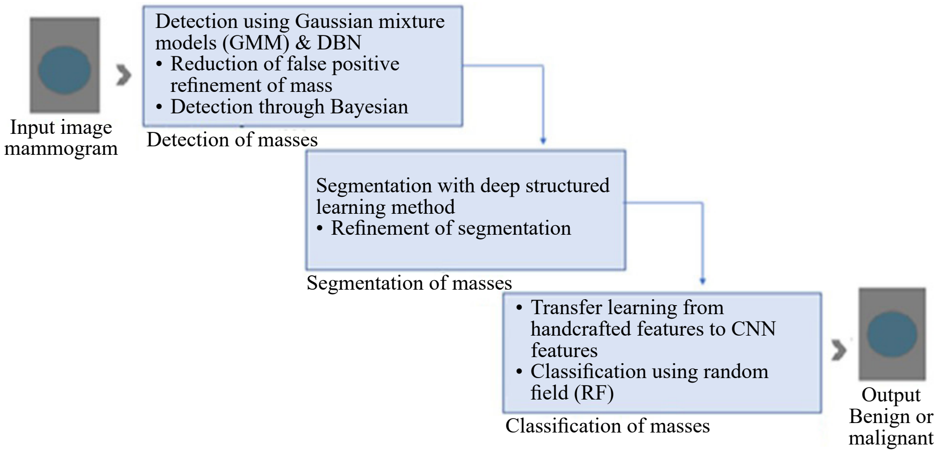

Figure 7. Architectural layout of DL [58]

3.2.2 *Electroencephalography (EEG) imagery signals*

This section's main goal is to demonstrate the importance of DL techniques in terms of performance variation by considering classification. Deep belief networks were utilized by the authors of [56, 57], brain activity EEG waveforms according to categories. The DBN results show that even on raw data, this model's prediction task requires less time than those of support vector machine (SVM) and K-nearest neighbors (KNN) classifiers. Later, [58] proposed a brand-new method for categorizing electrocardiogram (ECG) signals, which are typically DL-based.

The resulting hidden representation layer in this model was then covered with a regression layer to produce a DNN after the feature learning phase. Less expert participation and a quicker online retraining phase boosted this novel method's accuracy compared to prior approaches.

The classification of breast cancer with both migratory and non-mitotic nuclei images was presented in [60] using a unique technique of data balancing utilizing the CNN model. Considering the substantial overlaps between cell divisions and non-mitoses, a CNN model is used in this model to deal with a classification example. K-means with a blue ratio histogram were developed in the second stage to under-sample the skewness in the majority of classes with little information loss. The study's findings showed that the model decreased training time while also increasing CNN's mitotic detection rate. The CNN model's construction in two phases is shown in Figure 8.

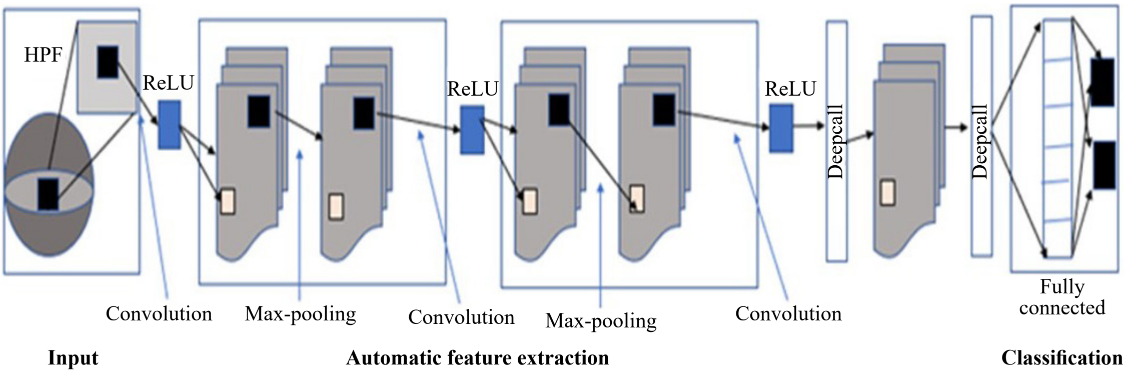

Figure 8. CNN model's construction with two-layer phases [55, 60]

3.2.3 *Multiple sclerosis*

To categorize mental workload, a denoising-stacked AE was created [56, 61]. Both within-session and across-session conditions were considered when calculating the classification's accuracy. Then, using various feature selection and noise corruption models, this is the new classification, which was contrasted with conventional categorizers for mental effort. Later, delayed multiple sclerosis (MS) patterns called lesion patterns were extracted from represented pictures using a CNN approach [59, 61]. It was suggested in [62] to apply a DBN and random forest on myelin images as well as T1W images where MS pathology can be found in brain tissue that appeared normal with an MRI. To develop a latent feature representation, DBN with four layers (Figure 9) was applied to 3D images of normal-appearing gray matter (NAGM) and normal-appearing white matter (NAWM) in this model. Then, the picture patches were chosen using a voxel-wise t-test.

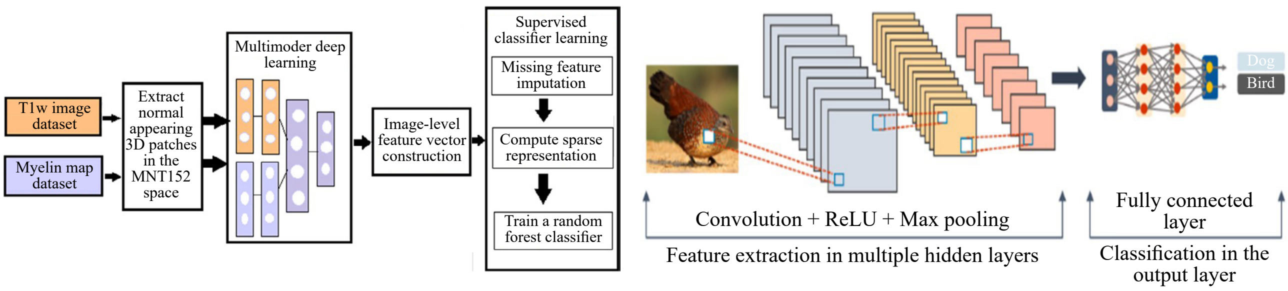

Figure 9. Modeling DBN with four layers [56, 57, 61]

3.2.4 *Brain cancer*

In [63], a multi-scale CNN-based approach to tissue segmentation for brain MRI was proposed. Different levels of irregularity were used to test the methodology. The findings demonstrate precisely divided brain lesions. Transparency in models is a significant problem in the clinical sector that has an impact on the prediction of patient therapies and real-world medical decision-making [64]. A new DL model for segmenting brain tumors was proposed in [65] in a distinct study by fusing fully CNN and conventional random fields (Figure 10).

To train the model, three different phases were used. Image slots were first used to train the fully connected neural networks (FCNN). Second, CRF-RNN was trained by image pixels. Finally, the entire network was tuned using the picture slices [65, 66]. The four steps of the method include pre-processing, fragmenting picture slices with DL models that incorporate FCNNs and CRF-RNNs, extraction of features, and identification.

