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SYSTEMS-LEVEL QUALITY IMPROVEMENT

Prevalence and Diagnosis of Neurological Disorders Using Different Deep Learning Techniques: A Meta-Analysis

Ritu Gautam [1] · Manik Sharma [1]

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Abstract

This paper dispenses an exhaustive review on deep learning techniques used in the prognosis of eight different neuropsychiatric and neurological disorders such as stroke, alzheimer, parkinson's, epilepsy, autism, migraine, cerebral palsy, and multiple sclerosis. These diseases are critical, life-threatening and in most of the cases may lead to other precarious human disorders. Deep learning techniques are emerging soft computing technique which has been lucratively used to unravel different real-life problems such as pattern recognition (Face, Emotion, and Speech), traffic management, drug discovery, disease diagnosis, and network intrusion detection. This study confers the discipline, frameworks, and methodologies used by different deep learning techniques to diagnose different human neurological disorders. Here, one hundred and thirty-six different articles related to neurological and neuropsychiatric disorders diagnosed using different deep learning techniques are studied. The morbidity and mortality rate of major neuropsychiatric and neurological disorders has also been delineated. The performance and publication trend of different deep learning techniques employed in the investigation of these diseases has been examined and analyzed. Different performance metrics like accuracy, specificity, and sensitivity have also been examined. The research implication, challenges and the future directions related to the study have also been highlighted. Eventually, the research breaches are identified and it is witnessed that there is more scope in the diagnosis of migraine, cerebral palsy and stroke using different deep learning models. Likewise, there is a potential opportunity to use and explore the performance of Restricted Boltzmann Machine, Deep Boltzmann Machine and Deep Belief Network for diagnosis of different human neuropsychiatric and neurological disorders.

Keywords Neurological disorders · Deep learning techniques · Convolutional neural network · Deep neural network

Introduction

Human disorders characterize defacement condition that intervenes or alter the essential functions of different parts of the human body. There is a colossal list of human disorders that can be categorized as cardio, genetic, psychological, brain, skin, trauma, infectious, tissue and digestive disorders [1]. Neurological disorders are also known as the brain, behavioural or cognitive disorders that generally affect the walking, speaking, learning and moving capacity of human beings [2]. These are life-threatening ailments that directly affect the brain and spine of the human body. These brain maladies have witnessed a high rate of disability and bereavement. The global rate of prevalence of these diseases found to be 10.2%. Additionally, the rate of causality of these disorders is also high (16.8%). The rate of disability and mortality of neurological and neuropsychiatric disorder is significantly higher as compared to other human disorders. There are around six hundred neurological problems. In this article, a detailed study related to the eight major neurological and neuropsychiatric disorders (cerebrovascular disease (Stroke), alzheimer, parkinson, epilepsy, cerebral palsy, multiple sclerosis, autism, and migraine) diagnosed using different deep learning techniques have been carried out [3]. The number of neurological disorders patients has been significantly increased [4]. As these are precarious, chronic and lethal diseases. Therefore, more attention is required in the early diagnosis of these human disorders [5].

Earlier, various mining techniques such as decision tree, random forest, support vector machine, k-means, naive bayes

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✉ Manik Sharma
manik_sharma25@yahoo.com

[1] Department of Computer Science and Application, DAV University, Jalandhar, India

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and neural network have been used for diagnosis of diverse immedicable diseases [6]. Moreover, different nature-inspired techniques have also shown remarkable performance in the diagnosis of chronic disorders in human beings [7, 8]. Generally, most of the work has been carried out for diabetes, cancer and cardio problems [9].

In the last few years, Deep Learning (DL) techniques have also been successfully engaged to solve disease diagnosis problems. The root of DL techniques lies in the Artificial Neural Network (ANN). These are also called representation learning techniques as these approaches can effectively identify hidden patterns of the data without using an explicit feature extraction mechanism. In other words, deep learning architectures support automatic feature extraction. It is found that unlike machine learning techniques there is no need to extract feature separately in deep learning. In addition to disease diagnosis, DL techniques have been successfully used to solve a different problem related to drug discovery [10], natural language processing [11], robotics [12], etc. The frequency of deep learning articles published in different domains is depicted in Fig. 1.

The past research revealed that several human disorders have been successfully diagnosed using different deep learning architectures. Table 1 depicts some of the major human diseases diagnosed using different DL techniques like Deep-Neural Network (DNN), Deep-Belief Network (DBN), Deep-Autoencoder (DA) and Convolutional-Neural Network (CNN).

Figure 2 shows the progress of deep learning in disease diagnosis. It is observed that the diagnosis of disease using deep learning has shown remarkable growth since the year 2016.

Despite the success of deep learning in several areas, the eminence of deep learning in the diagnosis of neurological disorders is yet to be explored. From the prevailing literature, it is found that no dedicated review related to the diagnosis of multiple neurological disorders such as cerebrovascular disease (Stroke), alzheimer's, parkinson's, epilepsy, cerebral palsy, multiple sclerosis, autism and migraine using DL methods has been carried out. The intention of this study is to fill this research gap. This study will summarize some of the major human neuropsychiatric and neurological disorders, their facts along with their major symptoms. Additionally, the publication trend of related articles is also analyzed. Lastly, future directions for the diagnosis of these disorders using DL models have been anatomized. The major aspirations of this study are:

- To introduce different DL techniques.
- To outline the major neuropsychiatric and neurological disorders such as Stroke, Alzheimer, Parkinson, epilepsy, autism, migraine, cerebral palsy, and multiple sclerosis.
- To inspect the publication trend of deep learning techniques such as DNN, DBN, RNN, DA, CNN, RBM, DBM in the diagnosis of neurological and neuropsychiatric disorders.
- To highlight the research work of different authors in early diagnosis of cerebrovascular disease (Stroke), Alzheimer, Parkinson, epilepsy, autism, migraine, cerebral palsy and multiple sclerosis with deep learning.
- To present the challenges and future direction related to this study.

The outline for the rest of the manuscript is mentioned in the left-over part of this manuscript. Related work is presented in section 2. Section 3 presents the review methodology used in this article. Section 4 thoroughly evaluates and reports the review results of major neuropsychiatric and neurological disorders. The publication and performance metrics, implication and the challenges lie in implementing DL techniques for

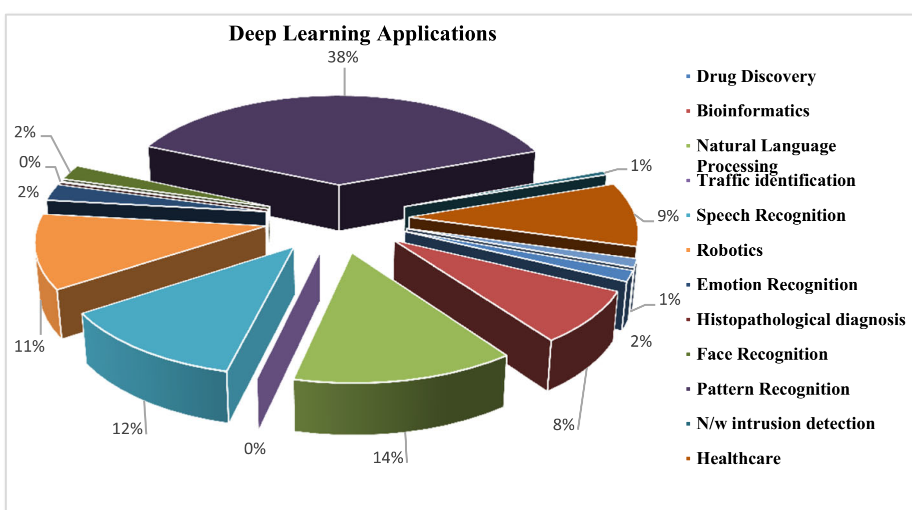


Fig. 1 Applications of Deep learning

Table 1 Deep Learning Techniques in human Disease Diagnosis

Algorithm	Disease Diagnosed
DNN	Breast Cancer [13],Diabetes [14],Depression [15], Autism [16], Epilepsy [17], Parkinson's [18], Alzheimer's [19]
DBN	Breast cancer [20], Cardio vascular disorder [21], Depression [22]
DA	Breast cancer [23], facial Emotional Recognition [24], Alzheimer's [25], Parkinson's [26], Stroke [27], Epilepsy [28].
CNN	Gastric cancer [29], Skin cancer [30] Head cancer [31], Neck cancer [32], Breast cancer [33], Brain tumor [34], Depression [35],Parkinson's [36], Migraine [37], Autism [38], Alzheimer's [39], Multiple sclerosis [40], Thyroid [41], Stroke [42]

diagnosis of neurological disorders is presented in section 5. Finally, conclusion and future directions are presented in section 6.

Related works

Several review articles related to the use of DL techniques in disease diagnosis has been written and published. Some of the related key studies are presented below:

Vieira S. et al., 2017 [43] have presented a survey on neurological and psychiatric disorders mined using deep learning techniques. The study covers 25 articles and the emphasis was given on multiclass data. Authors concluded that deep learning is an authoritative contrivance for the prognosis of various neurological and psychiatric diseases. The survey disclosed that for better results in neuro-imaging with deep learning modest sample size should be focused. Secondly, hybridization of CNN and RNN could give a new direction to deep learning in the processing of sequential and fMRI data. Furthermore, it was suggested that augmentation technique with deep learning can be beneficial in neuro-imaging. Akkus et al., (2017) [44] reviewed deep learning techniques for segmentation of brain lesions and anatomical brain structures. The article focused on different properties, performance and speed of deep learning architectures for analysis of brain MRI segmentation. Authors concluded that transfer learning with deep learning techniques can achieve better results. Moreover, augmentation approaches need a large amount of data for finding out the variations in MRI data. S. Tandel et al., (2019) [45] focused on brain cancer diagnosis using deep learning techniques. Authors compared brain cancer with other brain disorders diseases Alzheimer's, Parkinson's, Wilson's disease and leukoaraiosis disorders. Authors concluded that very less work has been done for the diagnosis of a brain tumor with deep learning techniques. Dinu A.J et al., (2017) [46] emphasized on artificial intelligence methods for disease diagnosis. Authors suggested that deep learning techniques of artificial intelligence can give optimal results in disease diagnosis.

Review methodology

Here, a systematic review methodology has been adopted to present a comprehensive survey on the prevalence and diagnosis of major human neurological and neuropsychiatric disorders using different deep learning techniques. The overall workflow of this manuscript is presented in Fig. 3.

Initially, five different research questions are designed. Based upon research questions, a logical search methodology is employed to extract relevant articles to covers basic introduction, critical assessment, evaluation and interpretation of existing literature or material related to major human neurological and neuropsychiatric disorders and DL techniques. The prevailing part of this section will depict the aggregation

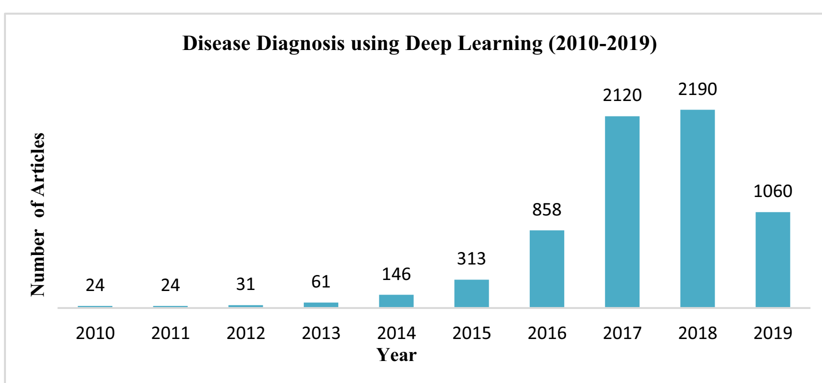


Fig. 2 Disease Diagnosis using Deep Learning (2010–2019)

strategy to collect and mine the related studies. Table 2 shows the year-wise rate of the manuscripts of the different journal, conferences, books, and web links included in this study.

Research questions

While conducting this literature review, Several distinct research questions have been formed. All five research questions have been answered.

Research Questions
RQ1: What are neurological disorders?
RQ2: What are various DL Techniques and frameworks?
RQ3: What are the consequences of using DL approaches in the neurological and neuropsychiatric disorder diagnosis?
RQ4: What is the publication trend of articles with DL techniques in the diagnosis of Neurological and Neuropsychiatric disorders?
RQ5: What are the common datasets of neurological and neuropsychiatric disorders?

Article Segregation Strategy (ASS)

This strategy is necessary to cognize the aptness of articles for directing the research questions. A systematic search process has been applied to shortlist relevant articles that successfully cover and answer all the questions designed above. Figure 4 presents the selection strategy of articles.

For optimal coverage, different keywords such as "deep learning", "neurological disorders" and their synonyms have been used while selecting and shortlisting the articles. The research was confined to the work which has been published during the last ten years (2010–2019). Total of 985 research articles was found in this analysis. After careful scrutiny based upon title, abstract and fully complete contents, 136 articles were finally selected.

Data synthesis and analysis

The questions framed in section 2 will be answered in this section. Each subsection will cover one distinct research question.

RQ1: What are neurological disorders?

Neurological disorders are also known as the brain, behavioral or cognitive disorders generally affect the walking, speaking, learning and moving capacity of human beings [2]. These are life-threatening ailments that may directly affect the brain and spine of the human body [3, 47]. These types of human disorders are chronic in nature and are directly related to the nervous system of the human being. Epilepsy, Alzheimer, Stroke, Parkinson, multiple sclerosis, autism, and migraine are some of the major neuropsychiatric disorders. Figure 5 depicts the symptoms and reasons associated with some of the major neurological and neuropsychiatric human disorders. The remaining part of this section will briefly introduce some of the major neurological disorders.

