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Techniques of deep learning for diagnosing brain diseases: A review

Manu Pratap Singh [1,*] and Reena Garg [2]

[1] *Department of Computer Science, Institute of Engineering & Technology, Dr. Bhimrao Ambedkar University, Khandari, Agra, India.*
[2] *Department of BCA, St. John's College, Agra, India.*

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Abstract

Deep learning has been proved as a tremendous evolution in machine learning and computer vision. Through deep learning, computer machines become capable of solving the problems those were beyond the imagination two decades prior. Nowadays, Deep learning is significantly used in Natural language processing, image classification, medical science, handwriting recognition, face recognition, speech recognition, biometrics matching and in various real life problem domains. In this present paper, a review of deep learning techniques is presented for the diagnoses of brain diseases. Today, Deep learning is playing a crucial role in automating the medical equipment for the diagnosis of various brain diseases like tumor, Alzheimer, Mild Cognitive Impairment, brain hemorrhage, Parkinson etc. Deep learning has been tremendously used in detecting the severity of such diseases. This paper covers the recent approaches, techniques, learning algorithms of deep learning those have been used to detect major or minor diseases in a human brain. The paper also explores the future possibilities for Deep learning in medical science specifically for the brain diseases.

Keywords: Computer Vision; Deep Learning; Convolution Neural Network; Recurrent Neural Network; Brain Diseases;

1. Introduction

Deep learning is a branch of Artificial Intelligence that is used to improve and enhance the performance of a computer system by learning from the experience of its own. Deep learning develops a model of neurons with a large number of hidden layers to extract the explicit features from the input data, learns from the extracted features, does the required updates in the weights of neurons and then classifies the input data as one of the output class, in this way the model learns from the features itself and predicts accordingly. Deep learning helps in automating the machines to think like a human and also enables the machines to adapt the changes and behave accordingly [1-3].

Today, digitalization of medical records is being done at a huge and rapid scale. The medical records are in the form of medical images like ultrasounds, X-Rays, Computed Tomography scans (CT), Magnetic Resonance Imaging Scans (MRI), Positron Emission Tomography Scans (PET), Retinal Tomography and many more [4]. In clinical perspective, these images are the only way to diagnose many of the diseases or to predict their severity, by a human radiologist expert. For an expert, it is a time consuming process and becomes a non-trivial task if he does not have so much experience. The chances of error are much possible in the diagnosis, even when, done by an experienced radiologist. Therefore, the idea for automating the machines, to diagnose a disease or to predict the severity conceived [5].

Deep Learning models work very well with the images as a raw data. They extract necessary features by itself from the images without a human intervention. Features that a human eye cannot interpret from the images can be easily

* Corresponding author: Manu Pratap Singh
Department of Computer Science, Institute of Engineering & Technology, Dr. Bhimrao Ambedkar University, Khandari, Agra.

detected by these network models of neurons. Besides that, a lot of computation on these images is required in this automation, which was a bottleneck for the experts to solve in the late years of 90's. It took several days, weeks and even months to train a model, but with the implementation of today's fast CPUs and GPUs, it takes just few seconds or minutes. Thus, the availability of digital images to a great extent with the GPU based computer machines attract the experts to work with deep learning to automate the machines for different recognition and prediction tasks [6].

In this paper, we have covered the brain diseases mainly, Brain Tumor (BT), Alzheimer Disease (AD), Mild Cognitive Impairment (MCI), Huntington and Brain Hemorrhage (BH). These are very common but automation of such diseases' detection is still in progress and seeking for 100% accuracy for their predictions. We have reviewed and analyzed the contributions in the automation for prediction of brain diseases that had been proved as milestones in the problem domain.

The paper is organized in the following sections. Section 2 depicts the various deep learning models CNN, RNN, LSTM, RBN, DBN, Autoencoders and different pre-trained models that are extensively used in medical science for certain brain diseases' diagnosis. In Section 3, the brain diseases Brain Tumor (BT), Alzheimer Disease (AD), Mild Cognitive Impairment (MCI), Huntington and Brain Hemorrhage (BH) have been discussed. Section 4 elaborates the types of images, used as the input. Required datasets have been described in Section 5. The next section i.e. Section 6 explores the flow of deep learning process that is adapted to detect a brain disease. Section 7 discusses the analysis of the study. Conclusions and future possibilities are mentioned in the Section 8, followed by the acknowledgement in section 9 and references are mentioned at the end.

2. Deep Neural Network Models

Deep Neural Network (DNN) models are categorized into supervised and unsupervised learning models. Autoencoders, Restricted Boltzmann Machines (RBM), Deep Belief Network (DBN), Generative Adversarial Network (GAN) fall under the unsupervised learning models whereas, Convolution Neural Network (CNN), Recursive Neural Network (RNN), Long Short Term Memory (LSTM) network follow supervised learning approach. Each model has a unique architecture and characteristics that make them effective and efficient, to be used in different applications of medical science [7]. In this paper, we discussed about CNN, LSTM, Autoencoder, RBM, RNN models of Deep Neural Networks as these models are frequently used in various applications of brain diseases diagnosis.

2.1. Convolution Neural Network (CNN)

CNN is the most prominent model that is being used widely in computer vision as it works very well in extracting the relevant features from the images, so as with the medical images in diagnosing certain diseases [8]. In diagnosing brain diseases, most of the times CNN models had been implemented and these models produced better results. A CNN model is mainly comprised of five important layers: Convolution layer, Pooling Layer, Dense Layer, Dropout Layer and Softmax Layer.

- Convolution Layer

Convolution layer in CNN performs convolution operations with different filters as provided with the different size and stride to extract the implicit features in 2D form from the input image. A CNN model is said to be shallow if it comprises with only 2 or 3 convolutional layers and going to be deep with the increased number of such layers.

- Pooling Layer

It is commonly pipelined with every convolution layer to reduce the number of features extracted (down sampling) with convolution layers. Max pooling, Min pooling, Median pooling or Average pooling are used with a specified size and stride. Max pooling is the most widely used strategy to pick the feature having the maximum activation value.

- Fully Connected Layer or Dense Layer

In a CNN model, any number of fully connected layers can be embedded after Pooling layers in order to convert the 2D features into 1D features and to learn from the relevant features. These layers behave like a feed forward neural network and are used specifically for the final classification.

- Dropout Layer

CNN model may suffer with the problem of overfitting while training it. Overfitting arises when the model achieves too high accuracy (low bias) with the trained data but too low accuracy (high variance) with the test data. Dropout layers are the layers in which some random neurons are dropped out in order to overcome the problem of overfitting.

- Softmax Layer

CNN model for multiclass classification i.e. more than two classes, is comprised of a softmax layer as an output layer. This layer is used for the application of activation function to predict the multinomial probability distribution. This probability shows the likelihood of an input data to each of the output class.

2.1.1. Pre-trained CNN models

Pre-trained refers to start the training of CNN models with already set weights and architecture, instead of setting new parameters randomly. Using such pre-trained models helps in training models to learn faster and in an efficient way with the input data. Many of these CNN models had already been implemented with different combination of the layers. VGG 16, VGG 19, ResNet, ResNet50, ResNeXt, U-Nets, LeNet, GoogLeNet, Inception-V3 and InceptionResNet are some of these pre-trained models that are extensively used in diagnosing brain diseases [9]. The architecture, the activation function and the optimization functions for each of these CNN models can be seen in Table 1. These Pre-trained models had produced the remarkable results in diagnosing brain diseases.