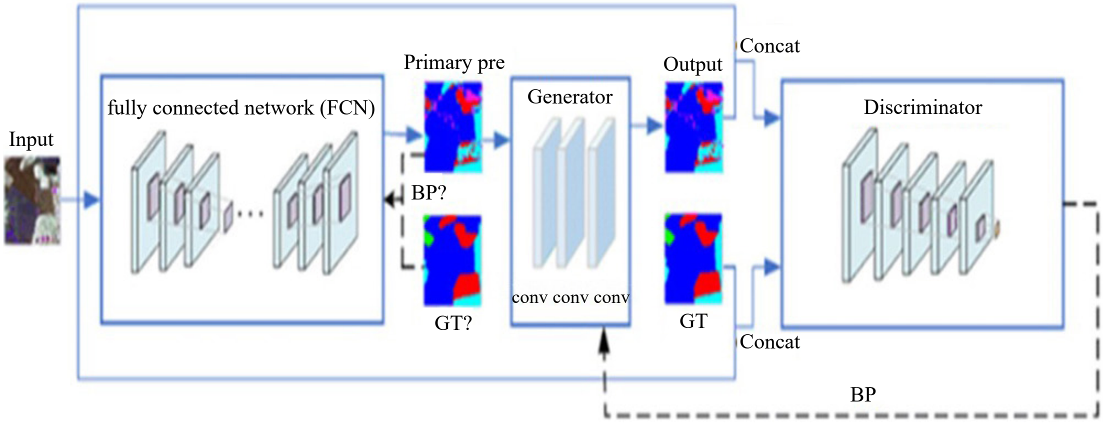

Figure 10. A fully integrated CRF and CNN [63, 64]

3.2.5 *Hybrid disease detection*

To identify three different cancer types [67] — LACAR (lung small/large adenocarcinoma), SACAR (stomach-related adenocarcinoma), and BICAR (breast-related invasive carcinoma) — hybrid DL approaches are used. They used studies of various gene expressions to pick the key genes in this model. Five CNN classifiers were trained using these chosen genes, and the combined output was then obtained. They showed that, in comparison to a single classifier or the algorithm for qualified majority, their approach can improve the reliability of cancer diagnosis across all tested datasets of RNA-Seq. The authors of [67] suggested a technique for automatically classifying gastric cancer using a CNN. Three deep structural algorithms with multichannel release of information (ROI) — stacked denoising AE, DBN, and CNN — were used in a different study [68] to diagnose lung cancer.

3.2.6 *Epilepsy diagnosis*

To diagnose epilepsy using the encephalogram signals, the authors of [69] explained a new system for computer-aided diagnosis that makes use of CNN. Its precision, efficiency, and responsiveness are contrasted with those of other ML techniques. The CNN method uses thirteen layers to develop a complicated and robust model to identify seizures. To the best of our knowledge, this is DL's only substantial application to the diagnosis of epilepsy.

3.2.7 *Heart disease*

Although this condition is common, DL has not been utilized frequently for it. The most important application of DL is to help identify this condition, as is done in [70]. For instance, [70] used an RNN to detect heart failure. To identify cardiac disease by examining the relationships between gated recurrent units, they suggested an RNN model using events that were time-stamped and a case-and-control observation window [71, 72].

3.2.8 *Eye disease*

A framework of ML for enhancing clinical decision-making systems was proposed in [73], along with an unsupervised deep feature learning method. To identify red lesions in fundus images, a combination of DL and domain expertise was developed in [74]. The addition of handcrafted features culminated in the learning process for CNN architecture. According to reports, this combination performs better than other separate classifiers [74].

The Sutter-PAMF dataset is utilized. The outcome shows a detection accuracy of 77.68 percent. It also displays the RNN technique for brain tumor detection. The Cancer Genome Atlas (TCGA) project provided the gene expression data that was utilized.

3.2.9 *COVID-19*

A viral illness called COVID-19 has infected billions of people worldwide and spread to additional countries at an accelerated rate [75, 76]. The World Health Organization (WHO) initially referred to this dangerous infection as SARS-CoV-2, and later COVID-19 became more well-known [77]. Fever, coughing, and a loss of taste or smell are some of the main COVID-19 symptoms that people experience [78, 79]. Chest pain, shortness of breath, diarrhea, headaches, sore throats, and other symptoms are among the main ones. The Nidovirales family includes COVID-19, which is regarded as a positive-sense non-segmented RNA virus. The COVID-19 illness spreads in an unanticipated way around the world, and on January 30, 2020, the WHO declared this epidemic a PHEIC (Public Health Emergency of International Concern) [80, 81]. According to the data study, there were 4,592,893 COVID-19 fatalities and 222,180,532 infections. According to records, nearly 198,785,372 people have been treated for COVID-19 as of September 7th, 2021.

3.3 *Summary of dataset used in healthcare*

In this area, we highlighted some important datasets that were applied to various DL algorithms for the detection of disease and healthcare. The most common healthcare or cancer dataset utilized with DL techniques is mentioned in Table 3.

Table 3. Most common healthcare dataset utilized with DL techniques

Paper Number	Dataset	CNN	RNN	DNN	DAE	DBN	KNN
P2 [46]	Lung image dataset	√			√	√	
P3 [55]	MITOS12, TUPCAC16	√					
P4 [57]	MRI dataset for relapsing-remaining MS					√	
P5 [58]	INBreast	√					
P6 [60]	MITBIH, SVDB and INCART			√	√		
P7 [61]	DDSM	√					
P8 [65]	BRATS	√	√				
P9 [64]	Dataset related popular disease from WebMD						√
P1 [66]	LUAD, STAD, BRCA			√			
P10 [71]	Electronic health record dataset		√				
P11 [74]	MESSIDOR and e-ophtha, DiareTDB1	√					
P12 [82]	Bonn University Dataset	√					
P13 [83]	PPMI, SNUH	√					
P14 [88]	Gastric cancer dataset	√					
P15 [92]	Myelin and T1W					√	

According to Table 3, the CNN algorithm has been implemented in more databases than any other. Take the MITOS12 system, which is offered by the ICPR competition's organizers and consists of five slides from different individuals that have been H&E stained and labeled by a skilled pathologist. For MITOS12 and TUPAC16, the CNN has been used. The University of South Florida (USF) makes their DDSM database available. Four breast photos are provided for each case in the DDSM, together with patient data.

3.4 *Summary of dataset used in healthcare*

Based on the design of the DL approaches used for illness detection, we discuss the results of the studies reported in this part. Then, we examine each study's advantages and disadvantages. We first go over each study in detail before contrasting it with the other techniques listed in Table 1. To assess the effectiveness of DL approaches, the entire number of DL articles listed in Table 1 were examined for two crucial factors: accuracy and area under the curve. Finally, we emphasized the methods that have the greatest influence on detection rates.

Acharya et al.'s [69] analysis of a dataset of EEG signals from Bonn University using a ten-fold merge procedure and the CNN technique. Results from this study were compared to those from other related studies that were identified in the literature. The findings from the investigation are suggested in [69]. These are the accuracy (a) and sensitivity comparison findings between different CNN models and various approaches established in the mentioned database (b).

To assess time-stamped events, a gated recurrent unit-based RNN was developed by Choiet al. [70]. The model's performance was compared to that using AUC values as the key metric, supporting vector machines, CNNs, K-nearest peers, etc. Figure 11 compares RNN's AUC for prediction between three and nine months to other approaches.