Figure 3 Workflow of Manuscript

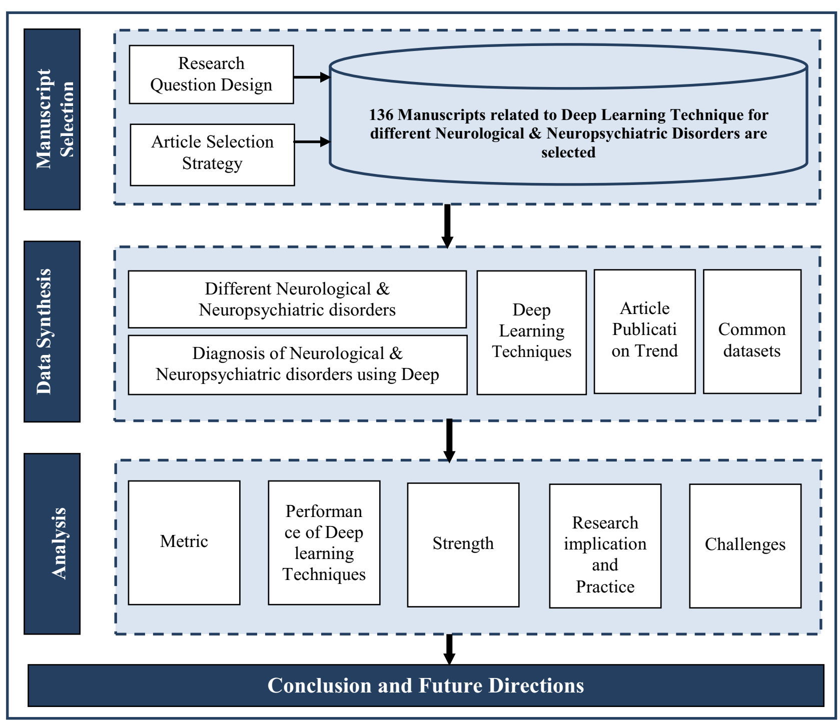


Table 2 Rate of articles from journals, conference, books, and links accessed

Year	Journal	Conference	Book	Links
2019	18	1	-	-
2018	26	17	-	1
2017	23	10	-	1
2016	7	13	–	–
2015	5	2	–	–
2014	4	2	–	–
2013	1	2	–	–
2012	2	–	–	–
2006	–	–	–	
2004	–	–	–	–
2003	–	–	–	–
2002	1	–	–	–
Total	94	38	1	3

Stroke (Cerebrovascular accident) is a major disorder which strikes the vessel of the human body that accordingly affect the flow of blood to the brain. The burst and blockage of blood vessel provoked the brain stroke. There are two main types of stroke: Ischemic strokes (Improper blood flow) and Hemorrhagic stroke (due to high bleeding). As per the study, till 2015, the rate of mortality due to stroke was 6.3 million out of these, 3 million deaths were due to Ischemic and 3.3 million were due to hemorrhagic stroke [48]. Parkinson's disease (PD) is a long-term neurodegenerative human disorder that directly affects the central nervous system. PD is characterized by rigidity, bradykinesia, loss of postural- reflexes and causing tremor, behaviour problem, the problem in sensing the smell, sleep disorder and especially speech problem. At present, there are nearly 6.2 million victims of this human disorder. In general, old aged people and men are the major victims of this human disorder [49]. Alzheimer's disorder (AD) is a chronic neurological brain disease of dementia that directly damages the brain cells and that starts very slowly and intensified over the age. Alzheimer's affects psychological activities as well as the daily routine life of humans. The rate of AD patients (29.8 million) is significantly higher than stroke, PD and MS patients [50]. Epilepsy is a devastating neurological disorder and characterized by spontaneous seizures. Altered behaviors, losing consciousness, jerky movements, and memory loss problems are some of the important characteristics of epilepsy. At present, 39 million people are affected by epilepsy disorder and the ratio of men is significantly higher for epilepsy patients [51]. Autism or Autism Spectrum Disorder (ASD) is a neuro-developmental human disorder. Repetitive behaviour, sociability problem, nonverbal and speech communication are important features of ASD. At present, worldwide 24.8 million populations autism is affected by ASD [52]. Multiple Sclerosis (MS) is an immune-mediated disease with an inflammatory disabling disorder of the brain. Globally, 2.3 million people are affected by MS and the rate of women is higher for this human disorder. Moreover, 18,900 global deaths have been noted for MS [53]. Cerebral Palsy (CP) is a lifelong movement disorder

Fig. 4 Article Selection Strategy

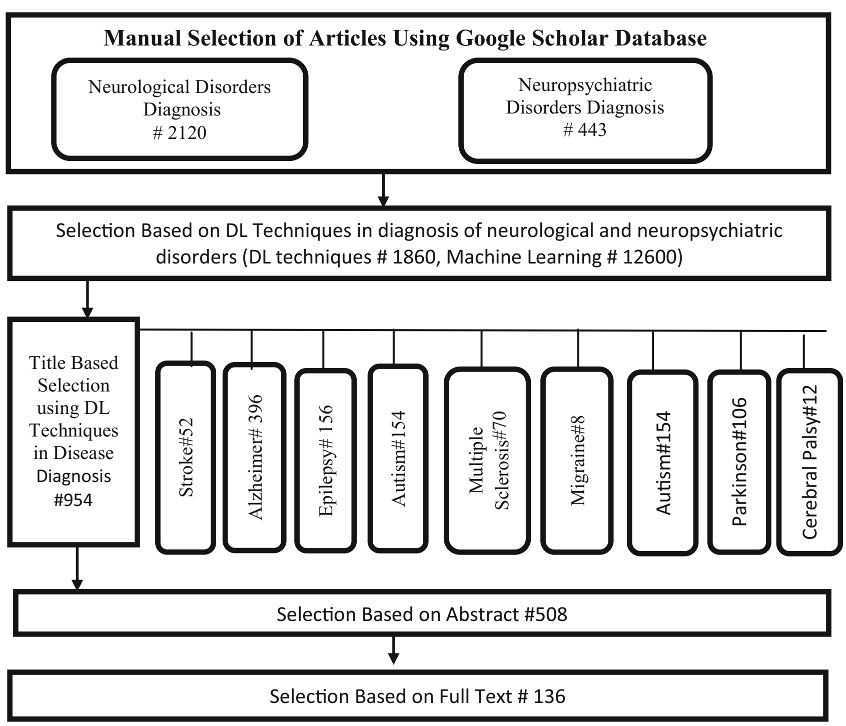
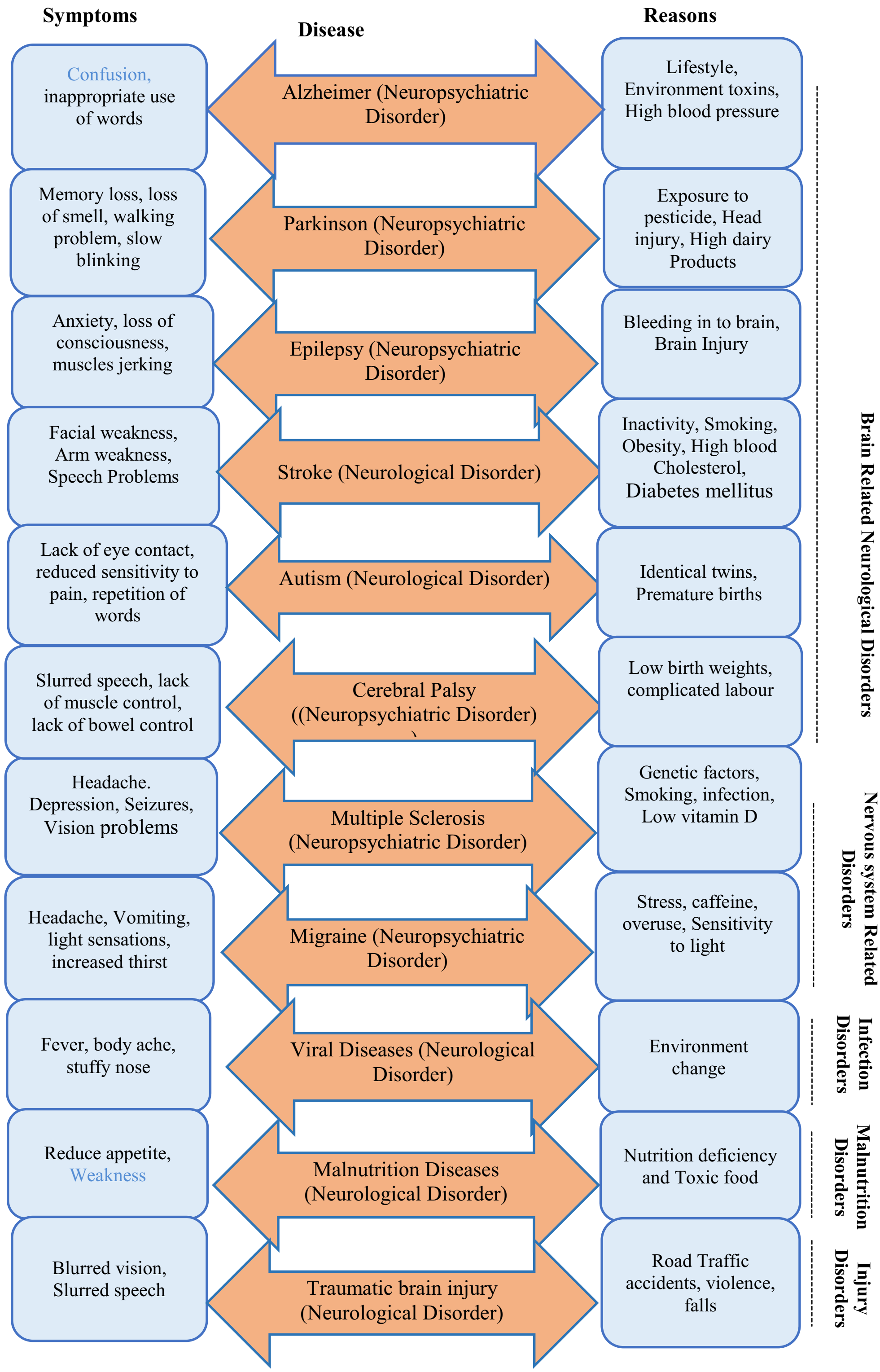


Fig. 5 Symptoms and reasons for Neurological and Neuropsychiatric Disorders



that damages the parts of the brain and generally arises in the childhood age and prevails in about 2.1 per 1000 live births [54]. Pain or discomfort related to the head, the upper portion of the neck and scalp is known as headache. Based upon different symptoms the headache can be broadly classified as migraine, exertional, tension and cluster headache. The rate of migraine-type headache (848 million) is higher than tension-type headache (1.6 million) [55]. Figures 6 and 7 shows the rate of the world population affected by neurological disorders [56].

Morbidity and mortality are two important metrics of a disease. Morbidity represents the presence of a disease or the symptoms associated with it. It is an indicator of health and comfort. Mortality represents the number of death or casualties. Figure 6 and Fig. 7 represents the rate of morbidity and mortality for some of the major neuropsychiatric and neurological disorders such as stroke, alzheimer, parkinson's, epilepsy, migraine, and multiple sclerosis. The rate of morbidity of stroke, alzheimer, parkinson's, epilepsy, migraine, multiple sclerosis is 61%, 12%, 1%, 7%, 17% and 1% respectively. Likewise, the rate of mortality of stroke, alzheimer, parkinson's, epilepsy, migraine, multiple sclerosis is 74%, 22%, 1%, 2%, 0% and 0% respectively. From Fig. 6, it is observed that a morbidity rate of stroke is very high followed by migraine and alzheimer disorder. While other neurological disorders are still in their emerging stage. It is further found that stroke is a most life-threating disorder with the highest mortality rate of 74% of the population. Other than stroke, the death rate of Alzheimer disorder is also very high.

RQ2: What are various deep learning techniques and frameworks?

Deep learning (DL) is one of the emerging soft computing techniques that has been originated from the neural network and is widely used to solve a variety of applications like speech recognition, disease diagnosis, face recognition, transportation problems etc. Restricted Boltzmann Machines (RBMs), Deep Belief Networks (DBNs), Deep Neural Network (DNN), Deep Boltzmann Machine (DBM), Recurrent Neural Network (RNN), Deep Auto-encoder (DA), and Convolutional neural networks (CNN) are some of the major deep learning models. Other than these architectures, Generative Adversarial Network (GAN), and Variation Auto-encoder (VAE) are some latest generative and unsupervised learning methods [11]. As the base of DL technique lies in neural network therefore, these are also known as extended neural network techniques. In last few years, tremendous use

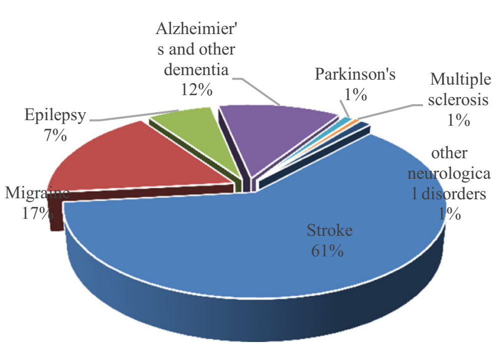


Fig. 6 Morbidity rate of Neurological and Neuropsychiatric Disorders [56]

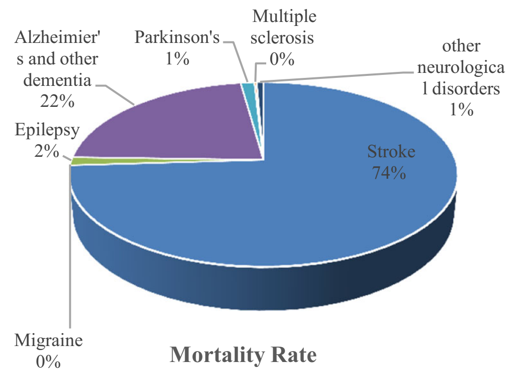


Fig. 7 The Mortality rate of Neurological and Neuropsychiatric Disorders [56]

of these techniques in different areas has been witnessed as these can be effectively employed to solve overfitting problems of the different domains. Moreover, the pre-training capability of these techniques also helps in assigning an initial value to the network that optimizes the working of supervised and unsupervised learning. Table 3 shows the evolution of deep learning.

In the last two decades, several DL techniques-based architectures have been designed and employed to solve different real-life problems.

Deep Neural Network (DNN) is a generative and discriminative architecture with an input layer, output layer and many hidden layers [57]. DNN follows the feed-forward property of a neural network for the computation of data. DNN model is trained through supervised and un-supervised learning approaches. In Supervised method, DNN model is trained through labelled data and weights are assigned to the layers for minimizing the error in the prediction. While, in the unsupervised approach, DNN is trained through unlabelled training data. Generally, feature extraction and clustering are performed through the unsupervised approach. Due to advancement in hardware, multicore processing, and cloud computing, DNN architecture has shown significant advancement in artificial intelligence. DNN generally used for classification and regression purposes. Speech recognition is a major application of DNN. Based on the types of layer and learning methods, different DNN architectures are formulated. Some of them are CNN, DBN, DE, RNN, and DBM. Figure 8 presents the classification of DL techniques.

