Brain Tumor Segmentation and Classification Using Convolutional Neural Networks

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Abstract: Automatic defects detection in MRI images is very important in many diagnostic and therapeutic applications. Magnetic resonance imaging (MRI) is a widely used imaging technique to assess these tumors, but the large amount of data produced by MRI prevents manual segmentation in a reasonable time, limiting the use of precise quantitative measurements in the clinical practice. So, automatic and reliable segmentation methods are required. Automatic brain tumor detection method increases the accuracy and decreases the diagnosis time. The proposed system is to classify the tissues into three classes of normal, benign and malignant. The diagnosis method consists of pre-processing of MR images, segmentation, feature extraction, and classification. Image segmentation is used to cluster the pixels which might be used to classify the disease or to detect a tumor. Neural Network (NN) are employed to classify into normal and abnormal brain. Convolutional Neural Network (CNN) is used as a classifier to compare the given image and the image in the database. If the tumor is identified while comparing each pixel, it display the message box the tumor is affected, after completing the NN training. Overall, this proposes a novel method of brain MRI image segmentation using the conventional neural network to increase the accuracy compared to the conventional methods.

Keywords: Neural Network (NN), Convolutional Neural Network (CNN), Magnetic resonance imaging (MRI), Space Invariant Artificial Neural Networks(SIANN), NYU Object Recognition Benchmark(NORB), Synthetic Aperture Radar(SAR), Optical Coherence Tomography(OCT).

1 INTRODUCTION

A brain tumor is an abnormal growth of cells inside the brain or skull; some are benign, others malignant. Tumors can grow from the brain tissue itself (primary), or cancer from elsewhere in the body can spread to the brain (metastasis). Treatment options vary depending on the tumor type, size and location. Treatment goals may be curative or focus on relieving symptoms. Many of the 120 types of brain tumors can be successfully treated. New therapies are improving the life span and quality of life for many people. Among the several brain tumors in human benign gliomas is the most common and aggressive. Primary brain tumors emerge from the various cells that make up the brain and central nervous system and are named for the kind of cell in which they first form. The most common types of adult brain tumors are gliomas as in astrocytic tumors. These tumors form from astrocytes and other types of glial cells, which are cells that help keep nerves healthy. The second most common type of adult brain tumors are meningeal tumors. These form in the meninges, the thin layer of tissue that covers the brain and spinal cord. Medical science neither knows what causes brain tumors nor how to prevent primary tumors that start in the brain.

1.1 Existing system

Artificial Neural Networks

Artificial neural networks (ANN) or connectionist systems are computing systems vaguely inspired by the biological neural networks that constitute animal brains. The neural network itself is not an algorithm, but rather a framework for many different machine learning algorithms to work together and process complex data inputs. Such systems "learn" to perform tasks by considering examples, generally without being programmed with any task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images.

Convolutional Neural Networks

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics. Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage. They have applications in image and video recognition, recommender systems, image classification, medical image analysis, and natural language processing.

2 PROPOSED SYSTEM

The CNN based brain tumor classification is divided into two phases such as training and testing phases. The number of images is divided into different category by using labels name such as tumor and non-tumor brain image, etc.

Block diagram

In the training phase, preprocessing, feature exaction and classification is performed to make a prediction model. Initially, label the training image set. In the preprocessing image resizing is applied to change size of the image. Finally, the convolution neural network is used for automatic brain tumor classification. The brain image dataset is taken from image net. Image net is a one of the pre-trained model. If you want to train from the starting layer, need to train the entire layer (i.e) up to ending layer. So time consumption is very high. It will affect the performance. To avoid this kind of problem, pre-trained model based brain dataset is used for classification steps. In the proposed CNN, trained only last layer. So computation time is low meanwhile the performance is high in the proposed automatic brain tumor classification scheme.The block diagram of proposed system is as shown in Fig 2.1.