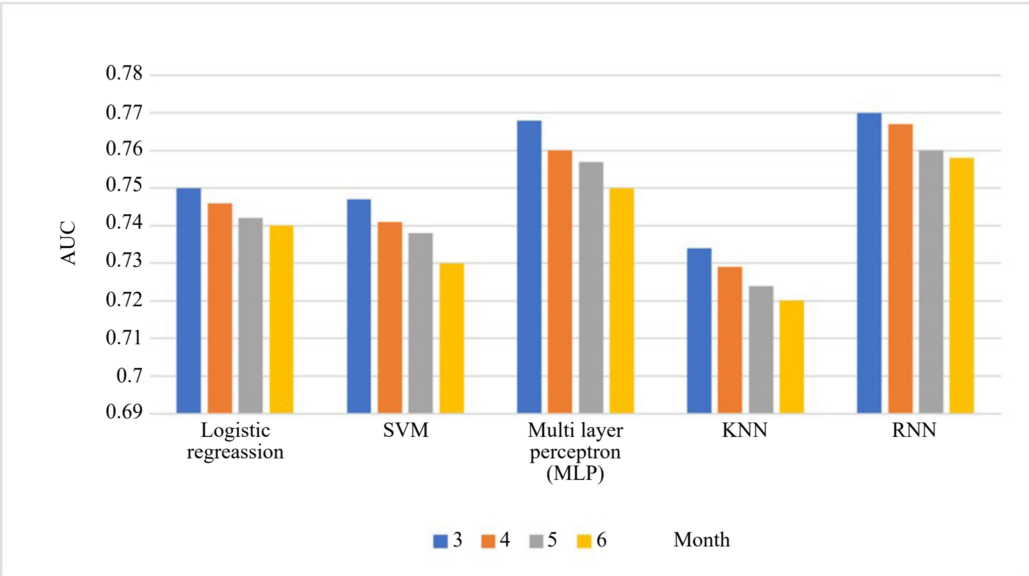

Figure 11. Comparing RNN's AUC for predictions between three and six months to different approaches [69, 70]

An automatic CNN technique for diagnosing Parkinson's disease was created by Choi et al. [71]. Accuracy, specificity, and sensitivity were compared between the visual interpretation and PD Net. The PPMI test set photographs were visually examined by two different readers who were unaware of the diagnosis and clinical details [72]. DAT binding was visually labeled as "normal" or "abnormal" on images. Readers' accuracy and that of PD Net were compared. The outcomes are displayed in Figure 12.

A Random Forest-based CNN was created by Dhungel et al. [58] for the INbreast dataset application in two settings: manual and minimal involvement. The outcomes in terms of accuracy for different CNNs and the area under the curve are displayed in Figure 13.

The CNN, which is based on the random forest technique used in manual configuration and supported by different CNN techniques in the setting with the least amount of user intervention, shows excellent accuracy of detection in Figure 13. This indicates that the RF's ability to classify data using an ensemble learning technique has a favorable impact on the CNN method. As a result, this capability raises the accuracy of the CNN technique [58].

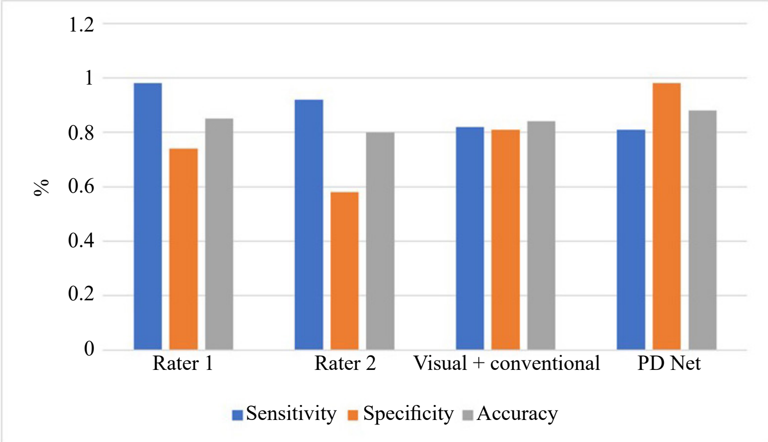

Figure 12. Results of sensitivity, specificity, and accuracy [71]

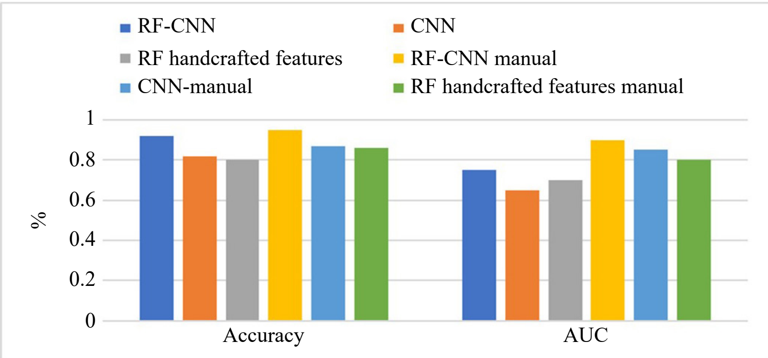

Figure 13. Outcomes of different CNN [58]

To estimate the rates of patients' survival using electronic medical information, Miotto et al. [73] introduced the deep patient unsupervised representation deep patient (URDP) technique. In terms of accuracy and area under the curve of the receiver operating characteristic (ROC) curve, the URDP approach was compared to other methods created in this area. The outcomes are shown in Figure 14.

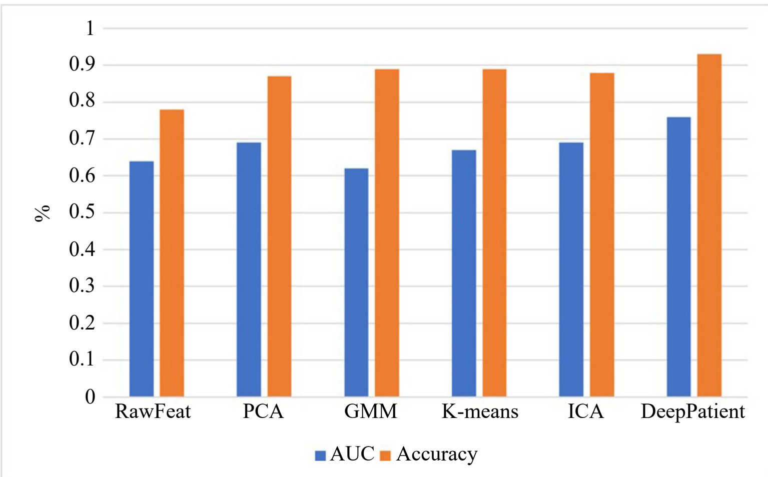

Figure 14. Comparison of URDP with other approaches [61]

An ensemble DL technique was created by the author of [74] Orlando et al. for the detection of a red lesion in fundus pictures. Figure 15 displays the results of CNN, hybrid CNN-hybrid CNN framework (HCF), and hand-crafted features in terms of sensitivity and AUC.