Table 1 Pre-trained models with their architecture, used activation function, optimizer and input data

Model	**Layer Architecture**	**Activation function + Optimizer**	**Input Data**	**Reference**
LeNet (1990)	2 Conv +2 MaxPool +3 FC	Sigmoid	USPS Database	LeCun Y. et al. [10]
Alexnet(2012)	5 Conv +3 MaxPool + 3 Dense	ReLU + SGD	ImageNet	Krizhevsky et al.[11]
VGG 16 (2014)	13Conv+5MaxPool+3FC+1Softmax	ReLU + SGD	ImageNet	Simonyan K, Zisserman[12]
VGG 19 (2014)	16 Conv+ 5 MaxPool + 3 FC + 1SoftMax	ReLU + SGD	ImageNet	Simonyan K, Zisserman [12]
U-Nets (2015)	23 Conv +4 MaxPool	ReLU +SGD	Medical images of ventral nerve cord (VNC)	Ronneberger O. et al.[13]
PCANet (2015)	3 stages with the combination of 2Conv +1 AvgPool layers in each stage. This group can be stacked as per the requirement.	ReLU	Extended Yale B, AR, and FERET data sets and on MNIST variations	T. Chan et al.[14]
GoogLeNet (2015)	22 Conv +4 MaxPool +1 AvgPool +1 linear + 1 Softmax	ReLU	ImageNet	C. Szegedy et al. [15]
Inception-V3 (2015)	42 Conv + 10 AvgPool + 4 MaxPool + 1 FC + 1 Softmax	ReLU, Sigmoid +RMSprop	ImageNet	C. Szegedy et al. [16]
ResNet (2016)	32 Conv+1 MaxPool+ 1 AvgPool +1FC	ReLU +SGD	ImageNet/ CIFAR 10	K. He et al. [17]
ResNet 50 (2016)	48 Conv +1 MaxPool + 1 AvgPool+ 1 FC	ReLU+SGD	ImageNet/ CIFAR 10	K. He et al.[17]

ResNeXt (2017)	Same as ResNet with Cardinality 32 (32 Groups of Convolution Blocks)	ReLU +SGD	ImageNet/ CIFAR 10	Xie et al.[18]
Inception ResNet (2017)	Same as Inception-V3 with factorized Convolution Filter and Residual links	ReLU + SGD	ImageNet	C. Szegedy et al. [19]
SegNet(2017)	Encoder of 13 Conv + 5 MaxPool (as in VGG 16) + Decoder of 13 Conv + 5 Upsample +1 Softmax	ReLU + SGD	CamVid	V Badrinarayan et al. [20]
DRN(Dilated ResNet) (2017)	Same as ResNet with different stride in downsampling	ReLU +SGD	ImageNet/ CIFAR 10	F. Yu et al. (2017) [21]

2.1.2. Transfer Learning of CNN models

It is the process of taking a pre-trained model and fine tuning that model with a new dataset. For this, first train the pre-trained model with its own dataset, once it is trained with minimum error, either replace the last layer with a new layer having random weights or freeze the weights in the model and then train the model with new dataset. This process had been extensively used for various problems of medical science, specifically for the prediction of diseases with new input images.

2.2. Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN) is another Deep Learning model that is being widely used, to diagnose the diseases of brain [22]. In RNN, output of the last layer achieved from a feed forward pass can be feed backed in the next pass, as the input to the first layer. The same computations are performed by the layers at each pass. This process is repeated in a recurrent way to achieve the desired results [23]. In medical science, RNN had shown its significance in detecting brain diseases [24].

2.3. Long Short Term Memory (LSTM)

LSTM is a special kind of RNN and is an important Deep Learning model that is being used effectively with CNN models in medical science [25]. With simple RNN, the information from the last step can be feed backed, but to get the information from two or more previous steps, a memory cell is embedded in the RNN that makes it capable of remembering information for long periods [26].

2.4. Restricted Boltzmann Networks/ Machines (RBN/ RBM)

RBN is a shallow network of neurons that consists of only two layers: an input layer and a hidden layer [27]. The number of neurons in the input layer is determined by the number of pixels in the input image. For example, if there are 256 pixels in an image then there will be 256 neurons in the input layer to accept one pixel value by one neuron. The name Restricted comes from a restriction, that no two nodes belong to a same layer are allowed to have a link or communication. RBNs allow to use input images without labeling them, this aspect makes them effective to be used in feature extraction, so as with the MRI images in classifying certain brain disease [28].

2.5. Deep Belief Network (DBN)

RBNs can be stacked to implement a new network formation, called Deep Belief Network (DBN). A DBN is implemented by combining multiple RBNs with a special training method [29]. The hidden layer of the first RBN behaves like an input layer of the second RBN. Second RBN is trained with the outputs of the first RBN; the hidden layer of the second RBN behaves like an input layer of the third RBN. The third RBN is trained with the outputs of the second RBN and so on. This method is used iteratively till the last RBN could not be trained. In this way RBNs are stacked and trained to implement a DBN without using a back propagation training method. In medical science, DBN had proved its significance in accessing features from MRI images and to classify certain brain disease [30].

2.6. Autoencoder

Autoencoders are deep neural networks that are used basically for input pattern construction. At first end, they encode the data into desirable lower dimensions and later at the other end, a decoder is paired to get back the original dimension. Encoding is done to extract the most relevant features and decoding is done to get back the original input data. An Autoencoder is implemented with RBNs and plays an important role for feature extraction [31]. Autoencoders had been used prominently in feature extraction process from the medical images too, to predict and further to classify Brain Tumor or Alzheimer's disease [32].

3. Brain Diseases

Brain is the main control center of a human body. Here resides the nervous system, a network of nerves and neurons that is responsible for the movements of other body parts. Any damage or injury in brain tissues, nerves or neurons may cause to loss the communication to other body parts. Patient may suffer from certain problems like dementia, memory loss, low concentration, vomiting, low heart rate, high blood pressure, paralysis and even heart attack, ultimately affects his routine daily life and even may cause death also. As per the symptoms, causes and the affected part of the brain, there are different diseases. These diseases must be detected on time, so that the patient can be treated properly before it is getting too late.

3.1. Brain Tumor

Brain tumor is caused by the uncontrolled and abnormal growth of the brain tissues and it is one of the fatal diseases [33]. As the skull has the limited capacity, this abnormal growth causes the pressure to the other tissues and nerves of the brain, and may cause the life threatening risk for a people. If a patient is having a brain tumor then it must be detected in its early stage for its proper treatment. For an expert radiologist, it is a non-trivial and a time consuming task to detect a tumor in brain. Moreover, the most challenging task is to classify the tumor correctly into different stages by just looking at the images. Therefore, it's a motivation for researchers to implement an automated model to segment, detect and classify a brain tumor [60].

3.2. Alzheimer Disease and Mild Cognitive Impairment

Alzheimer Disease (AD) is a neurologic disorder that causes the brain cells and connections among these cells to die, it shrinks the brain and destroys the memory, the patient eventually gets confused and losses his reasoning ability too with the time. He faces the problem of recognition, speaking, reading, and writing and sometimes even becomes unable to do his daily routine tasks [34-35].

Mark W Bondi et al. (2017) discussed about its history, various stages, causes and possible treatments that became available with the time [36]. Early stage of Alzheimer Disease is specified as Mild Cognitive Impairment (MCI), detection of it, can cure the patients in a better way. Thus, it became essential for experts to classify the Alzheimer Disease into MCI and Alzheimer Disease for the early treatment of Alzheimer Disease. Automation of such systems are required to detect the Alzheimer Disease as well as to classify it into MCI or Alzheimer [37].

3.3. Huntington Disease

Huntington disease or Huntington Chorea is a progressive form of dementia and is first described by Dr. George Huntington in 1872. Alzheimer's disease is a disease that generally occur in older people at the age of 50 to 60, but Huntington Disease's symptoms occur during the late 30's or early 40's. Huntington disease is an inherited disease and caused by a single gene, a mutation of chromosome 4, whereas Alzheimer's disease is inherited by two genes namely: "risk gene", ApoE and "deterministic gene". People suffering from Huntington Disease are at a great risk of Alzheimer's disease in later years. In Huntington Disease, people suffer not only with confusion, recognition difficulties, loss of memory like in Alzheimer's disease, but may also face the problems of jerking the limbs, trunk and even face with uncontrollable movements [38]. Thus, it is essential for experts to diagnose such a fatal disease in its early stage so that the patient can be cured without losing any of his capability. From here, automation of such systems came into existence [39].