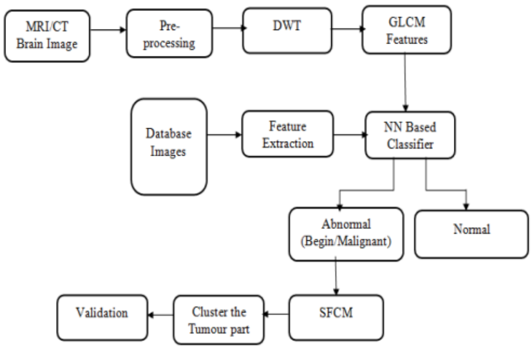

Fig 2.1 Block Diagram of Proposed system

3 WORKING

The input image is in DICOM format. This image can be converted into JPEG format and resize the image, because the image is having more size, it requires more time for segmentation process and less picture quality. So the size should be resized into 256*256.The input images we use here are Brain (MRI) images received from diagnosis hospitals. MR images are extremely rich in information content. The image pixel value can be considered as a function of a host of parameters, including the relaxation time constants T1 and T2, and the proton density (that has distinct values for different tissues). Therefore, by changing the effect of these parameters, MR images obtained from the same anatomical position can look drastically different. Note that left brain shown in an image is the right brain of the subject, and vice versa. These images can be further processed to produce new maps regarding water diffusion, blood flow, etc. Hence, the flexibility in data acquisition and the rich contrast mechanisms of MRI endow the technique with superior scientific and diagnostic values.

Fig. 3.1. Three weighted MRI images (a) T2-weighted (T2w), (b) T1-weighted (T1w), and (c) proton density (PD) images were obtained from the same cross section of a human head

Pre-processing is a common name for operations with images at the lowest level of abstraction—both input and output are intensity images. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. Every image contains some salt and pepper noise having some blurriness. To remove the noise and blurriness we use median filter.

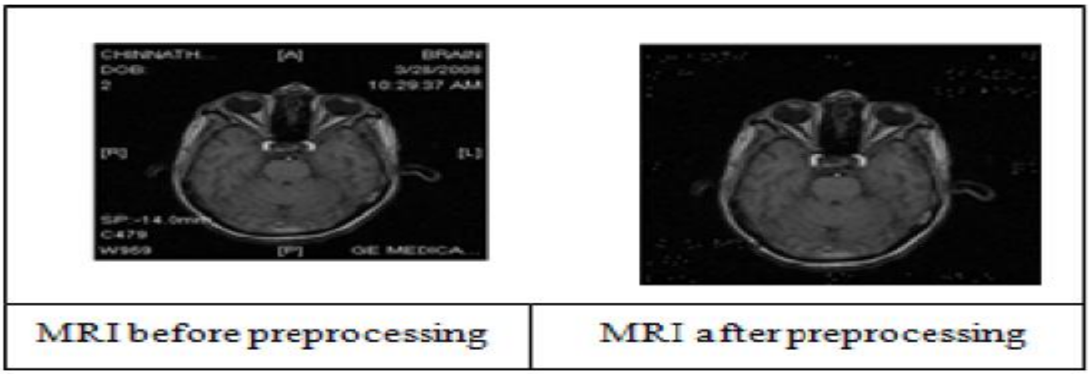

Fig. 3.2. MRI before and after Pre-processing

Discrete wavelet transform

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time). The DWT represents the signal in dynamic sub-band decomposition. Generation of the DWT in a wavelet packet allows sub-band analysis without the constraint of dynamic decomposition. The discrete wavelet packet transform (DWPT) performs an adaptive decomposition of frequency axis. The specific decomposition will be selected according to an optimization criterion.