Convolutional Neural Networks (CNN) is a member of the multi-layer neural network family and was introduced in 1980. CNN is the most extensively used one-way model in which information transmitted from input to output only. It is a discriminative model which was motivated by a simple and complex cell of alternating layers of the visual cortex of the brain. CNN is composed of input, output, and multiple hidden layers. The hidden layer is composed of convolution layers, pooling and fully connected layer along with activation

Table 3 Evolution of Deep Learning

Evolution	Year
Shallow Neural Network	1960
Backpropagation Network	1960–1970s
First Artificial Intelligence winter	1974–1980
Convolutional Emerges	1980
Second Artificial Winter	1987–1993
Unsupervised Deep Learning	The 1990s
Supervised Deep Learning	1990–2000
Modern Deep Learning	2006 to present

function. The convolution and pooling layers are clustered in the form of a stack (deep architecture). Convolution layer and pooling layers are responsible for feature extraction of the objects and dimension reduction. The basic architecture of CNN is shown in Fig. 9 [32, 37].

CNN was initially designed for the handling the multiple array data such as one-dimensional data of signals, two-dimensional data of image and three-dimensional data of video or heavy images. Natural language processing, speech processing, and computer vision face recognition, and document reading are some of the major applications of CNN [11].In spite of this, some of the different architecture of CNN are Alxenet, Lenet, R-CNN, ZFnet, google net, ResNet [58].

Recurrent Neural Network (RNN) is another important deep learning architecture which was proposed in 1986. Although, RNN has acquired less attention and exploration than CNN. Since sequential nature for handling the data is a very powerful concept of the RNN. The Cyclic structure of RNN helps in processing of sequential information. There is strong inter-dependency between the input, output and hidden or memory layers (that maintains all previous information) of the RNN architecture. Memorized nature of RNN makes RNN deeper architecture. Three different approaches or solution of RNN architecture includes deep “input to hidden”, “hidden to hidden” and hidden to output”. These three

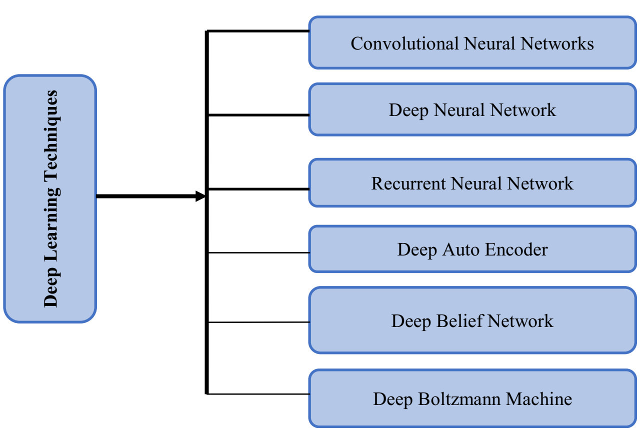


Fig. 8 Deep Learning Techniques

approaches make learning easy in deep networks. After, receiving the data from the input layer, the hidden layer performs all the recurrent computation. The architecture of RNN is shown in Fig. 10 [11, 57].

Unlike other DNN models, RNN shares the same weight across all layers. The vanishing gradient is one of the main problems of RNN architecture. This problem really makes very tough to learn and tuning of parameters of previous layers. RNN outperform in the sequential data applications viz. time series, speech and video processing. [59]. Speech Processing and NLP are the most widely used areas of RNN. Although RNN is not the first choice of biomedical imaging-processing, it is believed that fusion of CNN and RNN can achieve good results in the same domain. Long short-term memory (LSTM) is a variation of the RNN.

Deep Auto Encoder (DA) is a special type of neural network with the unsupervised approach. The stacked structure of DA is made up of three layers: input (encoder), output (decoder) and hidden (code). Encoder and decoder are two basic building blocks of the DA architecture. Auto-encoders are trained to copy its input to output. Encoder and decoders are the foundations of the deep auto-encoders. Generally, the number of input and output layers is the same in the auto-encoders with a smaller number of hidden layers. The encoder encodes the input data (Images) and reduces the dimension of input and hidden layer presents the data to the decoder. Further, the decoder decodes the input data to its original form. Structure of DA is presented in Fig. 11 [11].

Hidden layer or bottleneck layers generally decides which data to be selected or discarded. Feature extraction and data denoising are two main applications of DA. Due to the non-linear feature extraction technique, DA does not need class labels for training data. Some variations of deep auto-encoders are Sparse Auto-Encoder (SAE), Denoising Auto-encoder (DA) and convolutional auto-encoder (CAE) [60].

Deep Belief Network (DBN) was proposed around 2006, a generative model composed of several layers of RBMs. DBN models are pre-trained by greedy- learning method. It is unsupervised probabilistic DLT. Stacking layers of RBM from bottom to up give rise to DBN architecture. Each RBM layer in DBN contains a hidden and visible layer. In DBN, there is an undirected connection or symmetric connection between the top two layers and direct connection between the lowest layers. The construction process of DE and DBN are same: Initially, first RBM is constructed through training then freezing of weights and setting of the hidden layer as the next visual layer of RBM is performed. After that, the same training procedure is applied to get the next RBM. Figure 12 shows the structure of the DBN.

Some Variants of DBNs are Convolutional deep belief networks (CDBNs) and Deep Convex Networks (DCNs) [60]. Face recognition and audio classification are successful applications of CDBN [61].

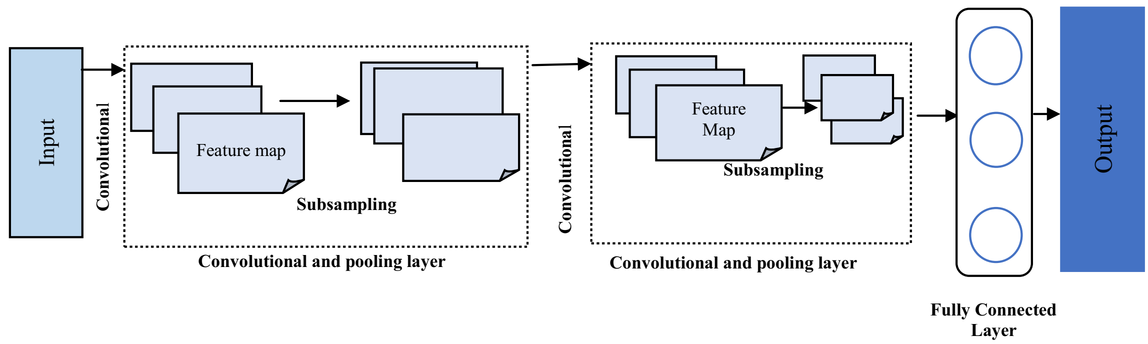


Fig. 9 Convolutional Neural Network

Deep Boltzmann Machine (DBM) is a generative and unsupervised learning method proposed in 2009, made up of stacked layers of RBM. Similarly, Deep Boltzmann machine (DBM) is also constructed by putting multiple RBMs in a recursive way. DBM model is converted to DBN by an associative memory layer (exist at the top of the DBM.) There is an undirected connection between all layers of DBM architecture. Like a DBN, DBM method can also manage ambiguous inputs and complex internal representation of input data in a robust way. Object and Speech recognition is some robust applications of DBM. Structure of DBM is shown in Fig. 13.

R3: What are the consequences of using DL approaches in the neurological and neuropsychiatric disorder diagnosis?

The literature related to the use of different deep learning techniques used in the diagnosis of different neuro disorders such as stroke, epilepsy, Alzheimer's, Parkinson's, cerebral palsy, multiple sclerosis, migraine, and autism has been studied and examined. Firstly, nine different articles related to the use of DL techniques in stroke diagnosis has been studied. Likewise, 38 and 13 distinct manuscripts related to the use of DL techniques in the prognosis of Alzheimer and Parkinson disorders have been studied and depicted here. In Alzheimer, three different classes such as MCI, LMCI (Late MCI) and HP (Healthy Persons) have been considered. For Parkinson, different types of data like audio, EEG signals, handwriting, sonography images, and MRI image have been considered and evaluated. Additionally, six distinct research articles related to the diagnosis of epilepsy have also been incorporated in this study. The important and brief details of some of the key studies have also been highlighted.

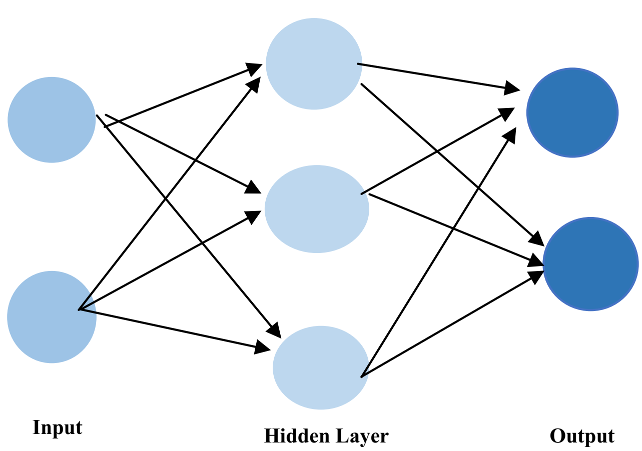


Fig. 10 Recurrent Neural Network

Olli Öman et al. (2019) [42] have used CT-angiography images for ischemic stroke diagnosis. A 3-D CNN based stroke diagnostic techniques have been designed to explore these CT-angiography images. Authors found that this method can be very useful for both radiologist and clinicians. Haridas and Wilson (2018) [62] have studied 1500 CT and MRI scan images of different patients and found that the amalgamated use of PCA and deep learning techniques are more effective for stroke diagnosis. Praveen G.B et al., 2018 [63] have proposed another stacked sparse auto-encoder based deep learning architecture for early and precise diagnosis of Ischemic stroke among humans. Experiments were performed over ISLES 2015 dataset. The results obtained using stacked sparse auto-encoder based deep learning architecture was more encouraging as compared to other techniques.

Jung and Whangbo (2018) [64] have collected two eighty-seven CT images of the brain. Here, the intention was to find out the severity of stroke among different patients. Authors suggested that a modified neural network with the large dataset can provide more precise results for stroke diagnosis. Pre-processing, segmentation, and final judgment of ASPECT score was performed with the deep learning method. Zhiyang Liu et al.,2018 [65] proposed another deep learning-based stroke diagnostic method called residual-structured fully convolutional network (Res-FCN). The proposed method achieved best results with mean dice coefficient of 0.645 and means a number of false-negative lesions of 1.515. Authors concluded that the proposed technique was not able to distinguish between acute and sub-acute ischemic stroke. Stier et al., (2015) [66] have designed a framework to examine tissue fate features which are necessary for the diagnosis of

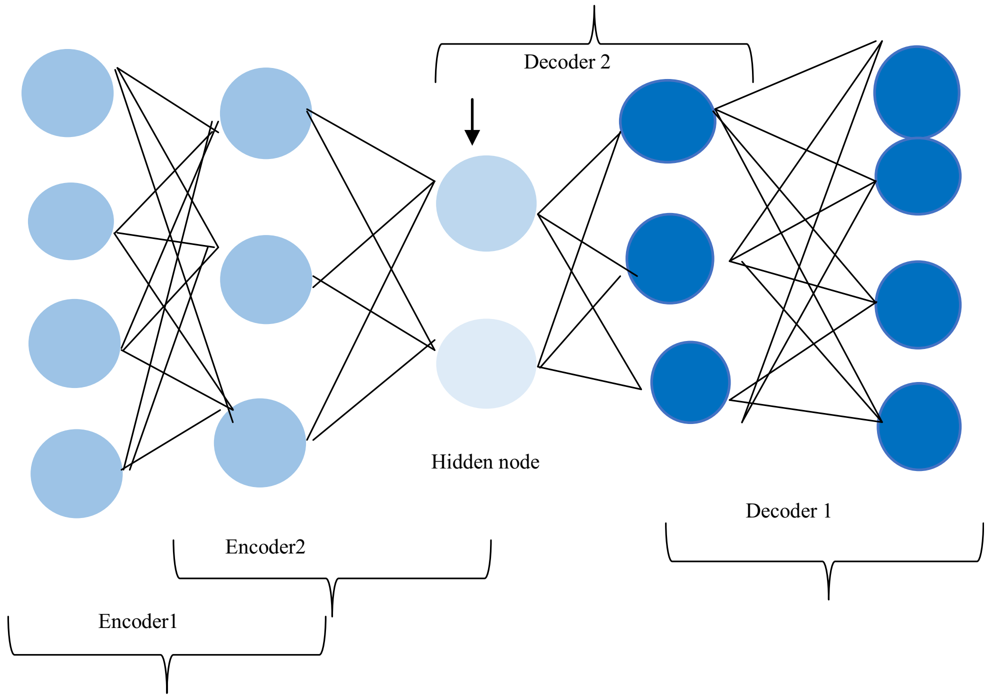


Fig. 11 Architecture of Deep Auto-encoder

ischemic patients. For the validity of this framework, Stier and his colleagues have tested this method on 19 patients. Authors found that the use of 1D-CNN gives better performance in forecasting tissue fate in ischemic patients. Cho J. et al., (2017) [27] have employed deep learning techniques to predict the post-stroke discharge disposition of ischemic patients. The results were validated with the support of the Tennessee Department of Health. The rate of classification achieved using stacked encoder deep learning architecture was 68%.

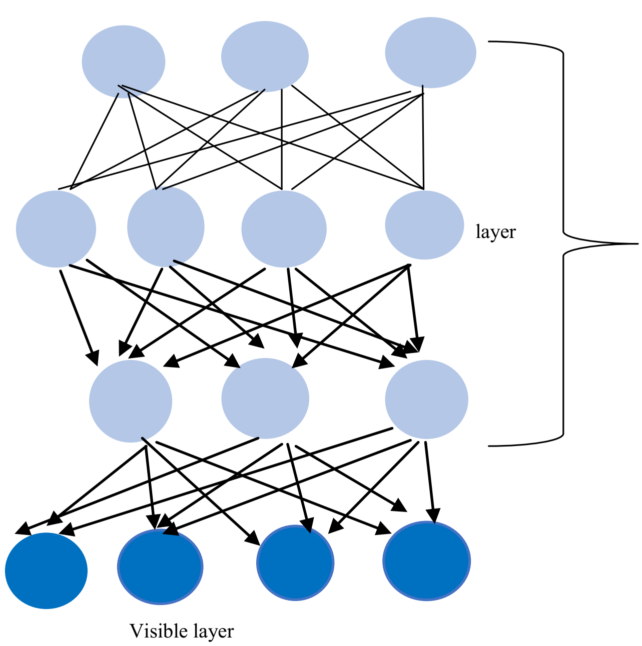


Fig. 12 DBN Architecture

The author found that more effort is required to explore the effectiveness of DL techniques for the same. E. Giri et al.,2016 [67] have used 1D-CNN to design a classifier that can assist in classifying EEG and EOG ischemic stroke pattern from EOG and control data. The concept of both normalizations was employed to expedite the training process.