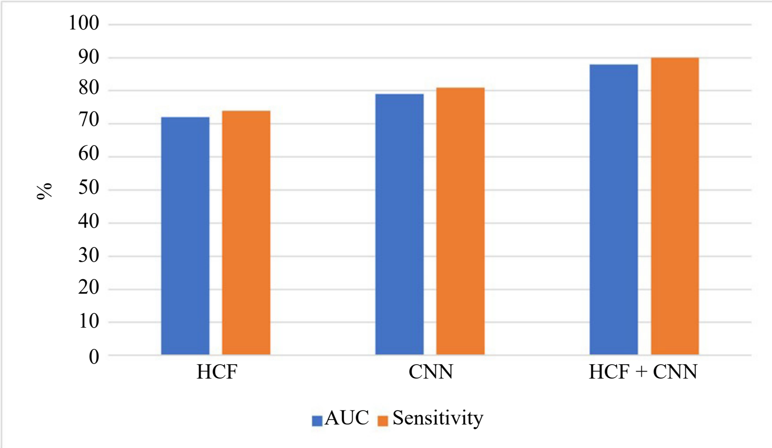

Figure 15. Results of CNN and hybrid CNN-HCF [74]

Based on the above findings, this review examines the value of mixed mode techniques since they combine several reliable models to create a classifier that is more accurate [75]. The hybrid method offers greater sensitivity and AUC in comparison to single methods, as demonstrated in Figure 20. The application of hybrid approaches in DL is highlighted in this work [76, 78].

An AE for denoising stacked and adaptive versions of SDAE algorithms for categorizing the levels of mental pressure was developed by Yin and Zhang [56]. Using EEG data that was obtained on different days, the procedures were practiced and evaluated. Figure 16 displays the study's findings in terms of sensitivity, specification, and accuracy.

According to the findings in Figure 16, when working on EEG features with cross-sessions, adaptive SDAE outperforms SDAE [79]. By examining the findings from this article, it becomes clear that A-SDAE is superior in situations involving the computing cost for iterative tuning, the best step length, and the data augmentation technique. A live web server is created using this method [80].

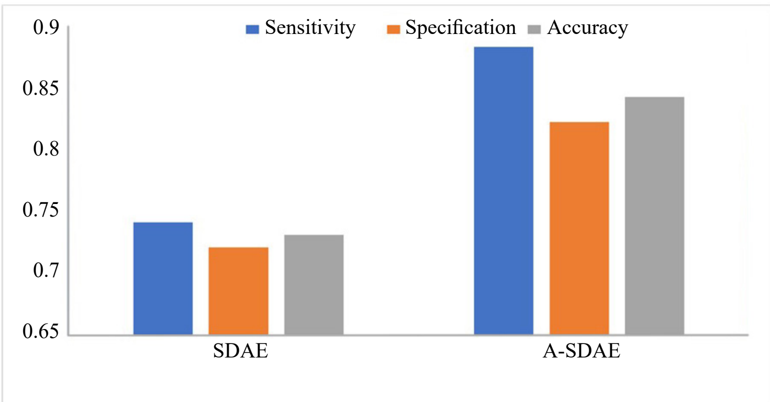

Figure 16. The review of findings of SDAE and A-SDAE [56]

To illustrate modeling in terms of AUC, reliability, and responsiveness, respectively, of output and performance, present DL approaches. It may be inferred that DBN's use of the CNN methodology has contributed the most to this field. This might be because of the features and nature of these techniques. Additionally, these two techniques have the greatest propensity to be combined with other techniques [81].

4. Challenges and opportunities

Although deep architectures have delivered some hopeful results, a number of problems remain that must be fixed before classifiers in medical can be applied therapeutically. We particularly call attention to these grave issues:

Quality of data: Medical information are extremely varied, confusing, rough and insufficient, in contrast to other fields where the data is organized and clean. With such expansive and varied data sets, it is challenging to train a reliable DL model. Several issues, such as data sparsity, complexity, and missing values, must be taken into account [82].

Complexity in domain: Compared to other application sectors, the problems in the bioscience and healthcare industries are more complicated. It is still unknown precisely what causes the majority of the disorders and how they evolve because of their tremendous heterogeneity [83]. In a meaningful therapeutic setting, the patient count is commonly limited, hence we are not allowed to accept an infinite number of patients [84].

Data volume: DL refers to a class of computer models that require a lot of manual labor. One typical example is fully linked multi-layer neural networks, where it is necessary to precisely anticipate a number of network properties. The basis for reaching this goal is the presence of a massive amount of data. It is sometimes advised to utilize at least ten times as many cases in a network as parameters, despite the lack of specific guidelines for the minimum amount of training materials that must be used [85]. DL's effectiveness in industries where enormous volumes of information can be quickly obtained is another aspect.

Interpretability: Even though DL models have demonstrated effectiveness along a diverse range of domains, they are occasionally perceived as "black boxes" [86]. In other, more deterministic areas like image identification, where the end user can unbiasedly check the tags assigned to the photos, this might not be a problem, but in the healthcare industry, this is a concern, and It is crucial to comprehend the algorithms' qualitative as well as quantitative performance. This form of model interpretability — namely, identifying the phenotypes that are driving the predictions — is essential for persuading medical practitioners to follow the predictive system's advice [87].

Feature enrichment: Due to the restricted number of patients worldwide, we must collect various features as we can fully describe each patient and develop creative ways to analyze them all at once. The data input for creating features should consider, but not be restricted to, EHRs and other social media wearable technology, surroundings, observations, virtual communities, transcriptomes, such as the genome, omics data, and so on [88]. A significant and difficult research problem would be how to use such extremely varied data effectively in a DL model.

Integrating expert knowledge: For health care issues, the current expert information for medical issues is priceless. The integration of expert details in the DL process to direct it in the appropriate way is a crucial research area topic due to the restricted quantity of medical data, their diverse quality issues [89]. For instance, it is advisable to mine online clinical/medical encyclopedias to find trustworthy knowledge that may be incorporated into the deep architecture and improve the system's overall performance. The ability to employ both labeled and unlabeled samples make semi-supervised learning, an efficient method consider for learning from many unlabeled a small number of tagged samples, very promising [90].

Temporal modeling: Because time is a significant factor in many healthcare-related issues, particularly those involving EHRs and monitoring equipment, to better comprehend patient circumstances and provide timely support for medical decision-making, it is imperative to train a thing DL model [91]. As a result, temporal DL is crucial for resolving problems in the healthcare industry. To do this, we believe that RNNs and layouts with capacity will greatly enhance clinical feature sets.

5. Conclusion

DL has shown enormous potential as an emerging technology for solving difficult healthcare issues. In this study, we concentrated on healthcare issues that DL has been applied to with positive outcomes. DL-based methods have been shown to be efficient tools for dealing with ailment detection in the preprocessing, edge detection, extraction of features, categorization, and grouping processes. In this paper, the detection of disease in healthcare systems served as the focal point for evaluating the technical features of ML and DL architectures [92]. The effectiveness of these techniques was discussed in terms of algorithm parameters and the precision of disease identification. Finally, the top DL technique architectures used in healthcare were examined and commented on.

We may conclude from this review that DL-based hybrid and ensemble approaches outperform single techniques in terms of accuracy. The existing classifier models [93] like ANN, adaptive neuro-fuzzy inference systems (ANFIS), CNN, and multi-objective differential evolution-based CNN (MODE_CNN) have obtained 88.8%, 90.39%, 92%, and 93.60% accuracy rates, respectively. DL techniques require a lot of memory and time, which is a drawback. Thus, creating and implementing ideal processes in healthcare systems is a significant problem [93, 94]. By integrating more procedures simultaneously and irrespective of the different types of datasets, these methods result in an enhancement of the process.