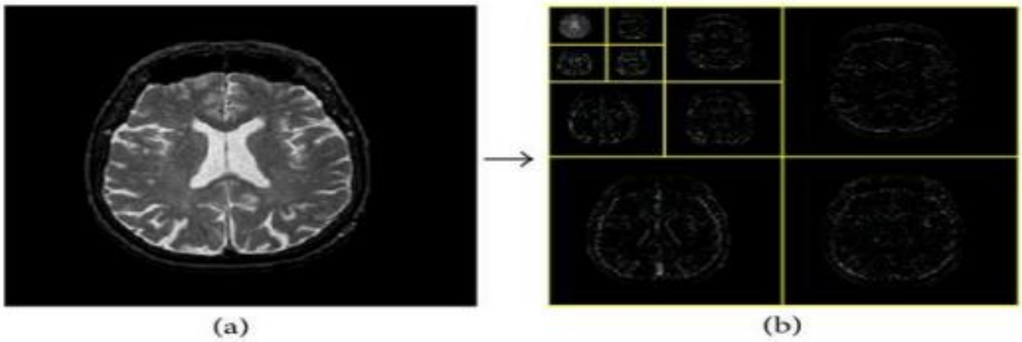

Fig. 3.3 a) Original image b) Image after performing DWT

The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression.

Feature Extraction

The feature extraction is a major process in recognition of applications and classifications, the texture based feature extraction is going on in this work, normally several texture based feature extraction classifications are there those are GLCM, LBP, SLBP. The grey scale invariant texture is measured and derived from definition of texture in local region. It is an efficient texture operator, it labels image pixels by the threshold process from the neighbourhood of each pixel and represents in binary number. In this the tumor part is extracted from the lung and brain images, this is based on the texture and contrast of an image. Input cancer image (MRI/CT) Pre-processing Segmentation Using Classification with CNN Feature Extraction Statistical values

Co-occurrence Matrix

Originally proposed by R.M. Haralick, the co-occurrence matrix representation of texture features explores the grey level spatial dependence of texture [2].

Grey level co-occurrence matrix (GLCM)

A statistical method of examining texture that considers the spatial relationship of pixels is the grey-level co-occurrence matrix (GLCM), also known as the grey-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix

$$C_{orr} = \frac{\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}(x,y)f(x,y) - M_x M_y}{\sigma_x \sigma_y}$$

Convolutional Neural Network

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNNs use relatively little pre-processing compared to other image classification algorithms.

CNN algorithm

CNN algorithm has two main processes: Convolution and Sampling.

Convolution process

Use a trainable filter F_x , deconvolution of the input image (the first stage is the input image, the input of the after convolution is the feature image of each layer, namely Feature Map), then add a bias b_x, we can get convolution layer C_x.

Sampling process

n pixels of each neighbourhood through pooling steps, become a pixel, and then by scalar weighting W_{x+1} weighted, add bias b_{x+1}, and then by an activation function, produce a narrow n times feature map Sx_{+1}. The key technology of CNN is the local receptive field, sharing of weights, sub sampling by time or space, so as to extract feature and reduce the size of the training parameters.

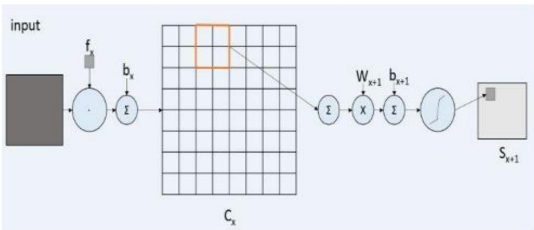

Fig. 3.4 Main process of CNN

CNN Architecture Design

CNN algorithm need experience in architecture design, and need to debug unceasingly in the practical application, in order to obtain the most suitable for a particular application architecture of CNN.

Based on grey image as the input of 96 * 96, in the pre-process stage, 32*32 of the size of the image. Design depth of the layer 7 convolution model: Input layer, Convolution layer C1, Sub sampling layer S1, Convolution layer C2, Sampling layer S2, Hidden layer H and Output layer F.

In view of the 32 * 32 input after pre-processing, there is a total of 17 different pictures. C1 layer for convolution, convolution layer adopts 6 convolution kernels, each the size of the convolution kernels is 5 *5, can produce six feature map, each feature map contains (32-5 + 1) * (32-5 + 1) = 28 * 28 = 784 neuron.