Li G. et al., (2018) [38] have designed a patch-level data expanding method (DE) for multi-channel CNN's (DE-MC) to identifying the risk of autism in infants of 24 months. Authors collected the MRI data of 276 infants (215 normal-controls, 31 subjects of the mild condition of autism and 30 subjects of autism) from NDAR dataset. Authors appraised the performance of the propounded framework with some

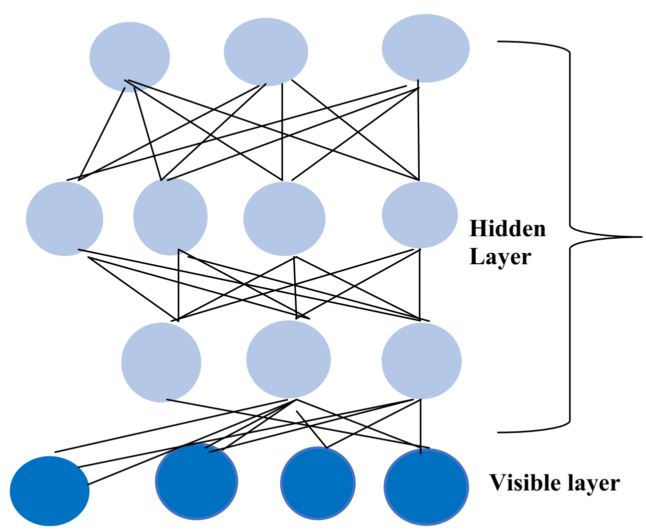


Fig. 13 DBM Architecture

hyper-parameters such as learning rate and landmark number. The accuracy achieved by the proposed technique i.e. DE-MC was 24% better over 3D-CNN. Authors further recommended that this proposed technique for diagnosis of risk of autism in 6-month-old infants. Liao D. and Lu H. (2018) [68] worked with NMI statistic matrix and denoising auto-encoder for classification between normal and autism patients. Experimentation was performed on three different fMRI datasets. Authors concluded that the proposed approach performed much better as compared to traditional methods. Heinsfield et al. (2017) [16] presented a study on the diagnosis of autism disorder with Deep neural network. Authors carried out the study on fMRI data of 505 Autism subjects and 530 typical control subjects from ABIDE dataset. Authors also used to leave one out cross-validation method for the purpose of validation. DNN outperforms SVM and random forest with accuracy, sensitivity, and specificity of 70%,74%, and 63% respectively. Xinyu Guo et al. (2017) [69] have designed a deep neural networks-based feature- selection method for diagnosis of autism among children. Authors found that this method outperforms feature selection DNN techniques as well as other feature selection-based techniques like an elastic net and two-sample t-test. Yazhou Kong et al. (2019) [70] have designed another innovative deep learning approach to classify autism spectrum disorder. A hybrid approach of brain network and DNN was proposed. The rate of classification achieved using this amalgamation for diagnosing autism was found to be propitious as juxtapose to another state of art methods used for classifying autism patients. Rad and Furlanello (2016) [71] proposed a CNN based automatic stereotypical motor -movement system (SSM) for the diagnosis of autism. The author culminated that the rendition of deep learning-based architecture in providing precise SSM detection is better as compared to other existing scenarios. Lukasz kidzinski et al. ((2019)[72] developed the LSTM method for predicting the gait movement between the normal and children affected with the cerebral palsy disorder. The analysis was performed through foot off and foot contact events through the marker and kinematic series. Authors stated that the results of the predicted model were excellent as compared to other competitive approaches. Sergi Valverde et al. (2017) [73] have presented an innovative method for white matter lesion segmentation of sclerosis patients. The performance of the proposed cascaded 3 D CNN method found to be more propitious as compared to other DL architectures. Roy et al. (2018) [74] have devised a fully CNN-based segmentation method for multi-contrast MR images. The performance is evaluated against four publicly available segmentation techniques like S3DL, OASIS, Lesion TOAPS and LST. The results obtained using fully CNN was found to better as compared to other methods. Yeliz Karaca et al. (2017) [75] have compared the presence of different deep learning and SVM techniques in finding unique features of multiple sclerosis in MR images. Authors concluded that deep learning techniques are more effective as compared to the SVM technique. Jiaqi Gong et al., (2016) [76] proposed CNN model for gait assessment through inertial-body sensors. Authors collected the dataset of forty-one patients. Authors well compared the performance of CNN with MSWS-12, distance walked, and causality index methods. CNN method proved to be best for the detection of MS and normal patients.

Tables 4, 5 and 6 depicts the summary of the works where different deep learning techniques have been used to solve Alzheimer, Parkinson and epilepsy diagnosis problems. It has been observed that most of the work for diagnosis of Alzheimer's disorder has been done on OASIS and ADNI datasets. However, very few researchers have worked on CUH dataset. A wide range of instances has been considered by different authors. The range of instances of studied articles lies between 20 and 1941 for both Alzheimer and Parkinson the diagnostic results obtained using CNN are more accurate than other deep learning architectures. However, RNN found to be more suitable for an epilepsy diagnosis.

RQ4 What is the publication trend of articles with DL techniques in the diagnosis of Neurological and Neuropsychiatric disorders?

This section is targeted to examine the publication trend of the articles where different DL techniques have been used to diagnose different neurological and neuropsychiatric human disorders like stroke, epilepsy, Alzheimer, Parkinson, cerebral palsy, multiple sclerosis, migraine, and autism. Several queries comprise of different relevant keywords have been designed and executed in Google Scholar platform to determine the last ten-year publication trend of the relevant articles. The results of different queries have been presented in Figs. 14 and 15.

It is revealed that the role of the publication of articles related to the diagnosis of Alzheimer using DL techniques is significantly higher as compared to other neurological and neuropsychiatric human disorders. Similarly, the good number of articles have been also found for Parkinson and epilepsy. Pondering over, it is noticed that very few authors have used deep learning techniques to diagnose migraine and cerebral palsy. Since migraine is one of the dominant human disorder. Therefore, there is a need to explore the use of DL techniques to diagnose different stages and types of migraine.

It is confirmed that Alzheimer's disorder has got more attention of researchers as this disorder is almost mined by all deep learning techniques except RNN. Additionally, autism disorder is also mined with all deep learning technique except DBM. As well, the results of epilepsy disorder seem to be better with all DL techniques. However, the rate of publication work of stroke, migraine, cerebral palsy and multiple sclerosis disorders with DL techniques are not much effective.

Table 4 Diagnostic Studies on Alzheimer's Disorder (# represents the empty value)

Author	Methods	Instances	Modality	Accuracy	Sensitivity	Specificity	Classification	Dataset
El Mehdi Benyoussef et al.,2018 [77]	KNN, DNN	416	MRI Data	#	#	#	Ternary	OASIS
G. J. Awate et al.,2018 [39]	CNN	400	MRI	99%	#	#	One Way	OASIS
Debesh Jha and Goo-Rak Kwon., 2017 [78]	SAE	95	MRI	91.6%	98.09%	84.09%	Binary	OASIS
Kajal Kiran Gulhare et al.,2017 [19]	DNN	150	MRI	96.6%	#	#	One Way	OASIS
Johannes Rieke et al.,2018 [79]	CNN	344	MRI Data	77%	#	#	Binary	ADNI
Karl Bäckström et al.,2018 [80]	3D -Deep ConvNet(3D_DC)	1198	MRI Scan	98.74%	#	#	Binary	ADNI
K.R. Kruthika et al., 2018 [81]	3D- CNN	1941	MRI	94.06%	#	#	Ternary	ADNI
Karim Aderghal et al.,2018 [82]	CNN	815	MRI and Diffusion tensor Images	92.5%	94.7%	90.4%	Ternary	ADNI
Mengya Yang et al., 2018 [83]	SVM, DPN	805	MRI, Clinical Scores	#	#	#	#	ADNI
Silvia Basaia et al.,2019[84]	DNN	1409	MRI	99.2%	98.9%	99.5%	Quadratic	ADNI
Hao Tang et al.,2018 [85]	3 D -Fine-tuning CNN(3D_FTCNN)		MRI	91.32%	#	#	Ternary	ADNI
Ruoxuan Cui et al.,2019 [86]	RNN	830	MRI	91.33%	#	#	Quadratic	ADNI
Ruoxuan Cui et al.,2018 [87]	3 D-CNN	811	MRI	92.29%	90.63%	93.72%	Ternary	ADNI
Hongfei Wang et al.,2019 [88]	3D- Densely connected CNN(3D-CNN)	1000	MRI	98.83%	#	#	Ternary	ADNI
Simeon Spasov et al.,2019 [89]	**CNN**	785	MRI	**100%**	100%	100%	Ternary	ADNI
Chuanchuan Zheng et al.,2018 [90]	AlexNets	835	PET	91%	99%	53%	Ternary	ADNI
Danni Cheng and Manhua Liu.,2017 [91]	Multi-Level CNN(M-CNN)	193	MRI and PET Images	89.64%	87.10%	92%	Binary	ADANI
C. V. Dolph et al., 2017 [25]	SAE	504	MRI	56.8%	#	#	Binary	ADNI
Ammarah Farooq et al.,2017 [92]	Deep CNN(DCNN)	355	MRI	98.8%	97.9%	99.5%	Quadratic	ADNI
K A N N P Gunawardena et al.,2017 [93]	SVM, CNN	36	MRI	96%	96%	98%	Ternary	ADNI
Jun Shi et al., 2017 [94]	SVM, DPN	202	MRI and PET	97.13%	95.93%	98.53%	Ternary	ADNI
Ronghui Ju et al.,2017 [95]	DL	170	RFMRI	86.47%	92%	81%	Binary	ADNI
Nicola Amoroso et al.,2018 [96]	DL	240	MRI	53.7%	#	#	Quadratic	ADNI
S.Sambath Kumar and M. Nandhini., 2017 [97]	SVM, MDL	158	MRI	74.625%	#	#	Ternary	ADNI
Xiao Zheng et al.,2016 [98]	Multi-modality Stacked DPN(MSDPN)	103	MRI and PET	97.27%	96.75%	97.50%	Binary	ADNI
SamanSarraf et al.,2017 [99]	CNN	302	MRI and Functional MRI	99.9%	#	#	Binary	ADNI
Bhatkoti Pushkar and Manoranjan Paul.,2016 [100]	modified k-sparse autoencoder (mKSA)	150	MRI, CSF, and PET	83.14%	#	#		ADNI
Bibo Shi et al.,2017[101]	Stacked-denoising sparse auto-encoder	338	MRI	91.95%	89.49%	93.82%	Ternary	ADNI
Ciprian D. Billones et al.,2016 [102]	CNN	900	MRI	98.33%	98.89%	97.78%	Ternary	ADNI
Adrien Payan et al.,2015 [103]	CNN	755	MRI	89.47%	#	#	Ternary	ADNI
Heung-IlSuk et al.,2014 [104]	DBM		PET and MRI	95.35%	#	#	Ternary	ADNI

Table 4 (continued)

Author	Methods	Instances	Modality	Accuracy	Sensitivity	Specificity	Classification	Dataset
Siqi Liu et al.,2014 [105]	SAE	311	MRI	87.76%	88.57%	87.22%	Ternary	ADNI
Heung-Il Suk et al.,2015 [106]	SAE	150	MRI and PET	98.8%	#	#	Ternary	ADNI
Heung-Il Suk and Dinggang Shen.,2013 [107]	SVM,SAE	202	MRI and PET Images	95.9%	#	#	Ternary	ADNI
Yilu Zhao and Lianghua He.,2014 [108]	SVM, DL	30	EEG data	92%	#	#	Binary	–
Shui-Hua Wang et al.,2018 [109]	CNN	196	MRI	97.65%	97.96%	97.35%	Binary	OASIS
Jyoti Islam and Yanqing Zhang et al.,2017 [110]	Deep CNN	416	MRI Data	73.75%	#	#	One Way	OASIS
Donghyeon Kim and Kiseon Kim.,2018 [111]	DNN	20	EEG Signals	#	#	#	Binary	CUH and GODC

Moreover, CNN, DNN, and RNN techniques have been more exploited in the diagnosis of these neurological and neuropsychiatric disorders as compared to other techniques (DA, RBM, and DBM).

Table 7 presents the rate of usage of different DL techniques in the diagnosis of distinct neurological and neuropsychiatric human disorders.

From Table 7, it is revealed that CNN technique is effectively used by researchers in the diagnosis of different neurological disorders as a comparison to other DL techniques. Additionally, Stacked Autoencoder (SAE) has also got the attention of the authors. The usage of other DL techniques namely DNN, DBN, RNN, DBM is minimum. Consequently, it is incumbent to employ and analyze the effectiveness of DNN, DBN, RNN, and DBM in the prognosis of different neurological and neuropsychiatric human disorders.

RQ5: What are the common datasets of neurological and neuropsychiatric disorders?

