A Comparative Approach of CNN Versus Auto Encoders to Classify the Autistic Disorders from Brain MRI

B.J. Bipin Nair, C. Adith, S. Saikrishna

Abstract--- In the present study, we are going to apply the deep learning methods to create a trained predictive model to recognize the neuro developmental diseases such as ASD, FASD. Deep learning is a dominant ML technique in classification. It will extract all kind (low to high) feature from a digital image. Classifying medical images tends to develop a predictive model in order to predict the neuro developmental disease. Classification of medical data for a medical condition for example ASD always a challenging task and selecting the important feature is also a difficult task. Using the deep learning techniques, we can successfully classify the MRI data of the neurodegenerative disease. Feature extracted by Convolution Neural Network and classification using the same advise a most robust method of classifying medical data especially MRI images. Stacked Auto encoders another better way for the feature extraction and prediction clinical data.

Keywords--- ASD-Autism spectrum disorder, ABIDE-Autism Brain Imaging Data Exchange

I. INTRODUCTION

Digital image processing (DIP) processes a digital image with the help of a computer. For that different kind of algorithms are using. DIP has numerous advantages over analog images. Algorithms are applied to the digital image to avoid some problems in image such as noise, unwanted objects in an image etc. Algorithms are performed on these pixels to eliminate noise or extract some details from the image. DIP is very much supportive in the medical field for the medical image processing with machine learning techniques. The computer-assisted analysis very useful and also very accurate. We can use machine learning techniques with the medical image processing to classify[1], identify and quantify the pattern in medical images. In machine learning, its sub deep learning methods give enhanced performance in the various medical applications includes cell structure detection, tissue segmentation, and computer-based diagnosis and so on. The neurodevelopmental disorder is hard to detect using only the image processing techniques from clinical data such as MRI images. Only machine learning techniques can extract the important feature from the clinical data. Here we use a convolution neural network to extract important feature as well as the stacked autoencoders. Any ML algorithm that is suited for classify the neurodevelopmental disorder will help scientist and doctors in detect the neuro developmental disorder. The CNN[11]and stacked autoencodersare widely used for medical image classification nowadays. Recognizing the neurodevelopmental disease from the MRI image is a very difficult process. It takes more time to detect by the medical professional. But using computer-assisted analysis it makes the process of detection is very easy. Our current system helps the clinician or the medical practitioner to detect the disorder easily without suffering too much. Researcher or scientist can use this work for further study on the neuro developmental disorder. Most of all the project use machine learning techniques such as SVM[2], Ada-boost etc. Deep learning techniques mostly used for detecting the neurodegenerative disorder. But in this work, we apply deep learning techniques to detect diseased brain. Here we classify the diseased brain and normal brain using two different deep learning technique and compute and plot the efficiency of the techniques we implemented.

II. LITERATURE REVIEW

AnibalSólonHeinsfeld et.al [1] had proposed a mechanism for detection of ASD using deep learning. They categorize control participants and ASD depended on their neural patterns. They used a deep learning method that combined two kindsML methods. Xia-an Bi et.al [2] classify ASD using random SVM. They used several SVMs to categorize ASD sufferer and typical controls. Then the key features are collected. We can achieve better accuracy by using only four features, whereas here they used seven feature to get better accuracy. This is a disadvantage of current method. Gajendra Jung Katuwal [3] provide method for ASD detection using MRI using machine learning. They estimate WM, CSF volumes, GM and TIV of ASD and TDC subjects by 3broadly used pre-processing approaches: FS, SPM, and FSL. They use several automatically extracted brain features and various classification techniques for this investigation. PegahKassraian-Fard et.al [4] they provide drawback and primary constrains for applying ML classifiers to detect autism. They describe possible classification for ASD. They compare several popular different machine learning classifiers. M Duda et.al [5] they proposed a method of machine learning technique for the behavioural distinction of ASD. They using under-sampling and forward feature selection.

Manuscript received February 01, 2019

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This specifies that ML can used to distinct amongst ADHD and autism with high correctness and this variations can be prepared by a less number of usually behaviours.