At this point, a total of 6 * (5 * 5 + 1) = 156parameters to be trained. S1 layer for sub sampling, contains six feature map, each feature map contains 14 * 14 = 196 neurons. the sub sampling window is 2 * 2 matrices, sub sampling step size is 1, so

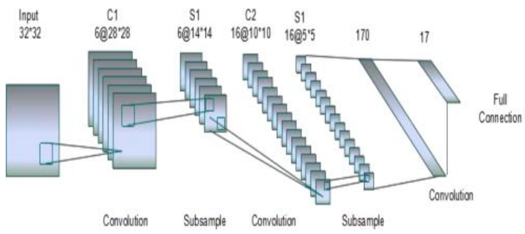

Fig. 3.5 Architecture of CNN in training face

4 SOFTWARE

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation.MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non interactive language such as C or FORTRA The name MATLAB stands for matrix laboratory. MATLAB was originally written to provide easy access to matrix software developed by the LINPACK and EISPACK projects. Today, MATLAB uses software developed by the LAPACK and ARPACK projects, which together represent the state-of-the-art in software for matrix computation. MATLAB has evolved over a period of years with input from many users. In university environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science. In industry, MATLAB is the tool of choice for high-productivity research, development, and analysis.

5 RESULTS AND DISCUSSIONS

a. Dataset images used for training CNN

The following are the MRI images of the different tumors of brain at different stages used for training CNN.

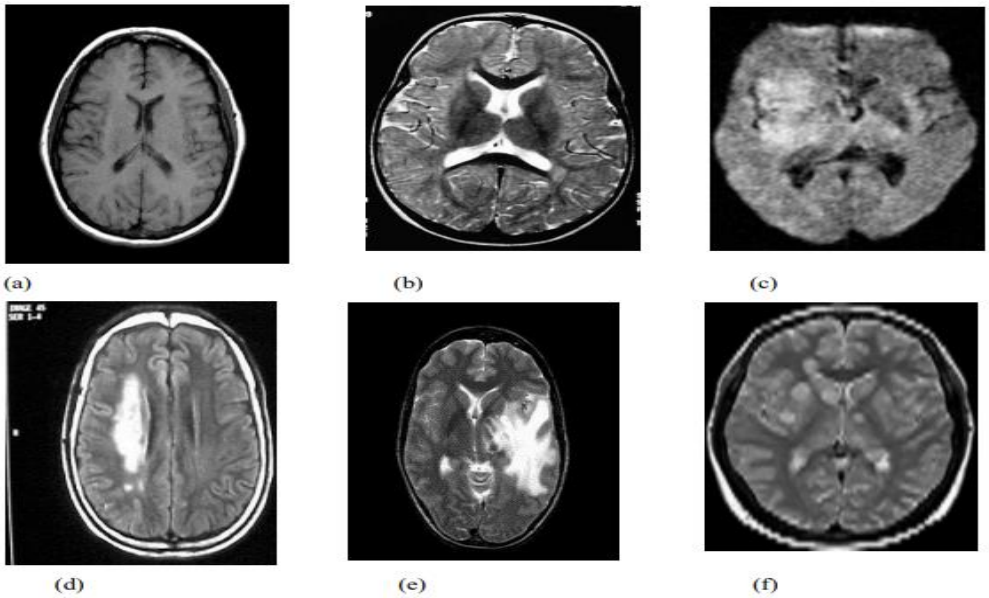

Fig. 5.1 (a) no tumor (b) benign tumor (c) no tumor (d) benign tumor (e) malignant tumor (f) no tumor

The database consists of different MRI images of patients affected with benign and malignant tumors in different regions of brain and MRI images without brain tumor are also taken.

Case 1

No Tumor

The following is the output of normal stage with no effect of tumor, the input MRI image is taken and processed further with some techniques and verified with dataset images to detect the tumor part and classify whether the tumor is normal or abnormal.