3.4. Brain Hemorrhage

Brain hemorrhage is a type of stroke in brain which causes an artery to burst and to bleed. This bleeding generally causes the brain cells to die and thus mostly causes a patient to die [40]. Brain hemorrhages are also termed as intracranial hemorrhages, cerebral hemorrhages or intracerebral hemorrhages. There are certain causes for a brain hemorrhage to occur, for a doctor he must have a good experience to detect the causes by just looking at the CT scans

as early as possible without wasting a fraction of time as time matters a lot to cure a patient's life. In some cases, doctors may not have so much experience to detect the reasons or they may do errors in detecting the actual causes of brain hemorrhage. Early and errorless detection of its causes is much important to give the treatment. Therefore, the automation of such systems is required in order to save a patient's life timely [41].

4. Images used to detect brain diseases

In medical science, there are certain images like MRIs, CT scans, X-Rays, Ultrasound, Angiography, PET scans etc., taken by different modes, to get the internal view of an organ. Clinicians and neurologists look at them and find the abnormalities to detect possible diseases. Deep learning works well with the images, these images have also been proved as an essential input to train a Deep Learning model so that the trained model can be used for the early prediction of certain brain diseases. The images used by the experts in diagnosing brain diseases through Deep learning models are as follows:

4.1. Magnetic Resonance Imaging (MRI) scans

MRIs are the most popular images in diagnosing the brain diseases. It has four different modalities as shown in figure 1: T1-weighted (spin-lattice relaxation), T2- weighted (spin-spin relaxation), FLAIR (fluid attenuation inversion recovery) and T1C (T1 weighted with contrast) with three views: sagittal view, axial view and coronal view. Neurologists inspect all these views of a brain to find the abnormalities. Despite of it, an MRI may be static (SMRI) or dynamic (FMRI)/ (functional MRI).

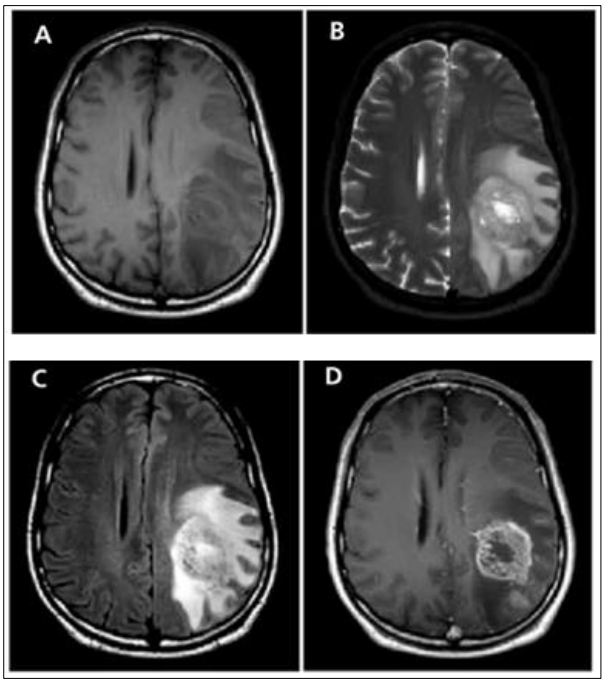

Figure 1 MRI images (A) T1-weighted image, (B) T2-weighted image, (C) FLAIR image, (D) T1C image [42]

4.2. Magnetic Resonance Spectroscopy (MRS)

Magnetic Resonance Spectroscopy **(**MRS), also known as Nuclear Magnetic Resonance (NMR), of a brain is a graph showing the different quantities of different chemicals (metabolites) present in the brain as shown in figure 2. MRS contains metabolic information that may be affected by diseases like Alzheimer's disease, Brain Tumor, and Brain Hemorrhage. Thus, MRS is helpful in diagnosing brain diseases. MRS can be taken using the same instrument of MRI but with different software [43].

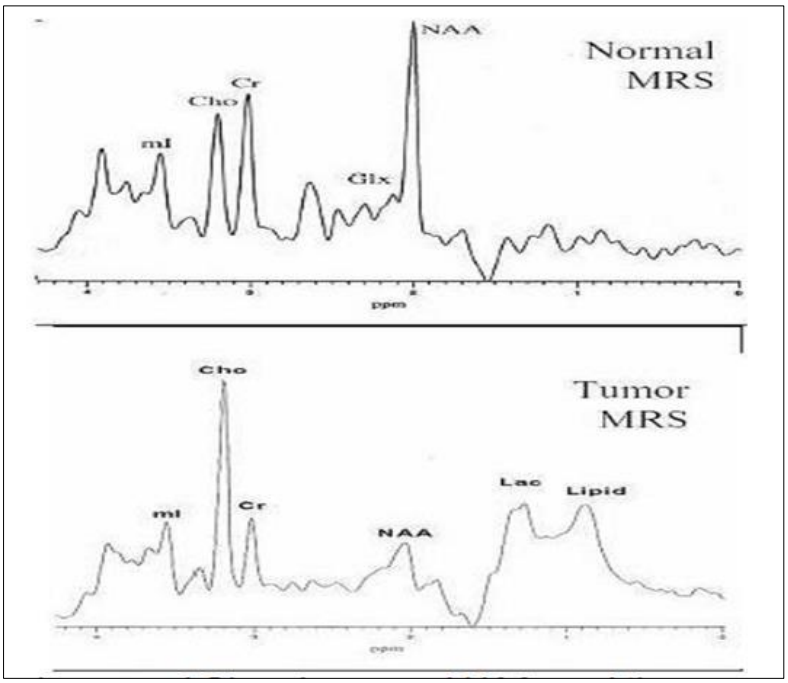

Figure 2 MRS of brain tumour with increased Cho, decreased NAA, and the presence of lipid and lactate in the spectra [44]

4.3. Computed Tomography (CT or CAT) scans

CT scans of a brain are special X-Rays of the brain that are taken from different directions to produce different views of the brain. CT scans provide detailed information about brain tissue and brain structure as compared to a standard X-ray. With the help of a CT scan, 3D image can be produced for the brain to effectively diagnose certain diseases or abnormalities of the brain as shown in figure 3 [45-46]

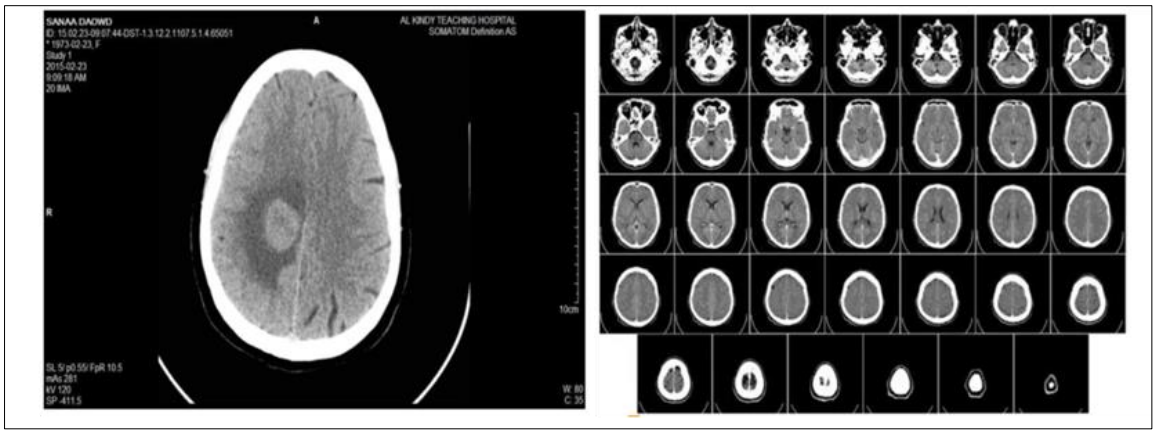

Figure 3 CT scans of a brain**.**

4.4. Positron Emitted Tomography (PET) scans

PET scans are the images of brain that contain the information about brain metabolism and amyloid load in the form of F-fluorodeoxyglucose (FDG) FDG-PET and F-florbetapir (AV-45) as shown in figure 4 [47].