Data sets are an important part of any artificial intelligence application. Several datasets have been used for diagnosis of different neurological and neuropsychiatric human disorders. Table 8 depicts some of the major types of datasets that have been used in the diagnosis of these human disorders by different authors. It is found that MRI and EEG based datasets are mostly used to diagnose stroke, Alzheimer, Parkinson,

Table 5 Diagnostic Studies on Parkinson's Disorder (# represents the empty value)

Author	Methods	Instances	Modality	Accuracy	Sensitivity	Specificity	AUC
Claudio Gallicchio et al., 2018 [112]	Deep Echo State Network (DESN)	76	Time Series Data	89.33%	90%	80%	#
Bangming Gong et al., 2018 [113]	DNMLDM, SVM	153	transcranial sonography and MRI Dataset	81%	82.92%	80.02%	#
Ivan Klyuzhin et al., 2018 [114]	D-CNN	50,000	DaTscan SPECT images	#	#	#	0.69
Shu LihOh et al., 2018 [115]	CNN	40	EEG Signals	#	88.25%	84.71%	#
P. Khojasteh et al., 2018 [116]	D- CNN	81	Speech Signals	#	75.7%	#	#
Clayton R. Pereira et al., 2018 [117]	CNN	95	Handwriting Image	95%	#	#	#
Julia Camps et al., 2017 [118]	DL	21	MRI	90%	#	#	#
Vinod J. Kadam and Shivajirao M. Jadhav.,2019 [18]	DNN	–	Binary, Real	90%	#	#	#
Hongyoon Choi et al., 2017 [119]	CNN	701	SPECT Images	98.8%	98.6%	100%	#
Sumeet Shinde et al.,2019[120]	CNN	55	Neuromelanin sensitive MRI	83.7%	#	#	#
Y. N. Zhang, 2017 [26]	SAE, KNN	195	Speech Records	98%	#	#	#
Francisco Jesús Martinez-Murcia et al.,2017 [121]	3 D-CNN		SPECT	95.5%	96.2%	#	#
Ali H. Al-Fatlawi et al.,2016 [122]	DBN	31	Voice Records	94%	#	#	#

Table 6 Diagnostic Studies on Epilepsy Disorder (# represents the empty value)

Article	Methods	Instances	Modality	Accuracy	Sensitivity	Specificity
Ramy Hussein et al.,2019 [123]	Deep Long Short-termmemory(DLSTM)	500	EEG Signals	**100%**	**100%**	**100%**
OzalYıldırım et al.,2018 [124]	Deep One-Dimensional CNN(D-1DCNN)	28,000	EEG Signals	79.34%	78.71%	#
Xiaoyan Wei et al.,2018 [125]	Three Dimensional CNN(3DCNN)	13	EEG Signals	90%	88.90%	93.78%
U. RajendraAcharya et al., 2018 [126]	Deep CNN(DCNN)	#	EEG signals	88.67%	90%	95%
Hisham G. Daoud et al.,2018 [17]	DNN	500	EEG Signals	98.6%	#	#
Xinghua Yao et al.,2018 [127]	BiDirectional LSTM(BLSTM)	686	EEG Signals	83.89%	83.72%	84.06%
Ihsan Ullah et al.,2018 [128]	Pyramidal one-dimensional CNN(P-1DCNN)	4097	EEG Signals	99.1%	#	#
Mohammad-ParsaHosseini et al.,2017 [129]	CNN	160	EEG signals and rs-fMRI	#	#	#
Le Thanh Xuyen et al.,2017 [130]	DBN	19	EEG Signals	96.87%	92.82%	96.41%
Mohammad-Parsa Hosseini et al.,2017 [131]	SSDA, IoT and Convolutional Auto-encoder(SSDA,IoT,CAE)	11	EEG Signals and ECoG Signals	96%	97%	#
Sachin Talathi,2017 [132]	RNN	4097	EEG signals	99.96%	#	#
Qin Lin.,2016 [28]	SAE	500	EEG Signals	96%	98.67%	93.83%
Pierre Thodoro et al.,2016 [133]	RNN	183	EEG Signals	85%	#	#
Dazi Li et al.,2016 [134]	CNN	1600	EEG Signals	95.7%	#	#
Andreas Antoniades et al.,2016 [135]	CNN	25	EEG signals	87.51%	#	#
Ye Yuan et al.,2019 [136]	SSDA and Convolutional Auto-encoder (SSDA, CAE)	23	Scalp EEG dataset	94.37%	#	#

epilepsy, and autism. These datasets were collected from different sources such as hospitals, research centres, and online repositories. Additionally, some of the authors have also worked with SPECT images and speech signal for the same.

Discussion

The early and precise diagnosis of neurological disorders is a very challenging task for both healthcare professionals and data scientists. These are chronic and fatal human disorders that are significantly influencing the lifestyle and overall behaviour of the person. This section highlights the major findings of this study. The performance and publication metrics are discussed. The publication details of the related manuscript have been deeply explored. Furthermore, research implications, as well as challenges, and weaknesses of this study has been conferred.

Metrics

This section will highlight the performance and publication metrics found during this research work. This comprehensive study revealed that in most of the cases, authors have examined the performance of different deep learning models in terms of three performances metric viz. accuracy, specificity and sensitivity. Moreover, it is very difficult and challenging to determine the real impact of the manuscript. Some of the important metrics which are normally used to find the overall impact of the manuscript are a journal, publisher, rate of citation, and impact factor of the journal. The publication analysis of some of the key article included in this survey is presented in Table 9.

In this study, many research articles from quality journals (IEEE, Springer, and Elsevier) using different key areas such as diagnosis of neurological diseases using learning

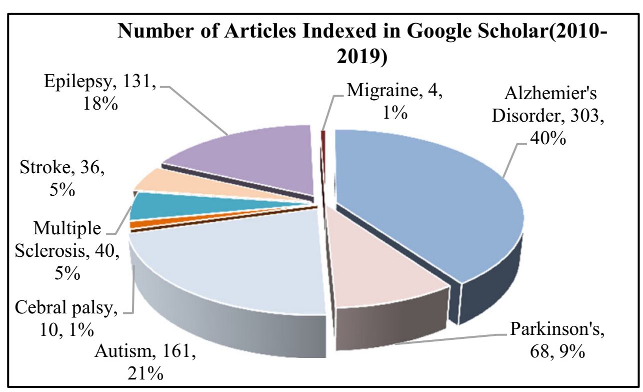


Fig. 14 Articles published in Google Scholar (2010–2019) using DL techniques

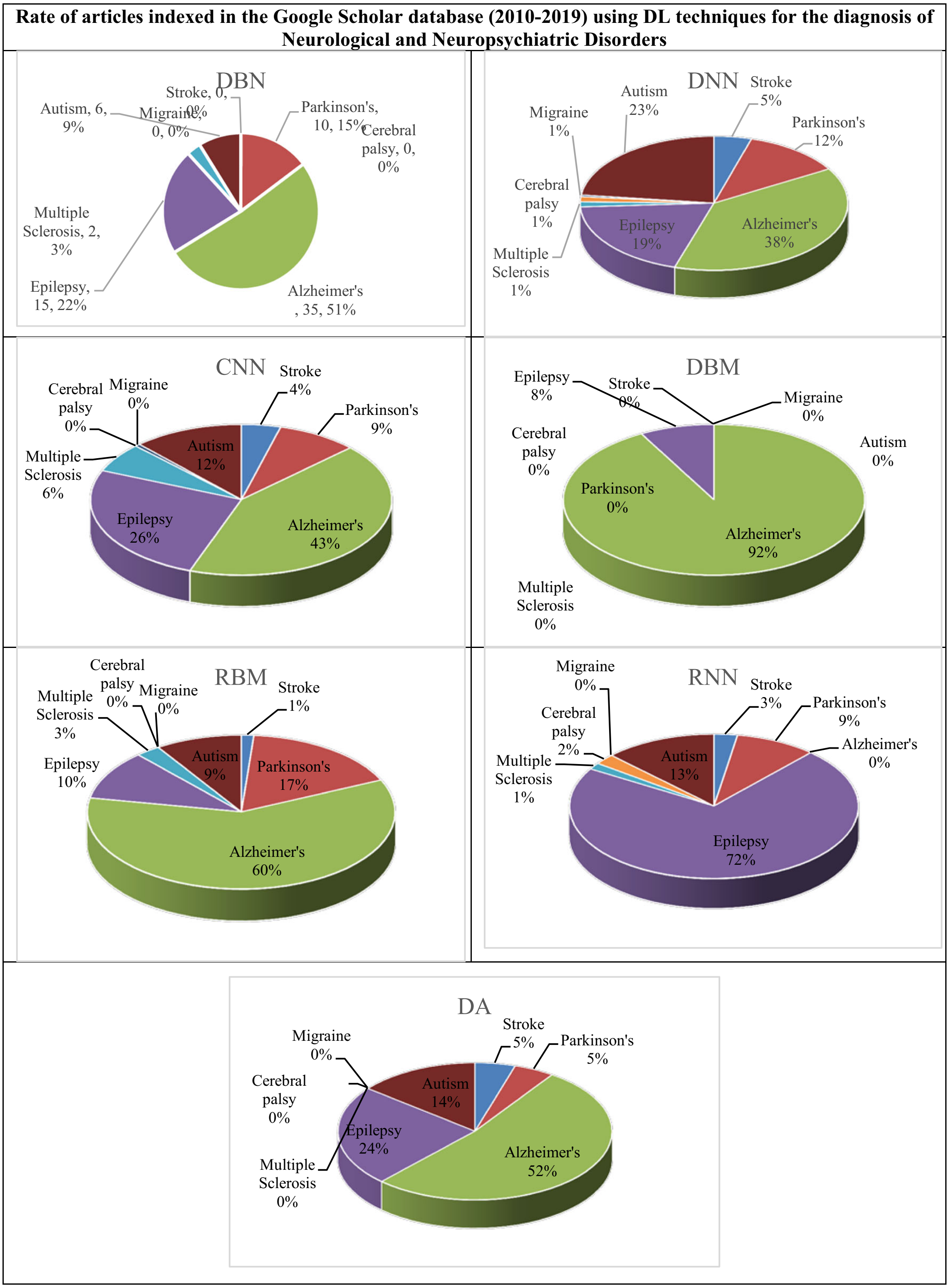


Figure 15: Rate of articles indexed in the Google Scholar database (2010–2019) using DL techniques for the diagnosis of Neurological and Neuropsychiatric Disorders

techniques have been analyzed thoroughly, which finally emanates this review work. The citation rate of articles lies between 0 and 276. It is observed that researchers of different countries like India, China, United States, Pune, Spain, and Brazil, etc. have paid more attention to the diagnosis of neurological disorders.

Table 7 Comparison of Deep Learning Techniques

Disease	SAE(DA)	CNN	DNN	DBN	RNN	DBM	Other Method
Stroke	22%	56%	0%	0%	0%	0%	22%
Alzheimer's	18%	47%	11%	0%	3%	3%	18%
Parkinson's	8%	54%	8%	8%	0%	0%	23%
Epilepsy	19%	44%	6%	6%	25%	0%	0%
Autism	17%	17%	50%	0%	0%	0%	17%
Migraine	0%	100%	0%	0%	0%	0%	0%
Cerebral Palsy	100%	0%	0%	0%	0%	0%	0%
Multiple Sclerosis	0%	67%	0%	0%	0%	0%	33%

Performance of DL techniques in different neurological disorders

Table 10 presents the performance of different deep learning techniques in prospecting different neurological diseases. Performance is measured in terms of best predictive accuracy and technique.

From Table 10, it is seen that classification accuracy in the diagnosis of particular neurological and neuropsychiatric disorders lies in the range between 90 and 100%. Diagnosis of

Table 8 Dataset used for neurological and neuropsychiatric disorders

Data Source	Disease	Modality
Tennessee Department of Health. [27]	Stroke	Integer
Medical College Institute [62]	Stroke	CT and MRI
National Database for Autism Research (NDAR) [38]	Autism	MRI
Helsinki University Hospital [42]	Stroke	CT and angiography source images
Ischemic Stroke Lesion Segmentation (ISLES) 2015 [63]	Stroke	MRI
Tianjin-Huanhu Hospital [65]	Stroke	CT image
University of California, Los Angeles Medical Center [67]	Stroke	Images
Autism Brain Imaging Data Exchange ABIDE) [69]	Autism	rs-fMRI
Gillette Children's Specialty Healthcare Center [72]	Cerebral Palsy	Integer, Real
MICCAI-2008 [73]	Multiple Sclerosis	MRI
ISBI [74]	Multiple Sclerosis	MRI
Remitting Relapsing Multiple Sclerosis (RRMS), Secondary Progressive Multiple Sclerosis (SPMS) and Primary Progressive Multiple Sclerosis (PPMS) [75]	Multiple Sclerosis	MRI
Open Access Series of Imaging Studies (OASIS) [78]	Alzheimer's	MRI
Alzheimer's Disease Neuroimaging Initiative (ADNI) [79]	Alzheimer's	MRI
Chosun University Hospital (GUH) and Gwangju Optimal Dementia Center (GODC) [111]	Alzheimer's	EEG Signals
Sprial Dataset (UC Irvine Machine Learning Repository) [112]	Parkinson's	Time Series Data
Shanghai East Hospital of Tongji University [113]	Parkinson's	MRI
Hospital-University Kebangsaan Malaysia Ethics Committee [115]	Parkinson's	EEG Signals
Dandenong Neurology, Centre, Melbourne, Australia [116]	Parkinson's	Speech Signals
Parkinson's Progression Markers Initiative (PPMI) [119]	Parkinson's	SPECT Images
National Inst. of Mental-Health and Neurosciences (NIMHANS) [120]	Parkinson's	MRI
Parkinson's Data Set [122]	Parkinson's	Voice data
Munzur University Tunceli, Turkey [124]	Epilepsy	EEG Signals
Hospital of Xinjiang Medical University [125]	Epilepsy	EEG Signals
University of Pennsylvania and the Mayo Clinic and sponsored by the American Epilepsy Society [129]	Epilepsy	EEG Signals
Signal and Systems Laboratory, University of Engineering and Technology, Vietnam National University [130]	Epilepsy	EEG Signals
Children's Hospital of Boston-Massachusetts Institute of Technology dataset (CHB-MIT) [133]	Epilepsy	EEG Signals
Huaxi MR Research Centre, West Bengal [37]	Migraine	MRI