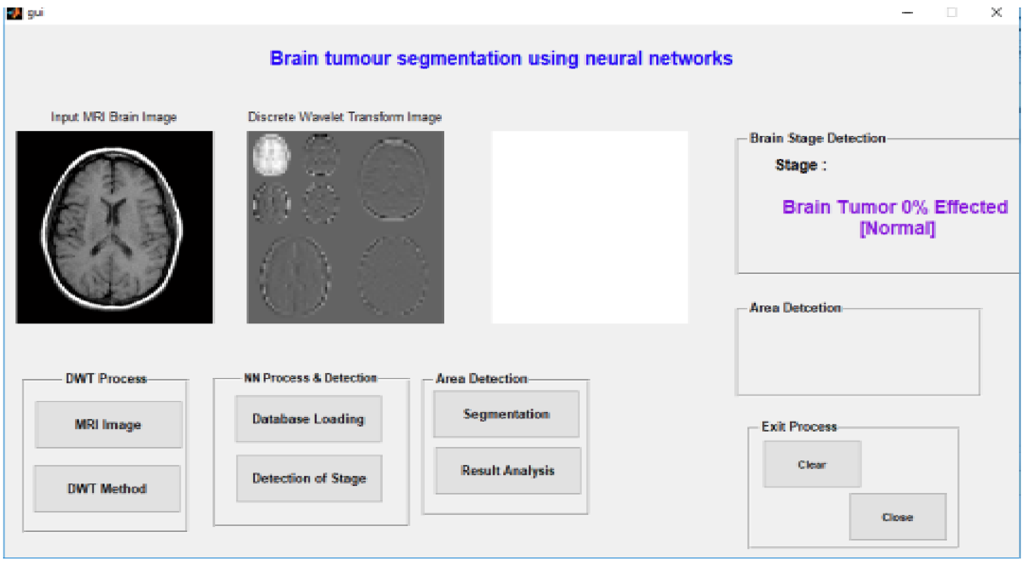

Fig 5.2 Output of MRI with no tumor

The input is preprocessed, the features are extracted and compared with the database. As there is no tumor clustering will not take place.

Case 2

Detection of Benign Tumor

The following is the output of brain effected with tumor and is in benign stage, the input MRI image is taken and processed further with some techniques and verified with dataset images to detect the tumor part and classify whether the tumor is normal or abnormal.