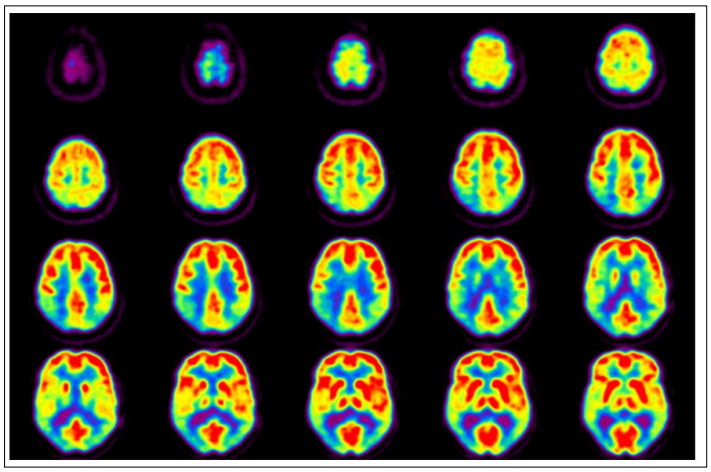

Figure 4 PET imaging of a brain

5. Datasets

It has been observed that some of the brain related inputs images had been collected from the different hospitals, but mostly, input images are used from the datasets that are freely available online or with some authorized access permissions. The information about these datasets is mentioned below in the Table 2. All of these datasets contain brain images of patients suffering from different diseases as well as of healthy persons.

Table 2 Datasets, the type, the format of the images, the organization and the diseases

Dataset	Image Type	Format	Organization	Disease
BraTS13, 15, 16, 17, 18 (Brain Tumour Segmentation)	MRI with Multiple Modalities	NIfTY	MICCAI (Medical Image Computing and Computer Assisted Interventions)	Brain Tumour
ADNI, ADNI-2 (Alzheimer's Disease Neuroimaging Initiative)	MRIs, PET with demographic information, cognitive assessment data	CSV		Alzheimer Disease, Mild Cognitive Impairment
CAD Dementia (Computer Aided Diagnose Dementia)	MRI		MICCAI (Medical Image Computing and Computer Assisted Interventions)	Alzheimer Disease, Mild Cognitive Impairment
OASIS-1 (Outcome and Assessment Information Set)	MRI, demographic information, clinical status, functional status, needed services, follow up		CMS (Centres for Medicare and Medicaid Services)	Many of the diseases
UCSF-4.4 (updated ADNI version 4.4 by University of California San Francisco)	CT	DICOM	University of California San Francisco	Alzheimer Disease
RSNA provided dataset	MRI	DICOM	RSNA (Radiological Society of North America)	Brain Haemorrhages
CQ 500	CT scans	DICOM	CARING (Centre for Advanced Research in Imaging, Neurosciences and Genomics), New Delhi	Critical Findings in Head (Haemorrhages)

6. Process flow to diagnose a brain disease

A general process which has been adopted for the prediction of brain diseases using deep learning models can be shown in figure 5.

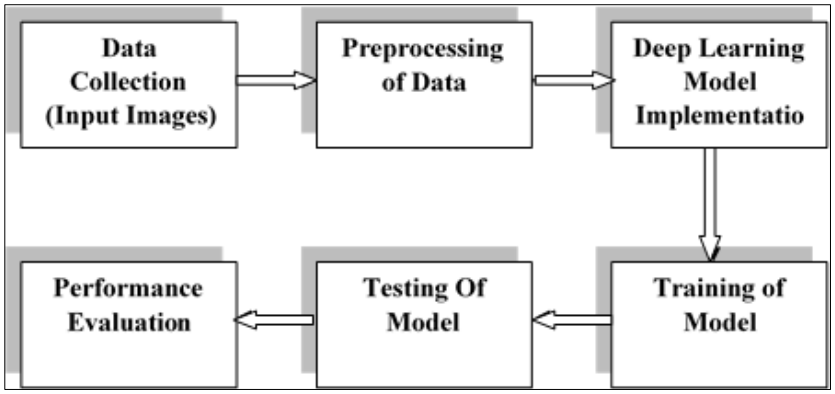

Figure 5 Necessary steps for the automation of brain disease diagnosis with a Deep learning Model

6.1. Data Collection

Images are essential for an expert to diagnose a brain disease, so as with the deep learning models too. These images are collected from various data centers as mentioned above in the Table 2. These images belong to the patients suffering from the certain brain diseases as well as of the healthy person. These images are the basic input to a deep learning model to diagnose a brain disease.

6.2. Preprocessing Data

Preprocessing of the collected images is done in order to remove the irrelevant data and to extract the relevant information [48]. Collected images may be of different sizes or resolutions, these images must be rescaled to fit the expected input size of the model. Bilinear, nearest neighbor, cubic interpolation are some techniques for rescaling. Besides rescaling, various augmentation and enhancement techniques like horizontal flips, translations, Gaussian function may also be applied onto the images to get the desired brightness, contrast or color and to remove the noise from the images [49-50]. At the same time, the available images of the patients are very limited but the requirement of input images for a model to be trained is too high. This difference can be overcome by doing the transformations like duplicating, sheering, mirroring on the original images [51].

6.3. Implementation of Deep Learning Model

Architecture of a Deep Learning model is decided as per the problem complexity and its requirements and then implemented with a relevant concatenation of necessary layers. The architecture of a model may have a combination of Convolution layers, Pooling layers, dense layers, Dropout layers and Softmax layers as discussed in Section 2.1.

6.4. Training of model

Once the model is implemented, learning is provided to the model through training. Training is done with a given set of input images with the specified output, termed as training dataset, for example a set of MRI images with brain tumor is used as an input to make the model learn about the certain features of the brain tumor. The input images are first transformed into input tensors **X** at the preprocessing step. Convolutional layers employed in a deep learning model convolve these tensors with a filter of weights i.e. a kernel of tensors **W** to extract the features from the input image. The new generated feature map $h_{k,}$ for the filter k, can be expressed as [52].

$$h_k = f(\mathbf{W}_k * \mathbf{X} + b_k) \quad \text{.....(1)}$$

$$\text{where, } \mathbf{W}_k * \mathbf{X} = \sum_{i=1}^{n} (wi * xi) \quad \text{..... (2)}$$

w_i belongs to $\mathbf{W}_k$, xi belongs to **X** and n is the number of weights in filter **X**.

This process can be repeated for any K number of filters to extract a rich set of features from the input image at a single layer, therefore, k= [1, 2, K]. b_k is the bias and ƒ is a differentiable non-linear function, termed as activation function, that could be anyone from the table 3, as mentioned below:

Table 3 Activation functions used for training deep learning models

Activation Function	**Equation**
Sigmoid Function σ(x)	$\sigma(x)= \frac{1}{1+e^{-x}}$
tanh Function	$f(x) = \frac{e^{x}- e^{-x}}{e^{x}+ e^{-x}}$
ReLU (Rectified Linear Unit) Function	f(x) = max(0, x)
Leaky ReLU Function	f(x) = max(0.01*x, x)
ELU (Exponential Linear Unit) Function	f(x) = x if x>0 f(x) = $\alpha(e^{x}$ -1) otherwise, α is the learning parameter, may be 0.01, 0.1, 0.2 and so on
PReLU (Parametric ReLU) Function	f(x) = x, if x>0 f(x) = α * x, if x<0 , α is the learning parameter
Softmax	f(x) = σ(x) sigmoid function, for 2 outputs $f(x) = \frac{e^{x_j}}{\sum_{k=1}^{K} e^{x_k}}$, j= 1,2,……..,K, for K classes

Thus, a deep learning model containing ℓ layers may have a hierarchy of features denoted as h_k^{ℓ}. The outputs at layer ℓ-1 is passed to the next layer ℓ in a forward propagation process as:

$$h_k^{\ell} = f(W_k^{\ell} * h^{\ell-1} + b_k^{\ell}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Here, h^0 =x for the first input layer. Among all the available activation functions, ReLU is the most prominent function that had been used extensively in feature extraction for diagnosing all the brain diseases as mentioned in tables 4, 5 and 6. Besides ReLU, Leaky ReLU, ELU, PReLU had also proved their relevance in feature extraction. Last layer of a deep learning model is an output layer that finally predicts and classifies a disease. Sigmoid activation function for binary classes and Softmax activation functions for the multiclasses are basic functions being used at final layer to calculate the probability of a disease belonging to a certain class.