DL techniques require a lot of memory and time, which is a drawback [95]. Designing and implementing the best practices in healthcare systems is thus a significant task.

Researchers may concentrate on creating and integrating effective technologies in the future to meet the technical specifications for all types of decision-making algorithms, including those with DNN designs [96, 97]. As stated throughout this research, it is also required to enhance the current neural network models' topologies to create more efficient systems. Therefore, it is essential to develop well-defined, general architectures that can deal with many types of health data to tackle complicated challenges in healthcare systems [98-102].

Ethical approval

This study was approved by our institution and does not require ethical approval for reporting individual cases or case series.

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Conflicts of interest

The authors declare that they have no conflicts of interest to report regarding the present study.

References

[1] Kalantari A, Kamsin A, Shamshirband S, Gani A, Alinejad-Rokny H, Chronopoulos TA. Computational intelligence approaches for classification of medical data: State-of-the-art, future challenges and research directions. *Neurocomputing*. 2018; 276: 2-22. Available from: https://doi.org/10.1016/j.neucom.2017.01.126.

[2] Kumar PM, Gandhi UD. A novel three-tier Internet of Things architecture with machine learning algorithm for early detection of heart diseases. *Computers & Electrical Engineering*. 2018; 65: 222-235. Available from: https://doi.org/10.1016/j.compeleceng.2017.09.001.

[3] Mijwil MM, Aggarwal K, Doshi R, Hiran KK, Sundaravadivazhagan B. Deep learning techniques for COVID-19 detection based on chest X-ray and CT-scan images: A short review and future perspective. *Asian Journal of Applied Sciences*. 2019; 10(3). Available from: https://doi.org/10.24203/ajas.v10i3.6998.

[4] Abdel-Hamid O, Mohamed A-r, Jiang H, Deng L, Penn G, Yu D. Convolutional neural networks for speech recognition. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*. 2014; 22(10): 1533-1545. Available from: https://doi.org/10.1109/TASLP.2014.2339736.

[5] Deng L, Li X. Machine learning paradigms for speech recognition: An overview. *IEEE Transactions on Audio, Speech, and Language Processing*. 2013; 21(5): 1060-1089. Available from: https://doi.org/10.1109/TASL.2013.2244083.

[6] Cho K, Courville A, Bengio Y. Describing multimedia content using attention-based encoder-decoder networks. *IEEE Transactions on Multimedia*. 2015; 17(11): 1875-1886. Available from: https://doi.org/10.1109/TMM.2015.2477044.

[7] Hannun A, Case C, Casper J, Catanzaro B, Diamos G, Elsen E, et al. Deep speech: Scaling up end-to-end speech recognition. *arXiv* [Preprint] 2014. Version 2. Available from: https://doi.org/10.48550/arXiv.1412.5567.

[8] Wikipedia contributors. Google DeepMind. Wikipedia, The Free Encyclopedia. Available from: https://en.wikipedia.org/w/index.php?title=Google_DeepMind&oldid=1184257608 [Accessed 10th November 2023].

[9] Watson IBM Health. Methodology: Watson health 15 top health systems study [Internet], 2020. 2020. Available from: https://www.ibm.com/downloads/cas/XERGJLK3.

[10] Cabrita M, op den Akker H, Tabak M, Hermens HJ, Vollenbroek-Hutten MM. Persuasive technology to support active and healthy ageing: An exploration of past, present, and future. *Journal of Biomedical Informatics*. 2018; 84: 17-30. Available from: https://doi.org/10.1016/j.jbi.2018.06.010.

[11] Avendi M, Kheradvar A, Jafarkhani H. A combined deep-learning and deformable-model approach to fully automatic segmentation of the left ventricle in cardiac MRI. *Medical Image Analysis*. 2016; 30: 95-106. Available from: https://doi.org/10.1016/j.media.2016.01.005.

[12] Li F, Tran L, Thung K-H, Ji S, Shen D, Li J. A robust deep model for improved classification of AD/MCI patients. *IEEE Journal of Biomedical and Health Informatics*. 2015; 19(5): 1610-1616. Available from: https://doi.org/10.1109/JBHI.2015.2429556.

[13] Shickel B, Tighe PJ, Bihorac A, Rashidi P. Deep EHR: A survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. *IEEE Journal of Biomedical and Health Informatics*. 2017; 22(5): 1589-1604. Available from: https://doi.org/10.1109/JBHI.2017.2767063.

[14] Lan K, Wang D-t, Fong S, Liu L-s, Wong KK, Dey N. A survey of data mining and deep learning in bioinformatics. *Journal of Medical Systems*. 2018; 42: 139. Available from: https://doi.org/10.1007/s10916-018-1003-9.

[15] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. *Communications of the ACM*. 2017; 60(6): 84-90. Available from: https://doi.org/10.1145/3065386.

[16] Chen G, Tsoi A, Xu H, Zheng WJ. Predict effective drug combination by deep belief network and ontology fingerprints. *Journal of Biomedical Informatics*. 2018; 85: 149-154. Available from: https://doi.org/10.1016/j.jbi.2018.07.024.

[17] Macías-García L, Luna-Romera JM, García-Gutiérrez J, Martínez-Ballesteros M, Riquelme-Santos JC, González-Cámpora R. A study of the suitability of autoencoders for preprocessing data in breast cancer experimentation. *Journal of Biomedical Informatics*. 2017; 72: 33-44. Available from: https://doi.org/10.1016/j.jbi.2017.06.020.

[18] Laksana E, Aczon M, Ho L, Carlin C, Ledbetter D, Wetzel R. The impact of extraneous features on the performance of recurrent neural network models in clinical tasks. *Journal of Biomedical Informatics*. 2020; 102: 103351. Available from: https://doi.org/10.1016/j.jbi.2019.103351.

[19] Alshazly H, Linse C, Barth E, Martinetz T. Explainable COVID-19 detection using chest CT scans and deep learning. *Sensors*. 2021; 21(2): 455. Available from: https://doi.org/10.3390/s21020455.

[20] Zheng C, Deng X, Fu Q, Zhou Q, Feng J, Ma H, et al. Deep learning-based detection for COVID-19 from chest

CT using weak label. *medRxiv* [Preprint] 2020. Version 2. Available from: https://doi.org/10.1101/2020.03.12.20027185.

[21] He X, Wang S, Shi S, Chu X, Tang J, Liu X, et al. Benchmarking deep learning models and automated model design for COVID-19 detection with chest CT scans. *medRxiv* [Preprint] 2021. Version 3. Available from: https://doi.org/10.1101/2020.06.08.20125963.

[22] Shah V, Keniya R, Shridharani A, Punjabi M, Shah J, Mehendale N. Diagnosis of COVID-19 using CT scan images and deep learning techniques. *Emergency Radiology*. 2021; 28(3): 497-505. Available from: https://doi.org/10.1007/s10140-020-01886-y.

[23] Purohit K, Kesarwani A, Kisku DR, Dalui M. Covid-19 detection on chest x-ray and CT scan images using multi-image augmented deep learning model. In: *Proceedings of the Seventh International Conference on Mathematics and Computing*. Singapore: Springer; 2022. p.395-413. Available from: https://doi.org/10.1007/978-981-16-6890-6_30.