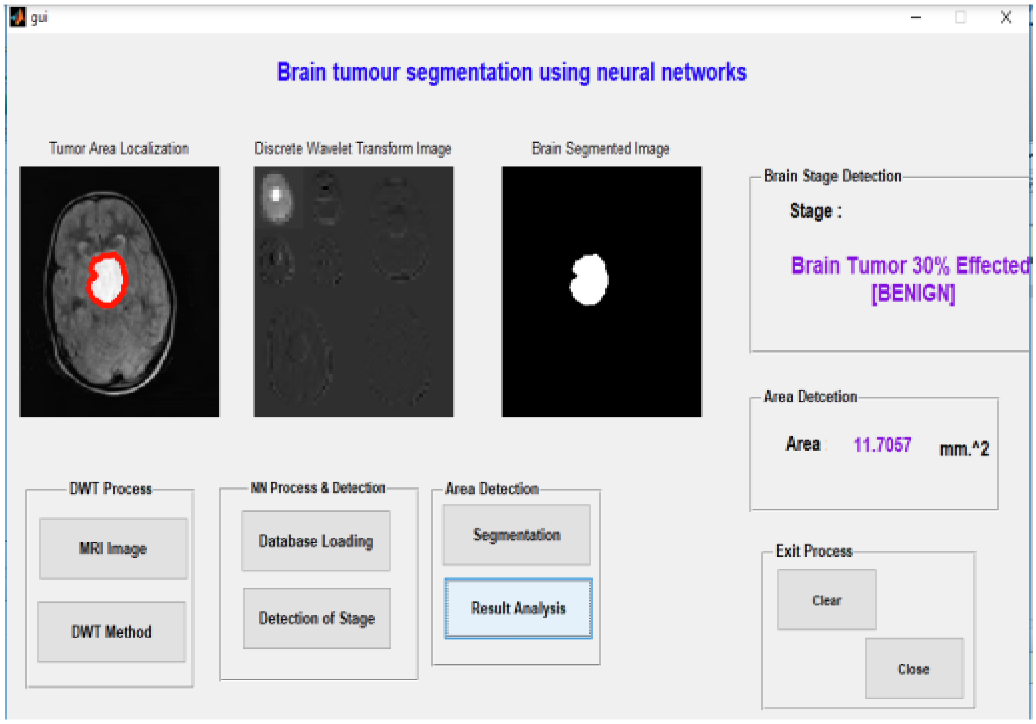

Fig 5.3 Output of MRI with benign tumor

The input image is preprocessed and the features are extracted using GLCM and compared with database. The tumor is classified as benign and the tumor part is clustered.

Case 3

Detection of Malignant Tumor

The following is the output of brain effected with tumor and is in malignant stage,the input MRI image is taken and processed further with some techniques and verified with dataset images to detect the tumor part and classify whether the tumor is normal or abnormal.

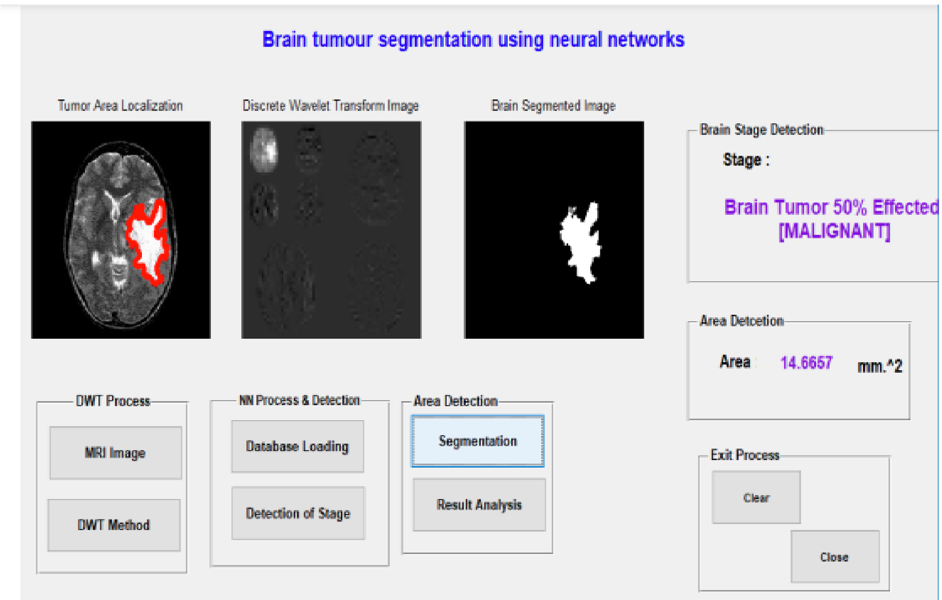

Fig 5.4 Output of MRI with malignant tumor

The input image is preprocessed and the features are extracted using GLCM and compared with database. The tumor is classified as malignant and the tumor part is clustered.

6 CONCLUSION

The proposed system is to design efficient automatic brain tumor classification with high accuracy, performance and low complexity. The conventional brain tumor classification is performed by using Fuzzy C Means (FCM) based segmentation, texture and shape feature extraction and SVM and DNN based classification are carried out. The complexity is low. But the computation time is high meanwhile accuracy is low. Further to improve the accuracy and to reduce the computation time, a convolution neural network based classification is introduced in the proposed scheme. Also the classification results are given as tumor or normal brain images. CNN is one of the deep learning methods, which contains sequence of feed forward layers. Image net database is used for classification. It is one of the pre-trained models. So the training is performed for only final layer. Also raw pixel value with depth, width and height feature value are extracted from CNN. The training accuracy, validation accuracy and validation loss are calculated. The training accuracy is high. Similarly, the validation accuracy is high and validation loss is very low.

7 REFERENCES

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