Once the output is generated, it is compared with the specified result in the training dataset. The error between these two results is then calculated by a Loss function L, also termed as Cost function. Cross Entropy had been used widely in the models implemented for diagnosing brain diseases [53] and it is expressed as:

$$L = -\sum_{i=1}^{C} pi \log(pi) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

This loss L must be minimized in order to achieve the best results, for this, weights are updated by the amount, proportion to the gradient J(W) as, i.e. the derivative of the loss function with respect to the current weight at each layer. The mathematical formulation can be expressed as:

$$\nabla J(W) = \frac{\partial L}{\partial w} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

$$\text{Thus, } w_{new} = w_{old} - \eta * \nabla J(W \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where, η is the learning rate having a predefined constant value, may be initialized with 0.01, 0.001, 0.02 or any such value. This process of weight updations is termed as fine tuning and it starts in a back propagation manner i.e. doing weight updates from the last layer up to the first layer of the model.

There are several techniques to calculate gradient ∇J (W) for optimizing the weights, termed as optimization techniques. Gradient Descent, Stochastics Gradient Descent (SGD), Mini Batch SGD, Adagrad, Adadelta, RMSProp and ADAM are optimization techniques that are being used widely with deep learning models. It has been observed that, SGD and Mini Batch SGD are the most frequently used Optimizaton techniques for diagnosing brain diseases and these two optimization techniques are generally termed interchangeably. ADAM optimizer had also produced the satisfactory results. RMSProp had also been used for Brain tumor detection and classification. There are different optimization techniques that have been used to obtain the better convergence for the network. Some of the commonly used techniques [54-56] are described as:

6.4.1. Gradient Descent

Gradients are calculated for the entire training dataset for a single iteration of weight updates. i.e.

$$W_{new} = w_{old} - \eta * \nabla J(W) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

$$\text{Where, } \nabla J(W) = \sum_{i=1}^{N} Li \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

N is the number of input images in the training dataset.

6.4.2. Stochastic Gradient Descent (SGD)

Stochastic Gradient Descent optimization technique updates weights for individual input image x_i and corresponding output y_i from training dataset. i.e.

$$W_{new} = w_{old} - \eta * \nabla J(W; xi; yi) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

This is done iteratively for N number of input images.

6.4.3. Mini Batch SGD

Mini Batch SGD updates the weights for every mini batch β of m images from training dataset in SGD manner instead of taking the entire training dataset of N images at once, as done in Gradient Descent. Thus, Mini Batch SGD can be defined as:

$$W_{new} = w_{old} - \eta * \nabla J_{\beta}(W) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

$$\text{Where } \nabla J_{\beta}(W) = \frac{1}{m}\sum_{i\in\beta} \nabla J(W;\ xi\ ;\ yi) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Batch Normalization

Batch Normalization is a technique to standardize the inputs to a layer for mini batches during training. It helps in reducing the number of learning iterations thus stabilizes the learning process of a deep learning model. Batch normalization is usually done on the inputs to the layer before or after the activation function.

In most of the cases, batch normalization is generally done before applying the activation function as:

$$h_k = f(BN(W_k * x + b_k)) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

BN is the Batch Normalization that is applied to each of the input xi, belong to the mini batch β of m images. It uses the mean and standard deviation as:

$$\mu\beta = \frac{1}{m}\sum_{i=1}^{m} xi \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Where μβ is the mean of that mini batch β,

$$\sigma^2{}_{\beta} = \frac{1}{m}\sum_{i=1}^{m}(xi - \mu\beta)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

Where $\sigma^2{}_{\beta}$ is the standard deviation for mini batch β and termed as variance, finally the normalized value of x_i is calculated as:

$$Xi^{\wedge} = \frac{xi-\mu\beta}{\sqrt{(\sigma_{\beta}^{2}+\in}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$$

6.4.4. Root Mean Square Propagation (RMSProp)

In all the Gradient optimization techniques mentioned above, learning rate η remains same for all the layers during all the iterations in training a model, whereas, in RMSProp approach, η should be changed with each iteration as :

$$Wt+_1 = wt - \frac{\eta}{\sqrt{E[g^2]t+\in}} * g_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots (16)$$

Where,

$$g_t = \nabla J(W_t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (17)$$

And

$$E[g^2]_t = \gamma\, E[g^2]_{t-1} + (1-\gamma)\, g_t^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (18)$$

$E[g^2]_t$ is a sum of gradients that is recursively defined as a decaying average of all past squared gradients, γ is a fraction with the default value 0.90 and ∈ is a small positive number to prevent the denominator value to become 0.

6.4.5. Adaptive Moment Estimation (ADAM)

ADAM basically combines some momentum with RMSProp to provide smoothening in order to reach to the minimum error (global minima) in less time. The weights are updated as:

$$Wt+_1 = wt - \frac{\eta}{\sqrt{E[g^2]t+\in}} * v_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots (19)$$

Where $E[g^2]_t$ is the sum of gradients, as same as defined in equation 18 for RMSProp, vt is the momentum and can be defined as:

$$v_t = \beta v_{t-1} + (1-\beta) g_t^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (20)$$

Where, $g_t = \nabla J(W_t)$, β is the fraction with the default value of 0.9.

Once all the weights get updated through any of the optimization technique, forward propagation is applied again to get the updated output. If still there exists some error, the complete process of fine tuning is done in an iterative manner until the error cannot be reduced any more. The model is said to be trained, once all the weights are adjusted to produce the desired output with minimum error.

6.5. Testing of model

Once a Deep Learning model is trained with the training dataset, it is tested over a testing dataset of images that were not included in the training dataset. This testing dataset contains the images with the specified diseases. The images are passed to the model and the trained model gives out the prediction. The predicted result is compared with the original output.

6.6. Performance Evaluation

After training and testing of the model, performance of the model is evaluated on the basis of the outcome of the testing results, to know how accurately, the model will predict a certain brain disease for a new patient. Confusion matrix and AUC-ROC curve had been used to evaluate the performance in terms of accuracy [57-58]. Sudden changes may still be required in the model either in the architecture itself, may be in the optimization technique or in the learning algorithms of the model to achieve the better accuracy.

7. Analysis and Discussion

Several deep learning methodologies, learning algorithms, optimization techniques have been applied over brain imaging techniques to segment, detect and to classify certain brain diseases. The models, their architectures, learning algorithms, activation functions, input datasets, image type, result and the performance in terms of accuracy are summarized in the tables from 4 to 6 as mentioned below for different brain diseases. Table 4 is for Brain Tumor, table 5 is for Alzheimer's and Huntington diseases and table 6 is for Brain Hemorrhage.

Table 4 Summary of Deep Learning Models implemented for Brain Tumor Segmentation and Classification

Reference	Model Architecture	Activation Function	Learning Algorithm	Dataset	Image	Output	Accuracy		
Tseng et al. (2017) [25]	4 Autoencoders (SegNet) +1 Conv Layer+ 1 LSTM + 1 Decoder	ReLU	ADAM optimizer	BraTS 15	MRIs with 4 modalities: T1, T1C, T2 and FLAIR	Tumor's 3D View	73%		
Yuexiang Li and Linlin Shen (2018)[59]	MvNet (ResNet + U-Net) CNN named SPNet (5Conv +4 MaxPool + 2 FC)	ReLU for ResNet and U-Net LeakyReLU for CNN	ADAM optimizer	BraTS 17	MRIs with HGG and LGG modalities (axial view, coronal view and sagittal views	Classification into three classes of tumor ET, WT and TC with MvNet Prediction of Survival Days with SPNet	ET 69% 55%	WT 88%	TC 71%
Zhao et al. (2018)[24]	Deep CNN + RNN	Softmax		BRATS 13, 15 , 16	MRIs with three modalities: T1c, T2, FLAIR	Tumor Segmentation	87%		
McKinley et al. (2019)[49]	Dense-U Net	ReLU	ADAM optimizer	BraTS 18	MRI images with four modalities: T1, T1C, T2 and FLAIR	Tumor Segmentation + Classification of tumor into three classes: ET, WT and TC	ET 79.7%	WT 90.3%	TC 85%
Rebsamen et al. (2019)[60]	Two separate Dense-U Net: one for each HGG and LGG modality , very similar to [49]	ReLU	ADAM optimizer	BraTS 18	MRI images with four general modalities: T1, T1C, T2 and FLAIR with additional HGG and LGG	Tumor Segmentation + Classification of tumor into three classes: ET, WT and TC	ET 83.8%	WT 91.6%	TC 90.2%
Saba, Mohamed, et al. (2019)[61]	VGG 19 for feature extraction +GrabCut Strategy for segmentation + Softmax layer to classify	ReLU	SGD optimizer	BraTs dataset 15, 16, 17	MRI images from BraTs Dataset with HGG and LGG modalities	Classification between Healthy and Tumor classes	BraTs15 98.78%	BraTs16 99.63%	BraTs 17 99.67%
Sharif et al. (2019)[50]	AlexNet +InceptionV3 to extract features + a softmax layer for classification	ReLU + Sigmoid	RMSProp	BraTs17, 18	MRI images	Automatic Segmentation + Classification into three classes ET, WT and TC	BraTs 17 ET 79.9% BraTs 18 ET 81.84% Average 92% for ET, WT, TC and healthy on different BraTs	WT 93.7% WT 91.2%	TC 83.73% TC 88.34%
		ReLU	Sigmoid	BraTS17,18	MRI images		BraTs	ET	WT	TC