Table 9 Publication Details of the study

Author	Author's Country	University	Journal	Publisher	Citation
Anibal Sólon Heinsfeldet al.,2017 [16]	Brazil	School of Computer Science	NeuroImage: Clinical	Elsevier	54
Y. N. Zhang, 2017 [26]	China	Beijing Institute of Technology	Parkinson's Disease	Hindawi	12
Hao Yang et al.,2018 [37]	China	Sichuan University, Chengdu, Sichuan	Biomedical Engineering	Springer	2
G. J. Awate et al.,2018 [39]	Andhra Pradesh	K.L.E.F. University	Computer Vision and Pattern Recognition	Arxiv Preprint	1
Olli Öman et al.,2019 [42]	Finland	University of Helsinki	European Radiology Experimental	Springer	0
Praveen G.B et al., 2018 [63]	Goa	BITS PILANI - K.K Birla	Computers in Biology and Medicine	Elsevier	8
Zhiyang Liu.,2018 [65]	China	Nankai University, Tianjin	IEEE Access	IEEE	3
Xinyu Guo et al., 2017 [69]	United States	Cincinnati Children's Hospital Research Foundation	Frontiers in neuroscience	Frontier	20
Yazhou Kong et al.,2019 [70]	China	South University, Changsha	Neurocomputing	Elsevier	5
Lukasz kidzinski et al.,2019 [72]	United States of America	Stanford University Department of Bioengineering, Stanford, CA	PloS One	PloS	1
Sergi Valverde et al.,2017 [73]	Spain	University of Girona	NeuroImage	Elsevier	67
Debesh Jha and Goo-Rak Kwon., 2017 [78]	Korea	Chosun University, Gwanju, Korea	International Journal of Machine-Learning–and-Computing	IJMLC organization	6
K.R. Kruthika et al., 2018 [81]	Bangalore	Acharya Institute of Technology	Informatics in Medicine Unlocked	Elsevier	0
Silvia Basaia et al.,2019 [84]	Italy	Vita-Salute San Raffaele University, Milan	NeuroImage: Clinical	Elsevier	2
Ruoxuan Cui et al.,2019 [86]	China	Shanghai Jiao Tong University	Computerized Medical-Imaging and Graphics	Elsevier	0
Ruoxuan Cui et al.,2018 [87]	China	Shanghai Jiao Tong University	Journal of BioMed. & health	IEEE	0
Hongfei Wang et al.,2019[88]	China	Chinese Academy of Sciences, Shenzhen	Neurocomputing	Elsevier	2
Simeon Spasov et al.,2019 [89]	United Kingdom	University of Cambridge	Neuroimage	Elsevier	2
Jun Shi et al., 2017 [94]	China	Shanghai University, Shanghai	Journal of Biomedical and Health Informatics	IEEE	66
Ronghui Ju et al.,2017 [95]	China	Huazhong University of Science and Technology Wuhan, Hubei	Transactions on Computational Biology and Bioinformatics	IEEE/ACM	7
Nicola Amoroso et al.,2018 [96]	Italy	Università degli studi di Bari	Journal of neuroscience methods	Elsevier	13
SamanSarraf et al.,2017[99]	Canada	Rotman Research Institute at Baycrest, Toronto, Ontario	BioRxiv	BioRxiv	47
Bibo Shi et al.,2016 [101]	United States	Duke University, Durham	Pattern recognition	Elsevier	27
Adrien Payan et al.,2015 [103]	United Kingdom	University of Warwick	Computer Vision and Pattern Recognition		165
Heung-IlSuk et al.,2014 [104]	USA	University of North Carolina	Neuroimage	Elsevier	276
Heung-Il Suk et al.,2015 [106]	USA	University of North Carolina	Brain-Structure and Function	Springer	170
Bangming Gong et al., 2018 [113]	China	Shanghai University	Neurocomputing	Elsevier	0
Ivan Klyuzhin et al., 2018 [114]	United States	University Baltimore MD	Journal of Nuclear Medicine	Soc Nuclear Med	0
Shu LihOh et al., 2018 [115]	Singapore	Ngee Ann Polytechnic Singapore	Neural-Computing & Applications	Springer	39
Clayton R. Pereira et al., 2018 [117]	Brazil	Federal University	Artificial Intelligence in Medicine	Elsevier	15
Julia Camps et al., 2017 [118]	Spain	Universitat Politècnica de Catalunya	Knowledge-based System	Elsevier	13
Hongyoon Choi et al., 2017 [119]	Korea	Seoul-National-University College of Medicine	NeuroImage: Clinical	Elsevier	14
Sumeet Shinde et al.,2019[120]	Pune	Symbiosis International (Deemed) University	NeuroImage: Clinical	Elsevier	0

Table 9 (continued)

Author	Author's Country	University	Journal	Publisher	Citation
Ramy Hussein et al.,2019 [123]	Canada	University of British Columbia	Clinical Neurophysiology	Elsevier	2
OzalYildırım et al.,2018 [124]	Turkey	Munzur UniversityTunceli	Neural Computing and Applications	Springer	5
U. RajendraAcharya et al., 2018 [126]	Singapore	Ngee Ann Polytechnic	Computers in Biology and Medicine	Elsevier	160
Ihsan Ullah et al.,2018 [128]	Ireland	National University of Ireland, Galway	Expert-Systems with Applications	Elsevier	14
Mohammad-Parsa Hosseini et al.,2017 [131]	USA	Rutgers University	Transaction on Big data	IEEE	19
Ye Yuan et al.,2019 [136]	China	Beijing University of Technology	journal of biomedical and health informatics	IEEE	1

Alzheimer's disorder has got the highest rate of accuracy i.e. 100% using CNN. Whereas, predictive rate of accuracy for stroke disorder is achieved using the hybridization of SAE and DNN is 90%. Though, fewer articles are published on migraine, epilepsy and multiple sclerosis disorders. Still, DL techniques CNN and RNN with migraine, epilepsy and multiple sclerosis disorders have achieved excellent predictive accuracy of 99.25%, 99.6%, and 99.78% respectively.

Research implication and practice

This exhaustive review will give major insights to the researchers who want to employ and examine the performance of different soft computing techniques (particularly DL techniques) in the premature diagnosis of disparate human disorders. No significant survey related to the title and objectives of this manuscript is available. This comprehensive survey revealed that there is need to use and explore the performance of the DBN, RBM and DBM deep learning methods as these techniques are very least explored as far as diagnosis of neurological disorders is considered. In spite of neurological disorders, different deep learning model and their hybrid approaches can also be employed to diagnose other chronic and fatal human disorders.

Challenges

The notion of using DL methods in the diagnosis of human chronic diseases is an attractive and augmenting research field. DL techniques have been dominantly used in different application likes speech recognition, face recognition and NLP. However, the data involved in the neurological disorders are normally available in the form of CT-images, EEG and MRI that consumed massive amount on storage media which is significantly higher as compared to the application above-mentioned applications. The challenge lies in the training and testing of this momentous volume of data. Additionally, the heterogeneous nature of neurological disorders data (CT-images, EEG and MRI) and the amount of noise involved in the data is another challenging job. Consequently, the privacy of the patient's data is a substantial challenge for this kind of research work.

Strength

This study has covered 136 different manuscripts related to the deep learning techniques and their use in the diagnosis of different neuropsychiatric and neurological disorders. Different deep learning techniques have been briefly elucidated. A sufficient amount of literature related to the use of deep learning techniques in the diagnosis of eight different neuropsychiatric and neurological disorders such as stroke, alzheimer, parkinson's, epilepsy, autism, migraine, cerebral

Table 10 Highest rate of accuracy achieved by different authors in the diagnosis of different neurological and neuropsychiatric disorders

Disease	Author	Methodology	Accuracy
Stroke	Praveen G.B et al., 2018 [63]	SVM, SAE	90%
Alzheimer's	Simeon Spasov et al.,2019 [89]	CNN	100%
Parkinson's	Hongyoon Choi et al., 2017 [119]	CNN	98.8%
Epilepsy	Sachin Talathi,2017 [132]	RNN	99.6%
Autism	Yazhou Kong et al.,2019 [70]	DNN	90.39%
Migraine	Hao Yang et al.,2018 [37]	CNN	99.25%
Multiple Sclerosis	YelizKaraca et al.,2017 [75]	Deep Learning	99.78%

palsy, and multiple sclerosis has been presented. The use of different deep learning techniques like DNN, DBN, RBM, DA, CNN, RNN and DBM in different fatal and chronic human disease has also been highlighted. An extensive publication trend has been explored and presented. The consequences of using DL techniques in the diagnosis of neuropsychiatric and neurological disorders have also been discussed. In addition, the dataset used in the diagnostic process of these human neuropsychiatric and neurological disorders has also highlighted. Moreover, the research implication and practices of this work have also been pointed out.

Limitations

The maximum effort was made to select the most relevant manuscripts related to the study. However, the compilation of the related manuscript in a single study is not possible. The manuscripts published in a non-English language like Spanish, French, Korean, German, Bengali, Italian, Punjabi, etc. were ignored in this study. Additionally, the manuscripts related to the prognosis of eight different neuropsychiatric and neurological disorders such as stroke, alzheimer, parkinson's, epilepsy, autism, migraine, cerebral palsy, and multiple sclerosis have only been considered. The use of deep learning techniques in the diagnosis of other neuropsychiatric and neurological disorders has not been considered during the synthesis of meta-analysis. The emphasis was given to highlight the use of different deep learning techniques. However, the mathematical details of different deep learning techniques and their consequences have not been explored in this study.

Conclusion and future directions

Neurological disorders are chronic and life-threatening disorders that badly affect the overall routine of human life. In the last few years, deep learning techniques have drawn the immense attention of researchers in the diagnosis of these disorders. Here, a comprehensive review of different deep learning techniques used in the diagnosis of major neurological and neuropsychiatric disorders has been presented. A two-dimensional search space related to these disorders and deep learning techniques has been deeply explored. Five different research questions have been formulated and answered.

First of all, categories of neurological and neuropsychiatric disorders along with their symptoms and reasons have been explored. Morbidity and mortality rate of these disorders have been also highlighted. It has been observed that worldwide mortality and morbidity rate of stroke disorder is outrageous among other neurological and neuropsychiatric disorders. The second research question aspires to present different deep learning techniques. The solemnity of using divergent DL techniques in the diagnosis of different neurological and neuropsychiatric disorders has been explicated in the third question. The performance of different deep learning techniques such as CNN, RNN, RBM, DBN, DBM, DNN and DE have been also conferred. It has been found that most of the authors have used CNN in prospecting different neurological disorders. As far as Ischemic stroke is concerned, the hybrid approach of SVM and SAE found to be more efficacious as compared to other deep learning techniques. For Alzheimer's and Parkinson's disorder, CNN found to present better results than other DL methods. In addition, RNN proves to be a more prominent technique in the diagnosis of epilepsy disorder. Moreover, DNN seems to be more effective in the diagnosis of autism disorder. In spite of a few articles on migraine, cerebral palsy and multiple sclerosis, CNN achieved exceptional results in the diagnosis of these disorders. The publication trend related to these disorders using deep learning techniques have been emphasized in the fourth question. It is found that deep learning in the diagnosis of Alzheimer disorder (40%) is more explored as compared to other neurological and neuropsychiatric disorders. However, very few articles have been published on migraine (1%), cerebral palsy (1%), stroke (5%), Parkinson's (9%), epilepsy (18%) autism (21%) and multiple sclerosis (5%) disorders using different deep learning techniques. So, there is a dire need to explore these disorders with the same. Moreover, three deep learning techniques namely CNN, DNN, and RNN have been more frequently employed in the diagnosis of these neurological and neuropsychiatric disorders as compared to other DLT (DA, RBM, DBN, and DBM). Different datasets used in the diagnosis of these disorders have been presented in the fifth question. Authors have collected data from different sources like hospitals, online repositories, and research centres. It is noticed that EEG and MRI based datasets have been effectively utilized in the diagnosis of epilepsy, stroke, Parkinson and Alzheimer disorders. It is found that CNN is more used and explored as compared to other techniques in the diagnosis of different neurological and neuropsychiatric disorders. However, there is a prospective scope to use and explore other deep learning techniques as DBN, RBM, RNN, DBM, DA and RNN techniques as these techniques are used very less in the diagnosis of neurological disorders. In the future, Deep learning techniques in the hybridization of nature-inspired techniques should be explored for more effective performance in the diagnosis of neurological and neuropsychiatric disorders.

Compliance with ethical standards

Conflict of interest Authors proclaim that they have no dissension of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