Yongxia Zhou et.al [6] had proposed method of MRI classification and Prediction of ASD using graph theory and ML to enhance characterization and prediction in ASDisorder. GopikrishnaDeshpande et.al [7] proposed method for detection of neural connectivity signature of ASD by applying machine learning techniques. They were investigated effectual connectivity among brain areas during intentional causal attribution in ASD and to exploitML techniques to catagorize participants based on effectual connectivity weights they were found. They use a deep learning algorithm to classify. DP Wall et.al [8] they propose a method that is the use of ML to observation-based screening and detection of ASD. For studying the complete set of the score from module 1 from ADOS they use a set of ML algorithms. The classifier demonstrating high test validity and find out the quantitative score which measures classification confidence. Christine Ecker et.al [9] provide a method of a multi-parameter classification approach to detect autism. To differentiate between people with autism and controls, they use group morphological parameters at each spot on the cortical surface and use to find a spatially distributed pattern of areas with highest classification weights. Wasifa Jamal et.al [10] had provide a method which classify ASD by supervised learning of connectivity of the brain. They study the existence of ASD using the functional brain connectivity from EEG result. They try on contrasting supervised learning techniques and explored the discriminant analysis. Tseng et.al [11] employ CDNN to extract visual features in real-time at the time of staring. Uses SVM and Ada-boost to classify children with FASD vs normal children. They use CNN and saliency model. SuhuaiLuo et.al [12] proposed a deep learning technique for the automatic classification of AD using 3-dimesional MRI. The algorithm apply a CNN to recognise AD. Mathew J. Summers et.al [13] proposed a method for detecting neurodegenerative diseases of aging using machine learning, which is very precise and authentic detection of neurodegenerative diseases. SamanSarraf et.al [14] they proposed a method of detection of Alzheimer's from fMRI using deep learning. They employ a CNN to separate an AD brain from a normal brain. Using the CNN and the LeNet-5. Gurpreet Singh et.al [15] proposed a method which uses ML for the recognition of neurodegenerative diseases. They applied PC analysis for feature extraction and after they quantify inter class discriminant ratio of the extracted feature using FDR. BhaskarSen et.al [16] provide a predictive model for the detection ASD using MRI. They extract feature using LEFMS from structural MRI and used as an input to the SVM classifier. Mohamed M. Dessouky et.al [17] they provide a mechanism for Alzheimer's disease feature extraction for the classification. Two proposed feature extraction algorithms are used. In addition, the system stability using the second proposed algorithm is better by reducing memory size by 70%. They used dataset is OASIS dataset. Bipin Nair BJ et.al [18] develop a chemical structure of suppressor drug for ASD. They designed three molecular compounds for structuring the suppressor. In their work, they developed a computational tool for structuring the suppressor drug. N Shobha Rani et.al [19]develop a method for recognizing the deformed characters using the CNN. They classified printed and handwritten Kannada characters. They are able to classify the characters at an accuracy of 83.5%.Bipinnairb.j et al [20] have proposed a new method on ASD on the base of melatonin and fluoxetine interaction with shank3 protein gene. They redesigned the drug 2D structure through prediction techniques. They proved that 2D structure of a protein is an significant basis of data for recognising the autism.

III. PROBLEM DEFINITION

A comparative deep learning approach to predict the neurodevelopmental disorders using brain MRI.

1. Pre-process the MRI image.
2. Train the dataset using Deep learning techniques.
3. Classify the new input data either diseased or not diseased using a classifier.
4. Measure the efficiency of the algorithm.

IV. METHODLOGY

In our current work, we are first collected pre-processed benchmarked diseased MRI dataset from different databases, mostly from the ABIDE dataset. ABIDE provides previously collected MRI. ABIDE dataset is gathered from the different imaging site. From ABIDE pre-processed brain MRI are available for download. We downloaded pre-processed data from Preprocessed Connectomes Project (http://preprocessed connectomes project.org/). We again pre-process the MRI once again using an inbuilt de-noising CNN, which is available in MATLAB. The neural network contains 59 layers in it. After that, we feed the neural network with the pre-processed MRI to train the CNN. Here we are using supervised learning techniques. The network we predict new image as either diseased or not disease.

Layers of CNN

There are four important layers in CNN architecture figure 1. They are

1) Convolution Layer
2) ReLU Layer
3) Pooling Layer
4) FC Layer

Convolution Layer

The main purpose of the convolution layer is to extract the feature from the image(s) of training set. The computer reads the image as pixel and expressed as (N*N*3)-(height by width by depth).