Chandan Ganesh et al. (2020)[62]	3 Dense-UNets, one for each class WT, TC and ET					Fully automated Tumor Prediction + Severity through classes using binary classification	17	78%	90%	80%
							BraTs 18	ET	WT	TC
								80%	90%	82%
Muhammad Attique Khan et al. (2020) [63]	VGG16 + VGG19 for feature extraction + an ELM classifier	ReLU	SGD	BraTS	MRI images	Prediction and classification of Multimodal Brain Tumor into ET, WT and TC classes	BraTs 15		97.8%	
							BraTs 17		96.9%	
							BraTs 18		92.5%	
Amjad Rehman et al. (2020) [58]	1 CNN (4 Conv + 2 MaxPool+1 softmax) for tumor segmentation + a VGG19 to extract features + Feed Forward NN	sigmoid + Softmax	Mini SGD	BraTS 15, 17, 18	MRI images with all modalities: T1, T2, T1CE, Flair, LGG and HGG	Detection and Classification of brain Tumor	BraTs 15		Detection	Classify
									95.53%	98.32%
							BraTs17		-	96.97%
							BraTs18		95.44%	92.67%
D. Lu et al. (2021) [43]	ResNet 7, with reduced number of blocks to 7	ReLU	SGD	Patients' Data collected from University Hospital, Frankfurt	MRS	Classification between Tumor and Healthy Controls	73%			

Table 5 Summary of Deep Learning Models implemented for Alzheimer Disease and Huntington Disease

Reference	Model Architecture	Activation Function	Learning Algorithm	Dataset	Images	Result	Accuracy	
R. Li et al.(2014)[37]	CNN model	ReLU	SGD	ADNI	MRI and PET: 198- AD patients 403- MCI 229-NC	Classification : AD vs NC, MCI vs NC and MCIp vs MCIs	ADvsNC	92.87%
							MCI vs NC	76.21%
							pMCI vs sMCI	72.44%
Suk et al. (2016)[32]	Deep Auto Encoder (DAE) + 2 HMM, one for each class (Healthy & MCI)	ReLU + Sigmoid	ADAM	ADNI2	MRI of 31 MCI and 31 NC subjects	Classification: Healthy vs MCI	ADNI2	72.58%
				in-house cohort	MRI images : 12 MCI + 25 NC		In-house Cohort	81.08%
Chen et al. (2017)[64]	Multiple CNN models + 1 Conv layer+ FC layers	ReLU + Softmax	SGD	ADNI	T1-weighted MRI : 199-AD 229- NC	Classification of AD vs NC	87.15%	
Aderghal et al. (2017)[65]	2D CNN model	ReLU + Softmax	SGD		815 MRI images from hippocampal region: 188 AD	Classification: AD, MCI and NC	91.41%	

					399- MCI 228-NC			
E. Hosseini-Asl et al. (2018)[66]	3D CNN comprised of an autoencoder to extract features + FC layers for classification	ReLU + Softmax	SGD	CAD Dementia	MRI scans	Classification: AD, MCI, NC	99%	
Lu, D. et al. (2018) [67]	MMDNN (6 DNN to extract the features + 1 DNN to concatenate the features)	ReLU + Softmax	SGD	ADNI	MRI and FDG-PET (fuorodeoxyglucose positron emission tomography) images: 238- AD 626-MCI 360-NC	Feature Extraction for AD diagnosis	82.9%.	
Choi and Jin (2018)[68]	MatConvNet (CNN)[78]	ReLU	SGD	ADNI-2	PET images: 139 AD , 171 MCI, 182 healthy controls	Prediction: MCI conversion into AD within 3 years (sMCI vs pMCI)	84%	
Bi et al. (2019) [69]	PCANet(CNN) to extract the features + K-means method for classification	ReLU	PCA	ADNI 1 1.5T	MRI images from 1075 subjects: 243-AD 525-MCI 307-NC	Classification: AD vs MCI AD vs NC MCI vs NC AD vs MCI vs NC	AD vs MCI	97.01%
							AD vs NC	89.15%
							MCI vs NC	92.6%
							AD vs MCI vs NC	91.25%
Spasov et al. (2019)[52]	CNN model to extract features + 2 FC layers for classification	ELU + Sigmoid	Gradient	ADNI	T1 weighted MRI images: 192 AD, 409 MCI 184 Healthy + Demograhic data	Predict the conversion of MCI to AD (pMCI)	pMCI and sMCI.	92.5%
							AD vs NC	100%
Fulton LV et al.(2019)[53]	ResNet-50	ReLU	SGD	OASIS-1	4,139 MRI images	Classification of AD into multiple classes	99.34%	
Liu et al. (2020)[57]	Deep CNN with ResNet blocks (to learn the hippocampus segmentation features) +	PReLU	SGD	ADNI	MRI images: 97-AD 233- MCI 119- NC	Automatic Segmentation + Classification: AD, MCI and NC	Segmentation	87%
							AD vs NC	88.9%
							MCI vs NC	76.2%

	DenseNet (to learn the features for classification)							
Plis et al. (2014)[30]	A DBN (stack of 3 RBN)	ReLU	SGD		3500 MRI scans: 2641-Huntington 859- Healthy	Classification: Huntington Disease(HD) vs Healthy(HC)	HD vs HC	
Perez, Matthew et al. (2018)[39]	DNN (2 FC + 1 softmax)	ReLU	SGD	From HD study conducted at the University of Michigan	Audio Recordings form 62 speakers: 31-Huntington 31- Healthy	Classification: HD vs HC	HD vs HC	87% for each model
	LSTM with softmax layer	ReLU						

Table 6 Summary of Deep Learning Models implemented for Brain Hemorrhage Segmentation and Classification

Reference	Model Architecture	Activation Function	Learning Algorithm	Dataset	Images	Result	Accuracy	
Phong et al. (2017)[70]	LeNet GoogleNet InceptionResNet	ReLU	SGD	Data collected from a Hospital, Ho Chi Minh City, Vietnam.	1700 CT images	Classification : Brain Hemorrhage (BH) vs Healthy Control	LeNet	99.7 %
							GoogleNet	98.2 %
							InceptionResNet	99.2 %
Grewal et al. (2018)[71]	Recurrent Attention DenseNet(RADNet) DenseNet (40 Conv) + RNN(LSTM) + 1FC layer	ReLU	SGD	From 2 local hospitals	329CT scans: 185-67-77 (Tr, Val, Ts)	Prediction of BH with small dataset of 72 CT Scans (as much as similar with expert radiologists' diagnose)	81.82%	
Kamal Jnawali et al.[41]	3 CNN to extract the features + 1 Layer for classification (Logistic Function)	ReLU	SGD	From multiple Radiology centers	1.5 Million CT scans	Fully Automated Segmentation and Classification of Brain Hemorrhage	87%	
Majumdar A. et al. (2018) [72]	2 Models: 9 CNN blocks with 1 Conv layer and 9 CNN with 2 Conv Layers respectively.	ReLU	SGD	CT scans from Boston University Medical Center	4300 CT scans from 134	Automatic Detection of Brain Hemorrhage	81% sensitivity (true positives) and 98% (true negatives) specificity.	