1. Ghorbani, R., and Ghousi, R., Predictive data mining approaches in medical diagnosis: A review of some diseases prediction. International Journal of Data and Network Science 3(2):47–70, 2019.
2. Kennedy, D. P., and Adolphs, R., The social brain in psychiatric and neurological disorders. Trends Cogn Sci 16(11):559–572, 2012.
3. World Health Organization (2006) Neurological disorders: public health challenges. World Health Organization.Link:https://www.who.int/mental_health/neurology/chapter_2_neuro_disorders_public_h_challenges.pdf?ua=1(Accessed on 23 July 2019).
4. Orru, G., Pettersson-Yeo, W., Marquand, A. F., Sartori, G., and Mechelli, A., Using SVM to identify imaging biomarkers of neurological and psychiatric disease: A critical review. Neurosci Biobehav Rev 36(4):1140–1152, 2012.
5. Chin, J. H., and Vora, N., The global burden of neurologic diseases. Neurology. 83(4):349–351, 2014.
6. Sharma, M., Singh, G., and Singh, R., Stark assessment of lifestyle based human disorders using data mining based learning techniques. IRBM. 38:305–324, 2017.
7. Gautam, R., Kaur, P., and Sharma, M., A comprehensive review on nature-inspired computing algorithms for the diagnosis of chronic disorders in human beings. Progress in Artificial Intelligence. 8(4):1–24, 2019.
8. Kaur, P., and Sharma, M., Diagnosis of human psychological-disorders using supervised-learning and nature-inspired computing techniques: A meta-analysis. J Med Syst 43(7):204, 2019.
9. Kaur, P., and Sharma, M., A survey on using nature-inspired computing for fatal disease diagnosis. International Journal of Info Sys Modelling and Design 8(2):70–91, 2017.
10. Gawehn, E., Hiss, J. A., and Schneider, G., Deep learning in drug discovery. Molecular informatics 35(1):3–14, 2016.
11. Pouyanfar, S., Sadiq, S., Yan, Y., Tian, H., Tao, Y., Reyes, M. P., and Iyengar, S. S., A survey on deep learning: Algorithms, techniques, and applications. ACM Computing Surveys (CSUR) 51(5): 92, 2018.
12. Wason, R., Deep learning: Evolution and expansion. Cogn Syst Res 52:701–708, 2018.
13. Cireşan, D. C., Giusti, A., Gambardella, L. M., and Schmidhuber. Mitosis detection in breast cancer histology images with deep neural networks. In International Conf. on Med. Image-Computing and Computer-assisted Intervention, Springer, Heidelberg, 411–418, 2013.
14. Ramesh, S., Caytiles, R. D., and Iyengar, N. C. S., A deep-learning approach to identify diabetes. Advanced Science and Tech Letter 145:44–49, 2017.
15. Ma, X., Yang, H., Chen, Q., Huang, D., and Wang, Y., Depaudionet: An efficient deep model for audio-based depression classification. In Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge, ACM, 35–42,2016.
16. Heinsfeld, A. S., Franco, A. R., Craddock, R. C., Buchweitz, A., and Meneguzzi, F., Identification of autism spectrum disorder using deep learning and the ABIDE dataset. NeuroImage: Clinical 17:16–23, 2018.
17. Daoud, H. G., Abdelhameed, A. M., and Bayoumi, M., Automatic epileptic seizure detection based on empirical mode decomposition and deep neural network. In 2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA) IEEE, 182–186, 2018.
18. Kadam, V. J., and Jadhav, S. M., Feature Ensemble Learning Based on Sparse Auto-encoders for Diagnosis of Parkinson's Disease. In Computing, Communication and Signal Processing, Springer, Singapore. 810:567–581, 2019.
19. Gulhare, K. K., Shukla, S. P., and Sharma, L. K., Deep Neural Network Classification method to Alzheimer's Disease Detection. International Journals of Advanced Research in Computer Science and Software Engineering 7(6):1–4, 2017.
20. Abdel-Zaher, A. M., and Eldeib, A. M., Breast-cancer classification using deep belief networks. Expert Syst Appl 46:139–144, 2016.
21. Kim, J., Kang, U., and Lee, Y., Statistics and deep belief network-based cardiovascular risk prediction. Healthcare Informatics Research 23(3):169–175, 2017.
22. Cai, H., Sha, X., Han, X., Wei, S., and Hu, B., Pervasive EEG diagnosis of depression using Deep Belief Network with three-electrodes EEG collector. In 2016 IEEE International Conference on Bioinformatics and Biomedicine, 1239–1246, 2016.
23. Xu, J., Xiang, L., Liu, Q., Gilmore, H., Wu, J., Tang, J., and Madabhushi, A., Stacked sparse autoencoder for nuclei detection on breast cancer-histopathology images. IEEE Trans Med Imaging 35(1):119–130, 2016.
24. Chen, L., Zhou, M., Su, W., Wu, M., She, J., and Hirota, K., Softmax regression-based deep sparse autoencoder network for facial emotion recognition in human-robot interaction. Inf Sci 428:49–61, 2018.
25. Dolph, C. V., Alam, M., Shboul, Z., Samad, M. D., and Iftekharuddin, K. M., Deep learning of texture and structural features for multiclass Alzheimer's disease classification. In 2017 International Joint Conference on Neural Networks, 2259–2266, 2017.
26. Zhang, Y. N., Can a smartphone diagnose Parkinson disease? A deep neural network method and telediagnosis system implementation. Parkinson's Disease 2017:1–11, 2017.
27. Cho, J., Hu, Z., and Sartipi, M., Post-stroke discharge disposition prediction using deep learning. In SoutheastConf IEEE, 1-2, 2017.
28. Lin, Q., Ye, S. Q., Huang, X. M., Li, S. Y., Zhang, M. Z., Xue, Y., and Chen, W. S., Classification of epileptic EEG signals with

stacked sparse autoencoder based on deep learning. In International Conference on Intelligent Computing. Springer, Cham, 802–810, 2016.
29. Wu, L., Zhou, W., Wan, X., Zhang, J., Shen, L., Hu, S., and Liu, J., A deep neural network improves endoscopic detection of early gastric cancer without blind spots. Endoscopy. 51(06):522–531, 2019.
30. Albahar, M. A., Skin lesion classification using convolutional neural network with novel Regularizer. IEEE Access 7:38306–38313, 2019.
31. Kumar, S., Negi, A., and Singh, J. N., Semantic Segmentation Using Deep Learning for Brain Tumor MRI via Fully Convolution Neural Networks. In Information and Communication Technology for Intelligent Systems, Springer, Singapore,11–19, 2019.
32. Ren, X., Xiang, L., Nie, D., Shao, Y., Zhang, H., Shen, D., and Wang, Q., Interleaved 3D-CNN s for joint segmentation of small volume structures in head and neck CT images. Med Phys 45(5): 2063–2075, 2018.
33. Lo, S. C. B., Li, H., Wang, Y., Kinnard, L., and Freedman, M. T., A multiple circular path convolutions neural network system for detection of mammographic masses. IEEE Trans Med Imaging 21(2):150–158, 2002.
34. Lang, R., Zhao, L., and Jia, K., Brain tumour image segmentation based on convolution neural network. In 2016 9th International Congress on Image and Signal-Processing, BioMed. Engg. and Informatics (CISP-BMEI) IEEE, 1402–1406, 2016.
35. Dham, S., Sharma, A., and Dhall, A., Depression scale recognition from audio, visual and text analysis. arXiv preprint arXiv: 1709.05865, 2017.
36. Wan, S., Liang, Y., Zhang, Y., and Guizani, M., Deep multi-layer perceptron classifier for behaviour analysis to estimate Parkinson's disease severity using smartphones. IEEE Access 6:36825–36833, 2018.
37. Yang, H., Zhang, J., Liu, Q., and Wang, Y., Multimodal MRI-based classification of migraine: using deep learning CNN. Biomedical engineering online 17 (1): 138, 2018.
38. Li, G., Liu, M., Sun, Q., Shen, D., and Wang, L., Early diagnosis of autism disease by multi-channel CNNs. In International Workshop on Machine Learning in Medical Imaging, Springer, Cham,303–309, 2018.
39. Awate, G., Bangare, S., Pradeepini, G., and Patil, S, Detection of Alzheimers Disease from MRI using Convolutional Neural Network with Tensorflow. arXiv preprint arXiv:1806.10170, 2018.
40. Gong, J., Lach, J., Qi, Y., and Goldman, M. D., Causal analysis of inertial body sensors for enhancing gait assessment separability towards multiple sclerosis diagnosis. 12th International Conf. on Wearable & Implantable Body-Sensor-Networks, IEEE, 1–6, 2015.
41. Ma, J., Wu, F., Zhu, J., Xu, D., and Kong, D., A pre-trained CNN-based method for thyroid nodule diagnosis. Ultrasonics. 73:221–230, 2017.
42. Öman, O., Mäkelä, T., Salli, E., Savolainen, S., and Kangasniemi, M., 3D convolutional neural networks applied to CT angiography in the detection of acute ischemic stroke. European Radiology Experimental 3(1):8, 2019.
43. Vieira, S., Pinaya, W. H., and Mechelli, A., Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications. NeurosciBiobehav Rev 74(1):58–75, 2017.
44. Akkus, Z., Galimzianova, A., Hoogi, A., Rubin, D. L., and Erickson, B. J., Deep learning for brain MRI segmentation: State of the art and future directions. J Digit Imaging 30(4):449–459, 2017.
45. Tandel, S., G., Biswas, M., Kakde, G., O., Tiwari, A., Suri, S., H., Turk, M., and Madhusudhan, K., B., A Review on a Deep Learning Perspective in Brain Cancer Classification. Cancers 11(1):111(1–32), 2019.
46. Dinu, A. J., Ganesan, R., Joseph, F., and Balaji, A study on Deep Machine Learning Algorithms for diagnosis of diseases. Int J Appl Eng Res 12(17):6338–6346, 2017.
47. Siuly, S., and Zhang, Y., Medical big data: Neurological diseases diagnosis through medical data analysis. Data Science and Engineering 1(2):54–64, 2016.
48. Vos, T. et al., Global-burden of disease study 2013 collaborators. Global, regional, and national incidence, prevalence, and years lived with disability for 301 acute and chronic diseases and injuries in 188 countries, 1990–2013: A systematic analysis for the global burden of disease study 2013. Lancet 386(9995):743–800, 2015.
49. Kalia, L. V., and Lang, A. E., Parkinson's disease. Lancet 386(9996):896–912, 2015.
50. Dementia Fact sheet (2017) World Health Organization. Link: https://www.who.int/news-room/fact-sheets/detail/dementia. (Accessed on 26 July 2019).
51. Theo, V. et al., Global, regional, and national incidence, prevalence, and years lived with disability for 310 diseases and injuries, 1990-2015: a systematic analysis for the Global Burden of Disease Study 2015. Lancet 388(10053):1545–1600, 2016.
52. Wang, H. et al., Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: a systematic analysis for the Global Burden of Disease Study 2015. Lancet 388(10053):1459–1544, 2016.
53. Global, regional, and national age-sex specific all-cause and cause-specific mortality for 240 causes of death, 1990–2013: a systematic analysis for the Global Burden of Disease Study 2013. Lancet. 385(9963): 117–71, 2014.
54. Oskoui, M., Coutinho, F., Dykeman, J., Jetté, N., and Pringsheim, T., An update on the prevalence of cerebral palsy: a systematic review and meta-analysis. Developmental Medicine & Child Neurology 55(6):509–519, 2013.
55. Stovner, L. J., Nichols, E., Steiner, T. J., Abd-Allah, F., Abdelalim, A., Al-Raddadi, R. M., and Edessa, D., Global, regional, and national burden of migraine and tension-type headache, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016. The Lancet Neurology 17(11):954–976, 2018.
56. Feigin, V. L., Abajobir, A. A., Abate, K. H., Abd-Allah, F., Abdulle, A. M., Abera, S. F., and Aichour, M. T. E., Global, regional, and national burden of neurological disorders during 1990–2015: A systematic analysis for the global burden of disease study 2015. The Lancet Neurology 16(11):877–897, 2017.
57. Deng, L., A tutorial survey of architectures, algorithms, and applications for deep learning. APSIPA Transactions on Signal and Information Processing 3:1–29, 2014.
58. Razzak, M. I., Naz, S., and Zaib, A., Deep learning for medical image processing: Overview, challenges and the future. In Classification in BioApp, Springer, Cham. 26:323–350, 2018.
59. LeCun, Y., Bengio, Y., and Hinton, G., Deep learning. Nature 521(7553):436–444, 2015.
60. Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., and Yang, G., Deep learning for health informatics. IEEE Journal Of Biomedical and Health Informatics 21(1):4–21, 2017.
61. Lan, K., Wang, D. T., Fong, S., Liu, L. S., Wong, K. K., and Dey, N., A survey of data mining and deep learning in bioinformatics. J Med Syst 42(8):139, 2018.
62. Haridas, H., and Wilson, A., An Artificial Intelligence Approach for Predicting Different Types of Stroke. In 2018 Second international conference on inventive communication and computational technologies, IEEE, 1858-1861, 2018.

63. Praveen, G. B., Agrawal, A., Sundaram, P., and Sardesai, S., Ischemic stroke lesion segmentation using stacked sparse autoencoder. Comput Biol Med 99:38–52, 2018.
64. Jung, S. M., and Whangbo, T. K., Evaluating a Deep-Learning System for Automatically Calculating the Stroke ASPECT Score. In 2018 International conference on information and communication technology convergence, IEEE, 564-567, 2018.
65. Liu, Z., Cao, C., Ding, S., Liu, Z., Han, T., and Liu, S., Towards clinical diagnosis: Automated stroke lesion segmentation on multi-spectral MR image using convolutional neural network. IEEE Access 6:57006–57016, 2018.
66. Stier, N., Vincent, N., Liebeskind, D., and Scalzo, F., Deep learning of tissue fate features in acute ischemic stroke. In 2015 IEEE international conference on bioinformatics and biomedicine, IEEE, 1316-1321, 2015
67. Giri, E. P., Fanany, M. I., Arymurthy, A. M., and Wijaya, S. K., Ischemic stroke identification based on EEG and EOG using ID convolutional neural network and batch normalization. In 2016 International conference on advanced computer science and information systems, IEEE, 484-491, 2016.
68. Liao, D., and Lu, H Classify autism and control based on deep learning and community structure on resting-state fMRI. In 2018 Tenth international conference on advanced computational intelligence, IEEE, 289-294, 2018.
69. Guo, X., Dominick, K. C., Minai, A. A., Li, H., Erickson, C. A., and Lu, L. J., Diagnosing autism spectrum disorder from brain resting-state functional connectivity patterns using a deep neural network with a novel feature selection method. Front Neurosci 11(1–19):460, 2017.
70. Kong, Y., Gao, J., Xu, Y., Pan, Y., Wang, J., and Liu, J., Classification of autism spectrum disorder by combining brain connectivity and deep neural network classifier. Neurocomputing 324:63–68, 2019.
71. Rad, N. M., and Furlanello, C., Applying deep learning to stereotypical motor movement detection in autism spectrum disorders. In 2016 IEEE 16th International Conference on Data Mining Workshops IEEE, 1235–1242, 2016.
72. Kidziński, Ł., Delp, S., and Schwartz, M., Automatic real-time gait event detection in children using deep neural networks. PLoS One 14(1):1–11, 2019.
73. Valverde, S., Cabezas, M., Roura, E., González-Villà, S., Pareto, D., Vilanova, J. C., and Lladó, X., Improving automated multiple sclerosis lesion segmentation with a cascaded 3D convolutional neural network approach. NeuroImage. 155:159–168, 2017.
74. Roy, S., Butman, J. A., Reich, D. S., Calabresi, P. A., and Pham, D. L., Multiple sclerosis lesion segmentation from brain MRI via fully convolutional neural networks. arXiv preprint arXiv.1803.09172:1–14, 2018.
75. Karaca, Y., Cattani, C., and Moonis, M., Comparison of Deep Learning and Support Vector Machine Learning for Subgroups of Multiple Sclerosis. In International Conference on Computational Science and Its Applications,Springer, Cha,142-153, 2017.
76. Gong, J., Goldman, M. D., and Lach, J., Deepmotion: a deep convolutional neural network on inertial body sensors for gait assessment in multiple sclerosis. In 2016 IEEE conference of wireless health, IEEE, 1-8, 2016.
77. Benyoussef, E. M., Elbyed, A., and El Hadiri, H., 3D MRI classification using KNN and deep neural network for Alzheimer's disease diagnosis. In International Conf. on Advanced Intelligent Sys. Sustainable Development, Springer, Cham, 154–158, 2018.
78. Jha, D., and Kwon, G., Alzheimer's disease detection using sparse autoencoder, scale conjugate gradient and softmax output layer with fine tuning. International Journal of Machine Learning and Computing 7(1):13–17, 2017.
79. Rieke, J., Eitel, F., Weygandt, M., Haynes, J. D., and Ritter, K., Visualizing convolutional networks for MRI-based diagnosis of Alzheimer's disease. In Understanding and Interpreting Machine Learning in Medical Image Computing Applications, Springer, Cham, 24-31, 2018.
80. Bäckström, K., Nazari, M., Gu, I. Y. H., and Jakola, A. S., An efficient 3D deep convolutional network for Alzheimer's disease diagnosis using MR images. In 2018 IEEE 15th international symposium on biomedical imaging, IEEE, 149-153, 2018.
81. Kruthika, K. R., and Maheshappa, H. D., Alzheimer's disease neuroimaging initiative: CBIR system using capsule networks and 3D CNN for Alzheimer's disease diagnosis. Informatics in Medicine Unlocked 14:59–68, 2019.
82. Aderghal, K., Khvostikov, A., Krylov, A., Benois-Pineau, J., Afdel, K., and Catheline, G., Classification of Alzheimer Disease on Imaging Modalities with Deep CNNs Using Cross-Modal Transfer Learning. In 2018 IEEE 31st international symposium on computer-based medical systems, IEEE, 345-350, 2018.
83. Yang, M., Yang, P., Elazab, A., Hou, W., Li, X., Wang, T., and Lei, B., Join and Deep Ensemble Regression of Clinical Scores for Alzheimer's Disease Using Longitudinal and Incomplete Data. In 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1254–1257, 2018.
84. Basaia, S., Agosta, F., Wagner, L., Canu, E., Magnani, G., and Santangelo, R., Alzheimer's Disease Neuroimaging Initiative: Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks. NeuroImage: Clinical 21(1-8):101645, 2019.
85. Tang, H., Yao, E., Tan, G., and Guo, X., A Fast and Accurate 3D Fine-Tuning Convolutional Neural Network for Alzheimer's Disease Diagnosis. In International CCF Conference on Artificial Intelligence, Springer, Singapore, 115–126, 2018.
86. Cui, R., Liu, M., Alzheimer's disease neuroimaging initiative: RNN-based longitudinal analysis for diagnosis of Alzheimer-disease. Computerized Med. Imaging and Graphics, 1-25, 2019.
87. Cui, R., and Liu, M., Hippocampus Analysis by Combination of 3D DenseNet and Shapes for Alzheimer's Disease Diagnosis. IEEE J Biomed Health Inform 23(5):1–8, 2018.
88. Wang, H., Shen, Y., Wang, S., Xiao, T., Deng, L., Wang, X., and Zhao, X., Ensemble of 3D densely connected convolutional network for diagnosis of mild cognitive impairment and Alzheimer's disease. Neurocomputing 333:145–156, 2019.
89. Spasov, S., Passamonti, L., Duggento, A., Lio, P., and Toschi, N., Alzheimer's Disease Neuroimaging Initiative. A parameter-efficient deep learning approach to predict conversion from mild cognitive impairment to Alzheimer's disease. NeuroImage 189: 276–287, 2019.
90. Zheng, C., Xia, Y., Chen, Y., Yin, X., and Zhang, Y., Early Diagnosis of Alzheimer 's disease by Ensemble Deep Learning Using FDG-PET. In International Conference on Intelligent Science and Big Data Engineering,Springer, Cham, 614–622, 2018.
91. Cheng, D., and Liu, M., CNNs based multi-modality classification for AD diagnosis. In 2017 10th international conference on image and signal processing, BioMedical Engineering and Informatics, IEEE, 1-5, 2017.
92. Farooq, A., Anwar, S., Awais, M., and Rehman, S., A deep CNN based multi-class classification of Alzheimer's disease using MRI. In 2017 IEEE international conference on imaging systems and techniques, IEEE, 1-6, 2017.
93. Gunawardena, K. A. N. N. P., Rajapakse, R. N., and Kodikara, N. D.,Applying convolutional neural networks for pre-detection of alzheimer's disease from structural MRI data. In 2017 24th international conference on mechatronics and machine vision in practice, IEEE, 1-7, 2017.