A filter is used to identify or detect a specific pattern from the input image. The filter is expressed as (M*M*3) which smaller in dimension but same depth as the input image. This filter slides over the input image and produces the feature map. A set of feature map is produced and passed to the next layer.

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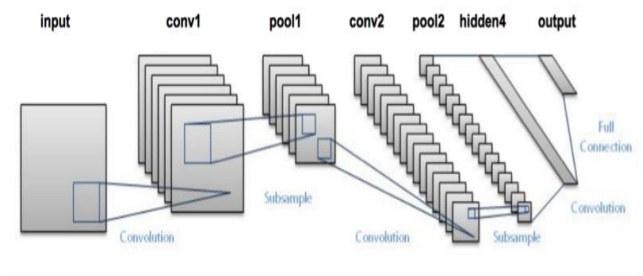

Figure 1

2) ReLU Layer

Widely used activation function NN. The greatest advantage of ReLu when compared to other activation function is it doesn't activate all the neuron at similar period. It's an element-wise process which substitute all the negative pixel value with zero in the feature map and produces a rectified feature map. The aim of ReLU is to bring non-linearity in convolution net.

3) Pooling Layer

Pooling layer decreases the feature map's dimensionality but kept the key feature in it. There two kind pooling max and average pooling.

Max pooling

It will take only maximum value from the pool. Here we define the filter window and filter moves through the rectified feature map and select a maximum value in each stride.

Average pooling

It will take average value from the pool. Here we define filter window and filter moves through the rectified feature map and select average value by adding all the value and divide it by window size(M*M)

4) FC layer

FC layer uses a softmax activation function in output layer. All the neuron in the earlier layer will connect to this fully connected layer. It will accept all the high-level feature from the previous layer and use these feature for categorizing the input image into different classes.

The neural network includes almost 30 layers in it. We provide almost 10000 images to the neural network for training purpose to get very high accuracy. After training, we save the neural network. Using that pre-trained network we classify the new input image. Then find out the efficiency of the algorithm that we are used based on the time taken to train and the accuracy of prediction. We are able to plot the graph of accuracy vs loss by monitoring the training progress.

Another method used for the classification is stacked autoencoders. We use the same processed data for this neural network for training and classification. Because then only we can calculate the accuracy of both method easily. Here stacked encoder is a combination of both supervised and unsupervised learning. In hidden layers, it uses the unsupervised fashion and in output layer which uses the supervised learning. After training, we provide some test data to the network and calculate the efficiency of the network by checking the confusion matrix. Figure 2 shows the architecture of the stacked autoencoders.

Layer of Stacked Autoencoders:

The layer of Stacked Autoencoders:

There are 3 layers in autoencoders. They are

1) Input layer.
2) Hidden Layers.
3) Output layer.

1) Input layer

Which is to accept the input data and pass these data to the next layers. Each node in the input layer is connected to each of the hidden layers.

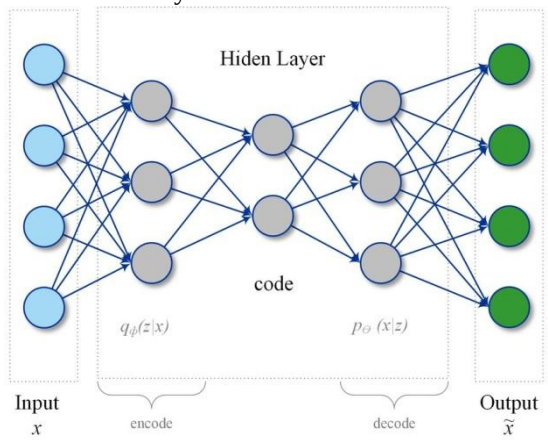

Figure 2

2) Hidden layer

Which accept the input from the previous layer and then reconstruct the input using a tied weight and pass to the next layer (output layer or the next hidden layer).

In this only some of the hidden layers or node active at the same time. Its working is based on encoding and decoding.

3) Output layer

Which will accept classify the data based on the feature learned by the previous layer.

Here in this neural network, we are included several layers for the better feature learning and the classification of the new input data. We trained the same number which we have used for CNN.