	8 CNN Blocks (Modified U-Nets) to extract the features with MaxPool layers + 1 CNN to detect the Brain Hemorrhage				subjects: 88- BH 46-HC			
Kuo et al. (2019)[73]	Dilated ResNet to extract the features (DRN implemented by[52]) + 2ConvLayers to predict the BH	ReLU	SGD	UCSF-4.4	4,396 CT scans: 3,265-NC 1,131-BH	Detection of Intracranial Hemorrhage	99.1%(Best of all)	
Lewick et al. (2020) [74]	ResNet-50 to extract the features + 2 Conv Layers to classify the BH	ReLU + Sigmoid	SGD	RSNA	7,52,803 MRI images in DICOM format	Detection and classification of BH into five different types: EPH, IVH, IPH, SAH, SDH	98.3%	
S. P. Singh et al. (2020) [75]	a shallow 3D CNN model with 3 Conv Layers +2 FC	ReLU	ADAM	CQ500	497 CT scans in DICOM: 222-NC 134-IPH 28-IVH 53 SDH 60 SAH	Classification of BH into five classes (SAH, IPH, SDH, IVH, NC)	normal vs SAH	96%
							normal vs IPH	95%
							normal vs SDH,	100%
							normal vs IVH	97%
							normal vs all abnormal	97%
Burduja M et al. (2020) [76]	ResNeXt-101 for Feature Extraction + 3 layered LSTM for classification	ReLU	ADAM	RSNA 2019	25,272 CT scans in DICOM format	Detection of BH and classification of BH into 5 Variants: EPH, IVH, IPH, SAH, SDH	Any BH	96%
							EPH99.70%	99.70%
							IVH	99.20%
							IPH	98.32%
							SAH	97.52%
							SDH	96.27%
Nael et al. (2021)[77]	Deep Convolution Neural Network model (DCNN): 1 CNN to detect Abnormality	ReLU	ADAM	HIPAA compliant imaging research warehouse	13,215 MRI Scans: T1W, T2W, FLAIR, T2*	Classification of BH into four classes: Abnormal, Acute Infarction,	91% Abnormality 95% -Acute Infarction 90%-Acute Hemorrhage 93% - Intracranial Mass Effect	

	+ 3 CNN to detect type of BH				and DWI	Acute Hemorrhage and Intracranial Mass effect.	Better than CT scans for ACUTE Infarction and Intracranial (Upto 91%)

It can be analyzed from the above tables 4, 5 and 6 that the use of pretrained models in feature extraction gave the excellent results for diagnosing a brain disease. Figure 6 shows a summary chart depicting the best accuracies achieved with several pre-trained models. VGG19 could give the accuracy upto 99% in Brain Tumor detection. The combination of VGG16 and VGG19 for Brain Tumor detection as well as for classification could produce the results with 97% accuracy.

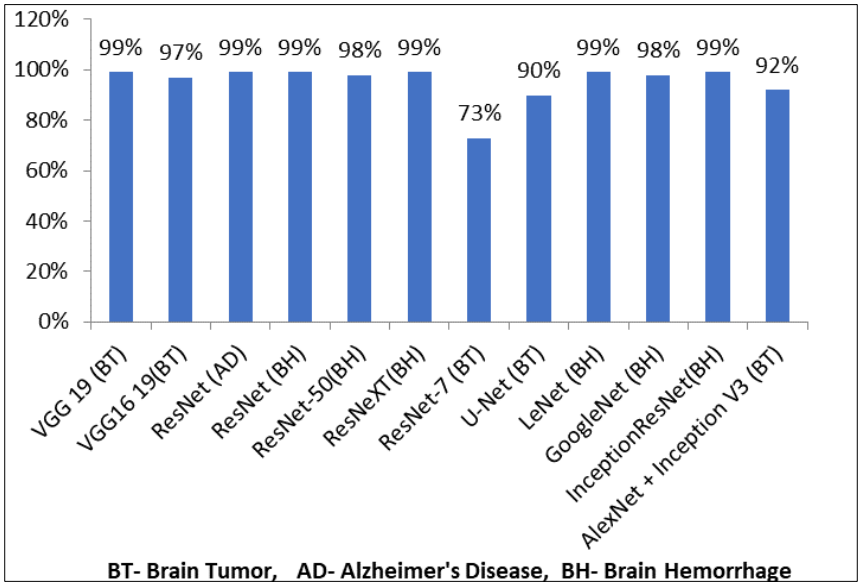

Figure 6 Best Accuracies achieved with pre-trained models for predicting or classifying certain brain diseases

ResNet had played an important role in diagnosing brain diseases. In diagnosing Alzheimer's disease, ResNet could achieve the accuracy of 99%. In Brain Hemorrhage, ResNet had given 99% accuracy. Modified ResNet with some layers, termed as ResNet-50 could achieve the accuracy of 98% in Brain Hemorrhage detection. The combination of ResNet and U-Net had also been proved successful in order to diagnose Brain Tumor. ResNeXT, another version of ResNet got the accuracy of 99% in diagnosing Brain Hemorrhage.

Recently, a modified ResNet-7 had been used with MRS data to detect Brain tumor and 73% accuracy is achieved. It is little low but it torched the light on the possibilities to use MRS data to detect Brain Tumor in future, as most of the models are using MRI images or CT scans as the input.

U-Net model has also been used successfully to produce the better results in diagnosing different brain diseases. Different combinations of U-Net had been used by the researchers in their models for the automatic detection and classification of Brain Tumor. They could achieve the accuracy of higher than 90%. U-Net could predict the Brain Hemorrhage with 81% sensitivity (true positives) and 98% (true negatives) specificity.

LeNet, GoogleNet and InceptionResNet could diagnose Brain Hemorrhage individually and achieved the accuracies of 99%, 98% and 99% respectively. A combination of AlexNet and Inception V3 got the accuracy of 92% for Brain Tumor classification.

It is observed that CNN, LSTM model had proved its significance in detection and classification of Brain Tumor, Huntington and Brain Hemorrhage brain diseases. Autoencoders have also been used successfully for Brain Tumor and Alzheimer's disease classification. Autoencoders have been used to classify the MRI scans into AD, MCI and NC with 99%

accuracy. RNN for Brain Tumor segmentation gave the accuracy of 87%. It has been noticed that the embedding of 7 DNNs for feature extraction could give the accuracy of 82.9% for Alzheimer Disease. A stack of 3 RBN (DBN) had also been used successfully for the classification of MRI scans between Huntington Diseased and Healthy controls. Figure 7 is showing the contribution of various Deep Neural Networks in the diagnosis of brain diseases.

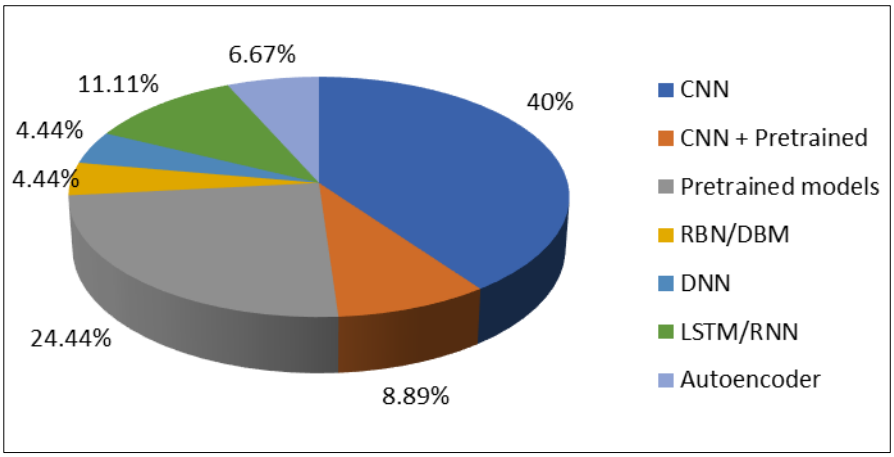

Figure 7 Contribution of various Deep Neural Networks in diagnosing brain diseases

In terms of input data, different types of images are being used by the experts. For brain tumor detection and classification, mostly MRI images had been used from different sources. With MRI images, Brain Tumor could be classified into three different classes with 99.62% accuracy. Recently MRS images have also been tried to predict Brain Tumor and could also been predicted with 73% accuracy. It is not so good, but in future there are possibilities to work with MRS data with different combination of models and optimizers to detect Brain Tumor as well as other brain diseases with better accuracies. Figure 8 shows the contribution of different input images in diagnosing different brain diseases.