[24] Deng L, Yu D. Deep learning: Methods and applications. *Foundations and Trends® in Signal Process.* 2014; 7(3-4): 197-387. Available from: https://doi.org/10.1561/2000000039.

[25] Lim WYB, Luong NC, Hoang DT, Jiao Y, Liang Y-C, Yang Q, et al. Federated learning in mobile edge networks: A comprehensive survey. *IEEE Communications Surveys & Tutorials*. 2020; 22(3): 2031-2063. Available from: https://doi.org/10.1109/COMST.2020.2986024.

[26] Yu D, Deng L. *Automatic speech recognition: A deep learning approach*. London: Springer; 2014. Available from: https://doi.org/10.1007/978-1-4471-5779-3.

[27] Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, et al. A survey on deep learning in medical image analysis. *Medical Image Analysis*. 2017; 42: 60-88. Available from: https://doi.org/10.1016/j.media.2017.07.005.

[28] Gawehn E, Hiss JA, Schneider G. Deep learning in drug discovery. *Molecular Information*. 2016; 35(1): 3-14. Available from: https://doi.org/10.1002/minf.201501008.

[29] Guo Y, Liu Y, Oerlemans A, Lao S, Wu S, Lew MS. Deep learning for visual understanding: A review. *Neurocomputing*. 2016; 187: 27-48. Available from: https://doi.org/10.1016/j.neucom.2015.09.116.

[30] Chen X, Xiang S, Liu C-L, Pan C-H. Vehicle detection in satellite images by hybrid deep convolutional neural networks. *IEEE Geoscience and Remote Sensing Letters*. 2014; 11(10): 1797-1801. Available from: https://doi.org/10.1109/LGRS.2014.2309695.

[31] Längkvist M, Karlsson L, Loutfi A. A review of unsupervised feature learning and deep learning for time-series modeling. *Pattern Recognition Letters*. 2014; 42: 11-24. Available from: https://doi.org/10.1016/j.patrec.2014.01.008.

[32] Gao S, Zhang Y, Jia K, Lu J, Zhang Y. Single sample face recognition via learning deep supervised autoencoders. *IEEE Transactions on Information Forensics and Security*. 2015; 10(10): 2108-2118. Available from: https://doi.org/10.1109/TIFS.2015.2446438.

[33] Kahou SE, Bouthillier X, Lamblin P, Gulcehre C, Michalski V, Konda K, et al. EmoNets: Multimodal deep learning approaches for emotion recognition in video. *Journal on Multimodal User Interfaces*. 2016; 10: 99-111. Available from: https://doi.org/10.1007/s12193-015-0195-2.

[34] Lawrence S, Giles CL, Tsoi AC, Back AD. Face recognition: A convolutional neural-network approach. *IEEE Transactions on Neural Networks*. 1997; 8(1): 98-113. Available from: https://doi.org/10.1109/72.554195.

[35] Chen S, Xu H, Liu D, Hu B, Wang H. A vision of IoT: Applications, challenges, and opportunities with China perspective. *IEEE Internet of Things Journal*. 2014; 1(4): 349-359. Available from: https://doi.org/10.1109/JIOT.2014.2337336.

[36] Zeiler MD, Fergus R. Visualizing and understanding convolutional networks. In: *European Conference on Computer Vision*. Cham, Switzerland: Springer; 2014. p.818-833. Available from: https://doi.org/10.1007/978-3-319-10590-1_53.

[37] Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, et al. Going deeper with convolutions. In: *Conference on Computer Vision and Pattern Recognition (CVPR)*. Boston, MA: IEEE Computer Society; 2015. p.1-9.

[38] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. *arXiv* [Preprint] 2014. Version 6. Available from: https://doi.org/10.48550/arXiv.1409.1556.

[39] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: *IEEE Conference on Computer Vision and Pattern Recognition (CVPR).* Las Vegas, NV: IEEE; 2016. p.770-778.

[40] Cong J, Xiao B. Minimizing computation in convolutional neural networks. In: Wermter S, Weber C, Magg S, Duch W, Honkela T, Koprinkova-Hristova P, et al. (eds.) *Artificial neural networks and machine learning – ICANN 2014*. Cham, Switzerland: Springer; 2014. p.281-290. Available from: https://doi.org/10.1007/978-3-319-11179-7.

[41] Nguyen P, Tran T, Wickramasinghe N, Venkatesh S. Deepr: A convolutional net for medical records. *IEEE Journal of Biomedical and Health Informatics*. 2017; 21(1): 22-30. Available from: https://10.1109/JBHI.2016.2633963.

[42] Gnanasankaran N, Subashini B, Sundaravadivazhagan B. *Amalgamation of deep learning in healthcare systems.* Denmark: River Publishers; 2023.

[43] Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Computation*. 1997; 9(8): 1735-1780. Available from: https://doi.org/10.1162/neco.1997.9.8.1735.

[44] Chung J, Gulcehre C, Cho K, Bengio Y. Empirical evaluation of gated recurrent neural networks on sequence modelling. *arXiv* [Preprint] 2014. Available from: https://doi.org/10.48550/arXiv.1412.3555.

[45] Fries JA. Brundlefly at SemEval-2016 Task 12: Recurrent neural networks vs. joint inference for clinical temporal information extraction. *arXiv* [Preprint] 2016. Available from: https://doi.org/10.48550/arXiv.1606.01433.

[46] Sun W, Zheng B, Qian W. Automatic feature learning using multichannel ROI based on deep structured algorithms for computerized lung cancer diagnosis. *Computers in Biology and Medicine.* 2017; 89: 530-539. Available from: https://doi.org/10.1016/j.compbiomed.2017.04.006.

[47] Zhang Q, Xiao Y, Dai W, Suo J, Wang C, Shi J, et al. Deep learning based classification of breast tumors with shear-wave elastography. *Ultrasonics*. 2016; 72: 150-157. Available from: https://doi.org/10.1016/j.ultras.2016.08.004.

[48] Wulsin DF, Gupta JR, Mani R, Blanco JA, Litt B. Modeling electroencephalography waveforms with semi-supervised deep belief nets: fast classification and anomaly measurement. *Journal of Neural Engineering*. 2011; 8(3): 036015. Available from: https://doi.org/10.1088/1741-2560/8/3/036015.

[49] Patterson J, Gibson A. *Deep learning: A practitioner's approach*. California, US: O'Reilly Media; 2017.

[50] Vieira S, Pinaya WHL, Mechelli A. Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications. *Neuroscience & Biobehavioral Reviews*. 2017; 74: 58-75. Available from: https://doi.org/10.1016/j.neubiorev.2017.01.002.

[51] Mannepalli K, Sastry PN, Suman M. A novel Adaptive Fractional Deep Belief Networks for speaker emotion recognition. *Alexandria Engineering Journal.* 2017; 56(4): 485-497. Available from: https://doi.org/10.1016/j.aej.2016.09.002.

[52] Al Rahhal MM, Bazi Y, AlHichri H, Alajlan N, Melgani F, Yager RR. Deep learning approach for active classification of electrocardiogram signals. *Information Sciences*. 2016; 345: 340-354. Available from: https://doi.org/10.1016/j.ins.2016.01.082.

[53] Saeed A, Trajanovski S, Van Keulen M, Van Erp J. Deep physiological arousal detection in a driving simulator using wearable sensors. In: *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*. New Orleans, LA: IEEE; 2017. p.486-493. Available from: https://doi.org/10.1109/ICDMW.2017.69.