94. Shi, J., Zheng, X., Li, Y., Zhang, Q., and Ying, S., Multimodal neuroimaging feature learning with multimodal stacked deep polynomial networks for diagnosis of Alzheimer's disease. IEEE Journal of Biomedical and Health Informatics 22(1):173–183, 2017.
95. Ju, R., Hu, C., and Li, Q., Early diagnosis of Alzheimer's disease based on resting-state brain networks and deep learning. IEEE/ACM Transactions on Computational Biology and Bioinformatics 16(1):244–257, 2017.
96. Amoroso, N., Diacono, D., Fanizzi, A., La Rocca, M., Monaco, A., and Lombardi, A., Alzheimer's Disease Neuroimaging Initiative: Deep learning reveals Alzheimer's disease onset in MCI subjects: Results from an international challenge. J Neurosci Methods 302:3–9, 2018.
97. Kumar, S. S., and Nandhini, M., Multi-tasks Deep Learning Model for classifying MRI images of AD/MCI Patients. International Journal of Engineering and Technology 9(3):1925–1930, 2017.
98. Zheng, X., Shi, J., Li, Y., Liu, X., and Zhang, Q., Multi-modality stacked deep polynomial network-based feature learning for Alzheimer's disease diagnosis. In IEEE 13th international symposium on biomedical imaging, IEEE, 851–854, 2016.
99. Sarraf, S., DeSouza, D. D., Anderson, J., and Tofighi, G., DeepAD: Alzheimer′ s disease classification via deep convolutional neural networks using MRI and fMRI. BioRxiv, 070441:1–15, 2017.
100. Bhatkoti, P., and Paul, M., Early diagnosis of Alzheimer's disease: A multi-class deep learning framework with modified k-sparse autoencoder classification. In International Conference on Image and Vision Computing New Zealand, IEEE, 1-5,2016.
101. Shi, B., Chen, Y., Zhang, P., Smith, C. D., and Liu, J., Alzheimer's Disease Neuroimaging Initiative:Nonlinear feature transformation and deep fusion for Alzheimer's Disease staging analysis. Pattern Recogn 63:487–498, 2017.
102. Billones, C. D., Demetria, O. J. L. D., Hostallero, D. E. D., and Naval, P. C., DemNet: A Convolutional Neural Network for the Detection of Alzheimer's Disease and Mild Cognitive Impairment. In IEEE Region 10 Conference, 3724–3727, 2016.
103. Payan, A., and Montana. Predicting Alzheimer's disease: a neuroimaging study with 3D convolutional neural networks. arXiv preprint arXiv:1502.02506:1–9, 2015.
104. Suk, H. I., Lee, S. W., and Shen, D., Alzheimer's disease neuroimaging InitiativeHierarchical feature representation and multimodal fusion with DL for AD/MCI diagnosis. Neuroimage. 101:569–582, 2014.
105. Liu, S., Liu, S., Cai, W., Pujol, S., Kikinis, R., and Feng, D., Early diagnosis of Alzheimer's disease with deep learning. In IEEE 11th international symposium on biomedical imaging. 1015–1018, 2014.
106. Suk, H. I., Lee, S. W., and Shen, D., Alzheimer disease neuroimaging-initiative:Latent feature representation with stacked autoencoder for AD/MCI diagnosis. Brain-Structure and Function 220(2):841–859, 2015.
107. Suk, H. I., & Shen, D.,Deep learning-based feature representation for AD/MCI classification. In International Conference on Medical Image Computing and Computer-Assisted Intervention , Springer, Berlin, Heidelberg, 583–590, 2013.
108. Zhao, Y., & He, L., Deep-learning in the EEG-diagnosis of Alzheimer’s disease. In Asian Conference on Computer Vision, Springer, Cham, 340-353, 2014.
109. Wang, S. H., Phillips, P., Sui, Y., Liu, B., Yang, M., and Cheng, H., Classification of Alzheimer’s disease based on eight-layer convolutional neural network with leaky rectified linear unit and max pooling. J Med Syst 42(5):85, 2018.
110. Islam, J., and Zhang, Y., A novel deep learning based multi-class classification method for Alzheimer’s disease detection using brain MRI data. In International Conference on Brain Informatics,Springer, Cham, 213–222, 2017.
111. Kim, D., and Kim. Detection of Early Stage Alzheimer’s Disease using EEG Relative Power with Deep Neural Network. In 40th Annual International Conference of the IEEE Engg. in Medicine and Bio. Society, 352–355, 2018.
112. Gallicchio, C., Micheli, A., and Pedrelli, L., Deep Echo State Networks for Diagnosis of Parkinson's Disease. arXiv preprint arXiv:1802.06708:1–6, 2018.
113. Gong, B., Shi, J., Ying, S., Dai, Y., Zhang, Q., Dong, Y., and Zhang, Y., Neuroimaging-based diagnosis of Parkinson's disease with deep neural mapping large margin distribution machine. Neurocomputing 320:141–149, 2018.
114. Klyuzhin, I., Shenkov, N., Rahmim, A., and Sossi, Use of deep convolutional neural networks to predict Parkinson’s disease progression from DaTscan SPECT images. J Nucl. Med 59(1):29–29, 2018.
115. Oh, S. L., Hagiwara, Y., Raghavendra, U., Yuvaraj, R., Arunkumar, N., Murugappan, M., and Acharya, U. R., A deep learning approach for Parkinson’s disease diagnosis from EEG signals. Neural Computing and Applications.1–7, 2018.
116. Khojasteh, P., Viswanathan, R., Aliahmad, B., Ragnav, S., Zham, P., and Kumar, D. K., Parkinson's Disease Diagnosis Based on Multivariate Deep Features of Speech Signal. In IEEE Life-Sciences Conf. , 187–190, 2018.
117. Pereira, C. R., Pereira, D. R., Rosa, G. H., Albuquerque, V. H., Weber, S. A., Hook, C., and Papa, J. P., Handwritten dynamics assessment through convolutional neural networks: An application to Parkinson's disease identification. Artif Intell Med 87:67–77, 2018.
118. Camps, J., Sama, A., Martin, M., Rodriguez-Martin, D., Perez-Lopez, C., Arostegui, J. M. M., and Prats, A., Deep learning for freezing of gait detection in Parkinson’s disease patients in their homes using a waist-worn inertial measurement unit. Knowl-Based Syst 139:119–131, 2018.
119. Choi, H., Ha, S., Im, H. J., Paek, S. H., and Lee, D. S., Refining diagnosis of Parkinson's disease with deep learning-based interpretation of dopamine transporter imaging. Neuroimage: Clinical 16:586–594, 2017.
120. Shinde, S., Prasad, S., Saboo, Y., Kaushick, R., Saini, J., Pal, P. K., and Ingalhalikar, M., Predictive markers for Parkinson's disease using deep neural nets on neuromelanin sensitive MRI. Neuroimage:Clinical. 22:101748, 2019.
121. Martinez-Murcia, F. J., Ortiz, A., Górriz, J. M., Ramírez, J., Segovia, F., Salas-Gonzalez, D., and Illán, I. A., A 3D convolutional neural-network approach for the diagnosis of Parkinson-disease. International Work-Conference on the Interplay Between Natural and Artificial Computation, Springer, Cham, 324–333, 2017.
122. Al-Fatlawi, A. H., Jabardi, M. H., and Ling, S. H., Efficient diagnosis system for Parkinson's disease using deep belief network. In IEEE Conference on Evolutionary Computation.1324–1330, 2016.
123. Hussein, R., Palangi, H., Ward, R. K., and Wang, Z. J., Optimized deep neural network architecture for robust detection of epileptic seizures using EEG signals. Clin Neurophysiol 130(1):25–37, 2019.
124. Yıldırım, Ö., Baloglu, U. B., and Acharya, U. R., A deep convolutional neural network model for automated identification of abnormal EEG signals. Neural Computing and Applications. 1–12, 2018.
125. Wei, X., Zhou, L., Chen, Z., Zhang, L., and Zhou, Y., Automatic seizure detection using three-dimensional CNN based on multichannel EEG. BMC Medical Informatics and Decision Making 18(5):73–127, 2018.

126. Acharya, U. R., Oh, S. L., Hagiwara, Y., Tan, J. H., and Adeli, H., Deep CNN for the automated detection and diagnosis of seizure using EEG signals. Comput Biol Med 100:270–278, 2018.
127. Yao, X., Li, X., Ye, Q., Huang, Y., Cheng, Q., and Zhang, G., A Robust Deep Learning Approach for Automatic Seizure Detection. arXiv preprint arXiv:1812.06562:1–13, 2018.
128. Ullah, I., Hussain, M., and Aboalsamh, H., An automated system for epilepsy-detection using EEG-brain signals based on deep-learning approach. Expert Syst Appl 107:61–71, 2018.
129. Hosseini, M. P., Tran, T. X., Pompili, D., Elisevich, K., and Soltanian-Zadeh, H., Deep learning with edge computing for localization of epileptogenicity using multimodal rs-fMRI and EEG big data. In IEEE International Conference on Autonomic Computing, 83–92, 2017.
130. Le, T. X., Le, T. T., Dinh, V. V., Tran, Q. L., Nguyen, L. T., and Nguyen, D. T., Deep learning for epileptic spike detection. VNU Journal of Science: Computer Science and Communication Engineering 33(2):1–13, 2017.
131. Hosseini, M. P., Pompili, D., Elisevich, K., and Soltanian-Zadeh, H., Optimized deep learning for EEG big data and seizure prediction BCI via internet of things. IEEE Transactions on Big Data 3(4):392–404, 2017.
132. Talathi, S. S., Deep Recurrent Neural Networks for seizure detection and early seizure detection systems. arXiv preprint arXiv: 1706.03283:1–9, 2017.
133. Thodoroff, P., Pineau, J., and Lim, A., Learning robust features using deep learning for automatic seizure detection. In Machine learning for healthcare conference, 178–190, 2016.
134. Li, D., Wang, G., Song, T., and Jin, Q., Improving convolutional neural network using accelerated proximal gradient method for epilepsy diagnosis. InUKACC 11th International Conference on Control, IEEE, 1–6, 2016.
135. Antoniades, A., Spyrou, L., Took, C. C., and Sanei, S., Deep learning for epileptic intracranial EEG data. In IEEE 26th International Workshop on Machine-Learning for Signal Processing, 1–6, 2016.
136. Yuan, Y., Xun, G., Jia, K., and Zhang, A., A Multi-View Deep Learning Framework for EEG Seizure Detection. IEEE Journal of Biomedical and Health Informatics 23(1):83–94, 2019.