MATHAMATICAL MODEL

CNN

$$O_{x,e}^{(l,b)} = \tanz\left(\sum_{t=0}^{p-1}\sum_{r=0}^{bhbw}\sum_{c=0} W_{(r,c)}^{(b,t)}\, O_{(x+r,x+c)}^{(l-1,t)} + Bias(l,b)\right)$$

Forward Pass

$$O_{x,e}^{(l,b)} = \tanz\left(W^{(b)} \sum_{r=0}^{S_h S_w(l-1,b)}\sum_{c=0} O_{(x\times sh+r,\, e\times sw+c)} + Bias^{(l,b)}\right)$$

$$O_{(l,j)} = \tanz\left(\sum_{b=0}^{s-1}\sum_{x=0}^{shsw}\sum_{e=0}^{(j,b)} W_{(x,e)}^{(l-1,b)}\, O + Bias^{(l,j)}\right)$$

***Backward pass*:**

Output deviation:

$\delta(O^{O}{}_{\beta}) = \varepsilon_{\beta} - \tau_{\beta}$

Ινπυτ δεϖιατιον:

$\delta(\vartheta^{O}{}_{\beta}) = (\varepsilon_{\beta} - \tau_{\beta})\varphi^{\vartheta}(\varpi_{\beta}) = \varphi^{\vartheta}(\varpi_{\beta})\,\delta(O^{O}{}_{\beta})$

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Ωειγητ ανδ βιασ παριατιον:

$\Delta\Omega^{O}_{\beta,\xi} = \delta(\vartheta^{O}_{\beta})\varepsilon_{\beta,\xi}$

$\Delta Biaσ^{O}_{\beta} = \delta(\vartheta^{O}_{\beta})$

Ουτπυτ βιασ:

$\delta(O^{H}_{\beta}) = \sum \delta(\vartheta^{O}_{\varphi})\Omega_{\varphi,\beta}^{\varphi=0}$

Ινπυτ βιασ:

$\delta(_{\vartheta\beta}^{H}) = \varphi^{3}(\varpi_{\beta})\delta(O^{H}_{\beta})$

Τοταλ βιασ παριατιον οφ τηε χονπολυτιον χορε:

$$\Delta Biaσ^{X,\beta} = \sum_{\xi=0}^{\pi\eta\pi\omega} \sum_{\varepsilon=0} \delta(\vartheta^{X}_{\xi,\varepsilon}{}^{\beta})$$

Stacked Autoencoders

Let X(j,1),X(j,2),e(j,1),e(j,2)denote the parameters X(1),X(2),e(1),e(2) for j th autoencoder.

Encoding step for the stacked autoencoder is given by:

$b^{(l)}=g(z^{(l)})$

$y^{(l+1)}=X^{(l,1)}b^{(1)}+e^{(l+1)}$

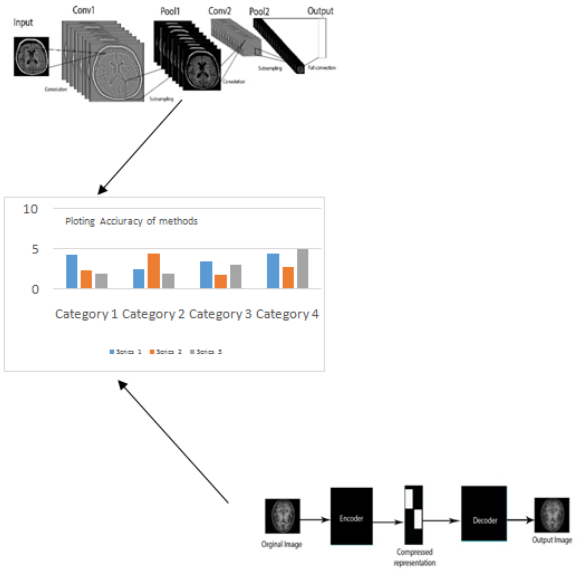
The decoding step is given:

$b^{(p+1)}=g(z^{yp+l)})$

$y^{(p+l+1)}=X^{(p-l,2)}b^{(p+1)}+e^{(p-l+1)}$

$a^{(q)}$ is the activation of the deepest layer of hidden unit. Feature extracted by hidden encoders used for the classification by providinga(q) to a softmax layer.

FLOW DIAGRAM



Step 1: Pre-process the MRI.

Step2: Feed the pre-processed MRI to the CNN and Stacked auto encoders for training.