[54] Tabar YR, Halici U. A novel deep learning approach for classification of EEG motor imagery signals. *Journal of Neural Engineering*. 2016; 14: 016003. Available from: https://doi.org/10.1088/1741-2560/14/1/016003.

[55] Wahab N, Khan A, Lee YS. Two-phase deep convolutional neural network for reducing class skewness in histopathological images based breast cancer detection. *Computers in Biology and Medicine*. 2017; 85: 86-97. Available from: https://doi.org/10.1016/j.compbiomed.2017.04.012.

[56] Yin Z, Zhang J. Cross-session classification of mental workload levels using EEG and an adaptive deep learning model. *Biomedical Signal Processing and Control*. 2017; 33: 30-47. Available from: https://doi.org/10.1016/j.bspc.2016.11.013.

[57] Yoo Y, Tang LY, Brosch T, Li DK, Kolind S, Vavasour I, et al. Deep learning of joint myelin and T1w MRI features in normal-appearing brain tissue to distinguish between multiple sclerosis patients and healthy controls. *NeuroImage: Clinical*. 2018; 17: 169-178. Available from: https://doi.org/10.1016/j.nicl.2017.10.015.

[58] Dhungel N, Carneiro G, Bradley AP. A deep learning approach for the analysis of masses in mammograms with

minimal user intervention. *Medical Image Analysis*. 2017; 37: 101-128. Available from: https://doi.org/10.1016/j.media.2017.01.009.

[59] Yoo Y, Tang LY, Li DK, Metz L, Kolind S, Traboulsee AL, et al. Deep learning of brain lesion patterns and user-defined clinical and MRI features for predicting conversion to multiple sclerosis from clinically isolated syndrome. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*. 2017; 7(3): 250-259. Available from: https://doi.org/10.1080/21681163.2017.1356750.

[60] Dubrovina A, Kisilev P, Ginsburg B, Hashoul S, Kimmel R. Computational mammography using deep neural networks. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*. 2016; 6(3): 243-247. Available from: https://doi.org/10.1080/21681163.2015.1131197.

[61] Jiao Z, Gao X, Wang Y, Li J. A parasitic metric learning net for breast mass classification based on mammography. *Pattern Recognition*. 2018; 75: 292-301. Available from: https://doi.org/10.1016/j.patcog.2017.07.008.

[62] Samala RK, Chan HP, Hadjiiski L, Helvie MA, Wei J, Cha K. Mass detection in digital breast tomosynthesis: Deep convolutional neural network with transfer learning from mammography. *Medical Physics*. 2016; 43(12): 6654-6666. Available from: https://doi.org/10.1118/1.4967345.

[63] Moeskops P, de Bresser J, Kuijf HJ, Mendrik AM, Biessels GJ, Pluim JP, et al. Evaluation of a deep learning approach for the segmentation of brain tissues and white matter hyperintensities of presumed vascular origin in MRI. *NeuroImage: Clinical*. 2018; 17: 251-262. Available from: https://doi.org/10.1016/j.nicl.2017.10.007.

[64] Nie L, Wang M, Zhang L, Yan S, Zhang B, Chua T-S. Disease inference from health-related questions via sparse deep learning. *IEEE Transactions on Knowledge and Data Engineering*. 2015; 27(8): 2107-2119. Available from: https://doi.org/10.1109/TKDE.2015.2399298.

[65] Zhao X, Wu Y, Song G, Li Z, Zhang Y, Fan Y. A deep learning model integrating FCNNs and CRFs for brain tumor segmentation. *Medical Image Analysis*. 2018; 43: 98-111. Available from: https://doi.org/10.1016/j.media.2017.10.002.

[66] Xiao Y, Wu J, Lin Z, Zhao X. A deep learning-based multi-model ensemble method for cancer prediction. *Computer Methods and Programs in Biomedicine*. 2018; 153: 1-9. Available from: https://doi.org/10.1016/j.cmpb.2017.09.005.

[67] Sharma H, Zerbe N, Klempert I, Hellwich O, Hufnagl P. Deep convolutional neural networks for automatic classification of gastric carcinoma using whole slide images in digital histopathology. *Computerized Medical Imaging and Graphics.* 2017; 61: 2-13. Available from: https://doi.org/10.1016/j.compmedimag.2017.06.001.

[68] Sun W, Zheng B, Qian W. Automatic feature learning using multichannel ROI based on deep structured algorithms for computerized lung cancer diagnosis. *Computers in Biology and Medicine.* 2017; 89: 530-539. Available from: https://doi.org/10.1016/j.compbiomed.2017.04.006.

[69] Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. *Computers in Biology and Medicine*. 2017; 100: 270-278. Available from: https://doi.org/10.1016/j.compbiomed.2017.09.017.

[70] Choi E, Schuetz A, Stewart WF, Sun J. Using recurrent neural network models for early detection of heart failure onset. *Journal of the American Medical Informatics Association*. 2017; 24(2): 361-370. Available from: https://doi.org/10.1093/jamia/ocw112.

[71] Choi H, Ha S, Im HJ, Paek SH, Lee DS. Refining diagnosis of Parkinson's disease with deep learning-based interpretation of dopamine transporter imaging. *NeuroImage: Clinical*. 2017; 16: 586-594. Available from: https://doi.org/10.1016/j.nicl.2017.09.010.

[72] Gunduz H. Deep learning-based Parkinson's disease classification using vocal feature sets. *IEEE Access*. 2019; 7: 115540-115551. Available from: https://doi.org/10.1109/ACCESS.2019.2936564.

[73] Miotto R, Li L, Kidd BA, Dudley JT. Deep patient: An unsupervised representation to predict the future of patients from the electronic health records. *Scientific Reports*. 2016; 6: 26094. Available from: https://doi.org/10.1038/srep26094.

[74] Orlando JI, Prokofyeva E, del Fresno M, Blaschko MB. An ensemble deep learning based approach for red lesion detection in fundus images. *Computer Methods and Programs in Biomedicine*. 2018; 153: 115-127. Available from: https://doi.org/10.1016/j.cmpb.2017.10.017.

[75] Ciotti M, Ciccozzi M, Terrinoni A, Jiang W-C, Wang C-B, Bernardini S. The COVID-19 pandemic. *Critical*

Reviews in Clinical Laboratory Sciences. 2020; 57(6): 365-388. Available from: https://doi.org/10.1080/10408363.2020.1783198.

[76] Chakraborty I, Maity P. COVID-19 outbreak: Migration, effects on society, global environment and prevention. *Science of The Total Environment*. 2020; 728: 138882. Available from: https://doi.org/10.1016/j.scitotenv.2020.138882.

[77] Nazir T, Kayani RR, Nazir SUR, Zaidi SMM, Manzoor S, Taha N. Epidemiology, genomic evolution and molecular features of severe acute respiratory syndrome-related coronavirus. *Advanced Journal of Biomedical Sciences*. 2019; 4: 3-7.

[78] Ahmad T, Rodriguez-Morales AJ. Emergence of COVID-19 (formerly 2019-novel Coronavirus): A new threat from China. *Revista Panamericana de Enfermedades Infecciosas*. 2019; 2(2): 37-38.