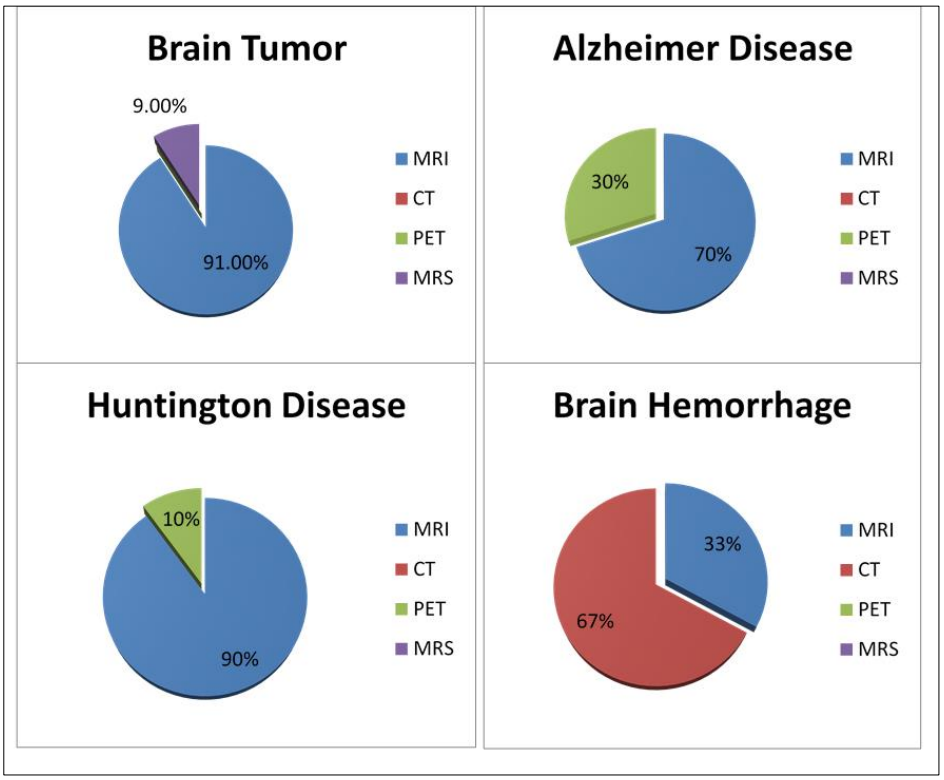

Figure 8 Contribution of different types of input images in diagnosing brain diseases

For Alzheimer Disease's detection and classification, again MRI scans are being widely used. Almost all of the models used MRI scans as the input images. 100% accuracy had been achieved in the detection of AD with MRI images. Besides MRI scans, PET scans had also been used to detect Alzheimer Disease as well as to predict the conversion of a Mild Cognitive Impairment to Alzheimer's Disease. PET scans provided the accuracy of 84% for the prediction of such conversions.

It has been analyzed that the combination of MRI and PET scans had been successfully used to extract the relevant features from the input and to predict the Alzheimer's disease with 92.8% accuracy. It is also analyzed that training with MRI images gave better results in the detection of Huntington Disease.

It is observed from the table 6, that Brain hemorrhage is mostly detected and classified by using the images of CT scans with the accuracy of 99%. Even 100% accuracy had been achieved in the prediction of SDH (Subdural Hematoma), a type of brain hemorrhage. Besides CT scans, MRI scans have also been used for the prediction and for the classification of brain hemorrhage. In this process, the better results have been found for different types of Brain Hemorrhage. The accuracy up to 98.2% had been achieved in the classification of Brain Hemorrhage into five classes with MRI images. Even Acute Infarction, one of a type of Brain Hemorrhage had been classified with 95% accuracy. It is found better than the other classification accuracies obtained with the images of CT scans. Figure 9 is depicting the best accuracies that could have been achieved till now for each of the brain diseases discussed here.

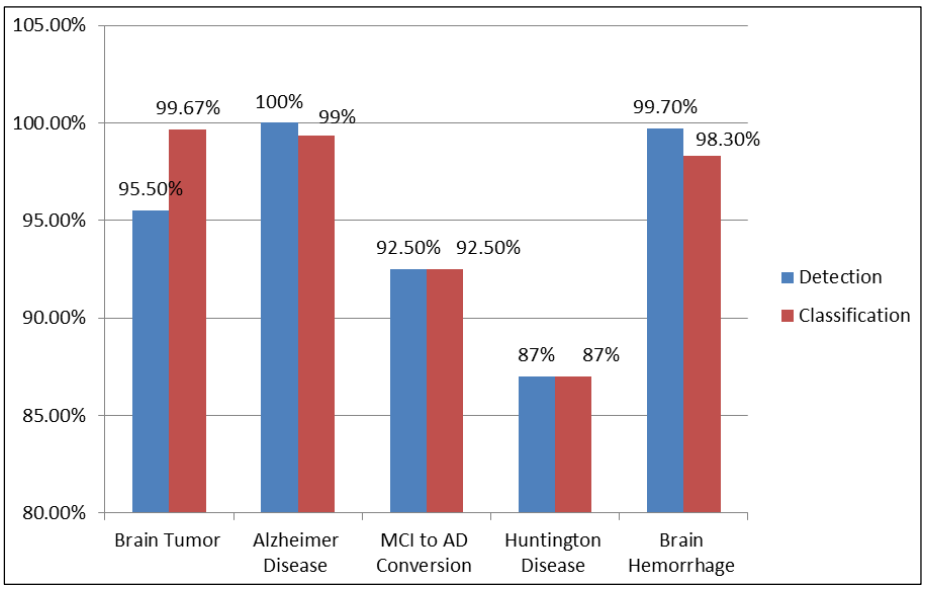

Figure 9 Best Accuracies achieved for certain brain diseases with deep learning methodologies

8. Conclusion

It can be concluded that most of the deep learning networks are implemented with CNN models for the brain diseases' prediction and classification. These CNN models had produced the most effective results for the segmentation, detection and classification of different brain diseases: Brain Tumor, Alzheimer Disease, and Brain Hemorrhage.

VGG16 and VGG19 had played an important role in Brain Tumor detection, so there is much possibility to use these helpful models in the detection of Alzheimer's disease, Huntington and Brain Hemorrhage too. It has also been analyzed that LeNet, GoogleNet, InceptionResNet, ResNet-50 and ResNeXT gave the excellent results in diagnosing Brain Hemorrhage, therefore there are possibilities to use these pretrained models for the prediction and classification of Brain Tumor, Alzheimer's disease and Huntington too. U-Net, AlexNet, Inception V3 or similar architectures can also be used in Alzheimer' Diseases or Brain Hemorrhage.

Autoencoders can be used to detect or to classify Brain Hemorrhage for better results as it gave the excellent results in Alzheimer's disease detection and classification. Therefore, a fine combination of CNN, Autoencoders, LSTM or DNN with input data like MRS, MRI, CT or PET scans may produce required results for certain brain diseases.

MRS is being used by the expert radiologists to detect and to classify the brain tumor, but this important input data had not been used with any deep learning models for the detection of Brain Tumor. MRS data can be included with MRI images or CT scans in order to detect brain tumor as well as Alzheimer's disease, Mild Cognitive Impairment or Huntington for better results. Audios of patients and EEG of their brains can also be used for the better diagnosis of brain diseases.

It has been analyzed that lots of work had already been reported in diagnosing the brain diseases through Deep learning models but the complete automation with 100% accuracy is still required for the detection of such diseases as there is no space of any incorrect diagnosis. Thus, there is a huge scope of research with deep learning methodologies for brain disease diagnoses in the demand of future.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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