Step 3: Test new input image is either diseased or normal brain.

Step 4: Compute the efficiency of the algorithm that we have used.

EXPERIMENTAL RESULT

Figure 3 shows the original image of the MRI. Figure 4 shows that the image after the image pre-processes. After pre-processing of all image in the dataset we feed the image to the neural network for training.

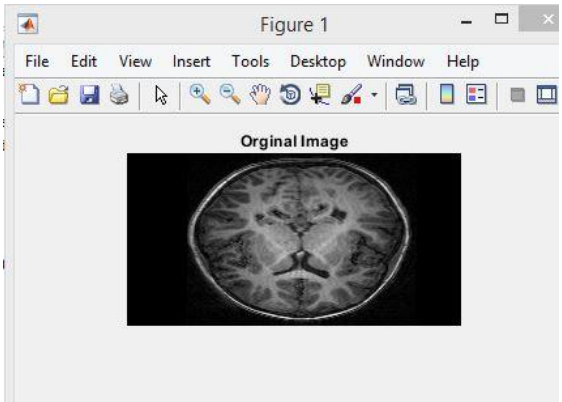


Figure 3: Original Image

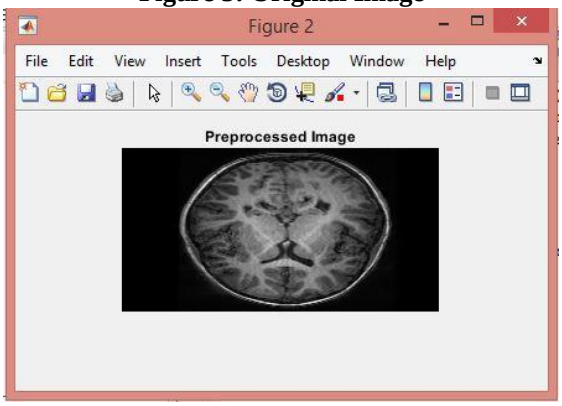


Figure 4: Pre-processed Image

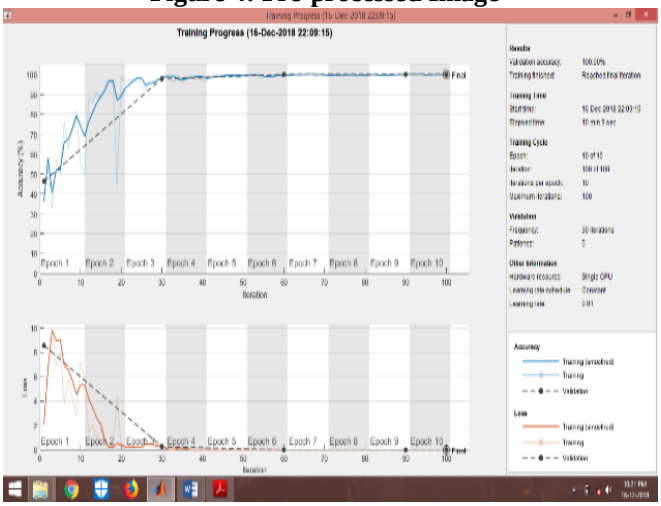


Figure 5: Training Accuracy plotted

The accuracy of the training progress is plotted in figure 5. Here we attain high accuracy and less loss. Above graph shows that in each epoch accuracy becoming high and the loss becoming low by using the smoothening algorithm.

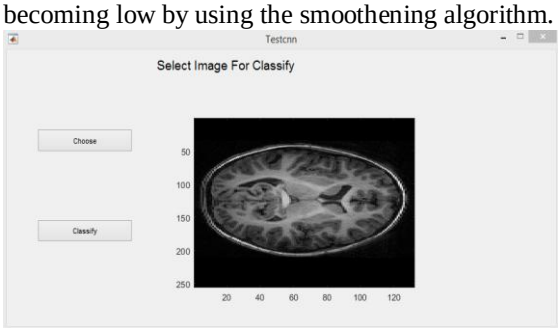


Figure 6: Selection of image

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Figure 6 shows interface for selecting an image for classification. Figure 7 is displaying the result that it's the autistic or normal brain.