[79] Chen X, Laurent S, Onur OA, Kleineberg NN, Fink GR, Schweitzer F, Warnke C. A systematic review of neurological symptoms and complications of COVID-19. *Journal of Neurology*. 2021; 268(2): 392-402. Available from: https://doi.org/10.1007/s00415-020-10067-3.

[80] Cheng A, Hu L, Wang Y, Huang L, Zhao L, Zhang C, et al. Diagnostic performance of initial blood urea nitrogen combined with D-dimer levels for predicting in-hospital mortality in COVID-19 patients. *International Journal of Antimicrobial Agents*. 2020; 56(3): 106110. Available from: https://doi.org/10.1016/j.ijantimicag.2020.106110.

[81] Pokhrel S, Chhetri R. A literature review on impact of COVID-19 pandemic on teaching and learning. *Higher Education for the Future*. 2021; 8(1): 133-141. Available from: https://doi.org/10.1177/2347631120983481.

[82] Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. *Computers in Biology and Medicine*. 2018; 100: 270-278. Available from: https://doi.org/10.1016/j.compbiomed.2017.09.017.

[83] Choi E, Schuetz A, Stewart WF, Sun J. Using recurrent neural network models for early detection of heart failure onset. *Journal of the American Medical Informatics Association*. 2017; 24(2): 361-370. Available from: https://doi.org/10.1093/jamia/ocw112.

[84] Nie L, Wang M, Zhang L, Yan S, Zhang B, Chua TS. Disease inference from health-related questions via sparse deep learning. *IEEE Transactions on Knowledge and Data Engineering*. 2015; 27(8): 2107-2119. Available from: https://doi.org/10.1109/TKDE.2015.2399298.

[85] Orlando JI, Prokofyeva E, del Fresno M, Blaschko MB. An ensemble deep learning based approach for red lesion detection in fundus images. *Computer Methods and Programs in Biomedicine*. 2018; 153: 115-127. Available from: https://doi.org/10.1016/j.cmpb.2017.10.017.

[86] Al Rahhal MM, Bazi Y, AlHichri H, Alajlan N, Melgani F, Yager RR. Deep learning approach for active classification of electrocardiogram signals. *Information Sciences.* 2016; 345: 340-354. Available from: https://doi.org/10.1016/j.ins.2016.01.082.

[87] Samala RK, Chan HP, Hadjiiski L, Helvie MA, Wei J, Cha K. Mass detection in digital breast tomosynthesis: Deep convolutional neural network with transfer learning from mammography. *Medical Physics*. 2016; 43(12): 6654-6666. Available from: https://doi.org/10.1016/j.compmedimag.2017.06.001.

[88] Sharma H, Zerbe N, Klempert I, Hellwich O, Hufnagl P. Deep convolutional neural networks for automatic classification of gastric carcinoma using whole slide images in digital histopathology. *Computerized Medical Imaging and Graphics*. 2017; 61: 2-13. Available from: https://doi.org/10.1016/j.compmedimag.2017.06.001.

[89] Xiao Y, Wang S, Ling R, Song Y. Application of artificial neural network algorithm in pathological diagnosis and prognosis prediction of digestive tract malignant tumors. *Journal of Zhejiang University (Medical Sciences)*. 2023; 52(2): 243-248. Available from: https://doi.org/10.3724/zdxbyxb-2022-0569.

[90] Sun W, Zheng B, Qian W. Automatic feature learning using multichannel ROI based on deep structured algorithms for computerized lung cancer diagnosis. *Computers in Biology and Medicine*. 2017; 89: 530-539. Available from: https://doi.org/10.1016/j.compbiomed.2017.04.006.

[91] Yin Z, Zhang J. Cross-session classification of mental workload levels using EEG and an adaptive deep learning model. *Biomedical Signal Processing and Control*. 2017; 33: 30-47. Available from: https://doi.org/10.1016/j.bspc.2016.11.013.

[92] Zhang T, Chen J, Lu Y, Yang X, Ouyang Z. Identification of technology frontiers of artificial intelligence-assisted pathology based on patent citation network. *PLoS ONE*. 2022; 17(8): e0273355. Available from: https://doi.

org/10.1371/journal.pone.0273355.

[93] Yoo Y, Tang LY, Li DK, Metz L, Kolind S, Traboulsee AL, et al. Deep learning of brain lesion patterns and user-defined clinical and MRI features for predicting conversion to multiple sclerosis from clinically isolated syndrome. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*. 2019; 7(3): 250-259. Available from: https://doi.org/10.1371/journal.pone.0273355.

[94] Zhang Q, Xiao Y, Dai W, Suo J, Wang C, Shi J, et al. Deep learning based classification of breast tumors with shear-wave elastography. *Ultrasonics*. 2016; 72: 150-157. Available from: https://doi.org/10.1016/j.ultras.2016.08.004.

[95] Firouzi F, Rahmani AM, Mankodiya K, Badaroglu M, Merrett GV, Wong P, et al. Internet-of-Things and big data for smarter healthcare: From device to architecture, applications and analytics. *Future Generation Computer Systems*. 2018; 78: 583-586. Available from: https://doi.org/10.1016/j.future.2017.09.016.

[96] Shafique M, Theocharides T, Bouganis CS, Hanif MA, Khalid F, Hafız R, et al. An overview of next-generation architectures for machine learning: Roadmap, opportunities and challenges in the IoT era. In: *2018 Design, Automation & Test in Europe Conference & Exhibition (DATE)*. IEEE; 2018. p.827-832. Available from: https://doi.org/10.23919/DATE.2018.8342120.

[97] Nikfarjam A, Sarker A, O'Connor K, Ginn R, Gonzalez G. Pharmacovigilance from social media: Mining adverse drug reaction mentions using sequence labeling with word embedding cluster features. *Journal of the American Medical Informatics Association*. 2015; 22(3): 671-681. Available from: https://doi.org/10.1093/jamia/ocu041.

[98] Ravi D, Wong C, Deligianni F, Berthelot M, Andreu-Perez J, Lo B, et al. Deep learning for health informatics. *IEEE Journal of Biomedical and Health Informatics*. 2017; 21(1): 4-21. Available from: https://doi.org/10.1109/JBHI.2016.2636665.

[99] Cheng Y, Wang F, Zhang P, Hu J. Risk prediction with electronic health records: A deep learning approach. In: *Proceedings of the 2016 SIAM International Conference on Data Mining (SDM)*. Society for Industrial and Applied Mathematics; 2016. p.432-440. Available from: https://doi.org/10.1137/1.9781611974348.49.

[100] Mantey EA, Zhou C, Srividhya SR, Jain SK, Sundaravadivazhagan B. Integrated blockchain-deep learning approach for analyzing the electronic health records recommender system. *Frontiers in Public Health*. 2022; 10: 905265. Available from: https://doi.org/10.3389/fpubh.2022.905265.

[101] Alharbi A, Abdur Rahman MD. Review of recent technologies for tackling COVID-19. *SN Computer Science.* 2021; 2(6): 460. Available from: https://doi.org/10.1007/s42979-021-00841-z.

[102] Raja AS, Sundarvadivazhagan B, Vijayarangan R, Veeramani S. Malicious webpage classification based on web content features using machine learning and deep learning. In: *2022 International Conference on Green Energy, Computing and Sustainable Technology (GECOST)*. IEEE; 2022. p.314-319. Available from: https://doi.org/10.1109/GECOST55694.2022.10010386.