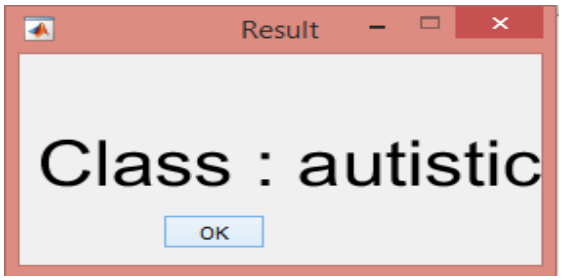

Figure 7: Classification result

The feature of the input image extracted by the trained network and which is compared with the stored feature to classify the input image.Using the CNN we are able to correctly classify the image as diseased or normal. We are able to attain the accuracy of 84% in predicting the disease which very much higher any other classifier.

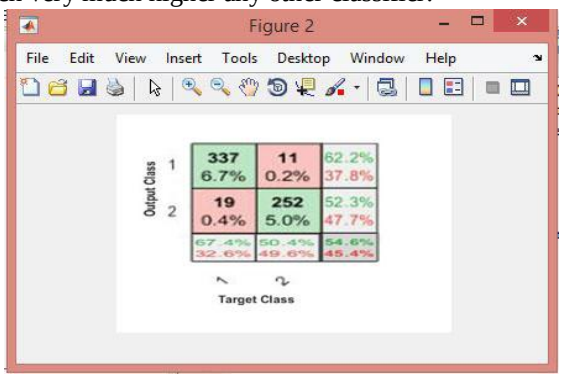

Figure 8: Confusion matrix for training

Figure 8 shows the confusion matrix for the training the network. Which indicate that how data has been correctly classified.Each column representing the actual class and the row representing the predicted class.

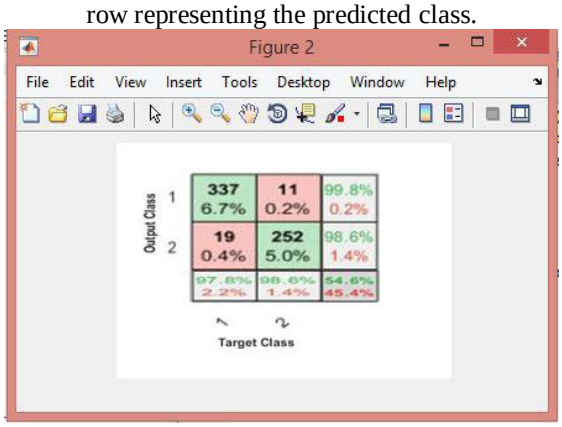

Figure 9: Confusion matrix for testing

Figure 9 shows the confusion matrix for test data. It clearly indicates that almost every classes have been predicted correctly. Only a few of the test input data has been classified wrongly.

For calculating the accuracy of the algorithms we consider parameter 1) accuracy in training and 2) accuracy in classification and we have attained an accuracy of 80%. We calculated the efficiency of the algorithm by considering the number of epoch needed to get high accuracy in training.

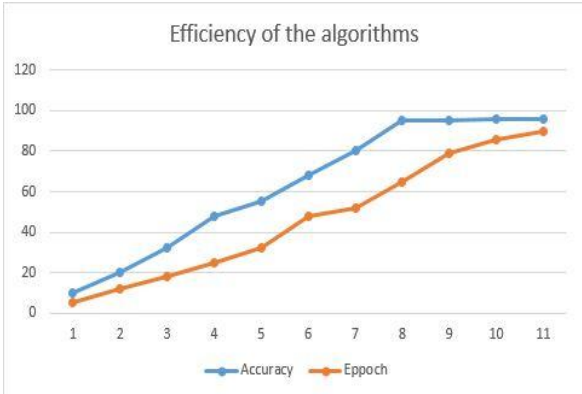

Figure 10: Efficiency of the algorithm

Above figure shows that the efficiency of both techniques based on accuracy and number of the epoch. We can clearly understand that for CNN its get a high accuracy in a lesser number of the epoch. But for stacked autoencoder, it takes a greater number of the epoch to attain high accuracy.

V. CONCLUSION

From this study, we conclude that convolutional neural network is better for medical image processing and also disease detection when compared to stack autoencoder. The convolutional neural network is able trained and classify an image with high accuracy than the stack autoencoder. From this, we conclude that the deep learning techniques are reliable and best techniques for classification of a multi-site dataset.

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