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Development of a Novel Approach for Classification of MRI Brain Images Using DCNN based onVGG16 Model

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Abstract
Brain tumor implies development of strange cells in brain. In cutting edge stages, brain tumor is most risky infection which can't be relieved. Thus, it ought to be identified in the beginning phases with the assistance of MRI (Magnetic Resonance Image). So, there will be more changes to the patient to endure. Quite possibly, the most functional and significant technique is to utilize Deep Neural Network (DNN). In this paper, a Deep Convolutional Neural Network (DCNN) based on VGG16 model has been developed to identify a tumor through brain Magnetic Resonance Imaging (MRI) dataset. In the clinical field, the strategies of machine learning (ML) and data mining hold a critical stand. It is effectively used to achieve the efficiency and exact location of tumor. The proposed technique involves automatic segmentation method based on Deep Convolution neural network (DCNN). It is layer based segmentation and classification technique. Different levels are engaged with the proposed technique, first step is data collection and then pre-processing & average filtering is done, after that segmentation, feature extraction and classification via DCNN is performed. In this paper, a fresh technique for classification of brain MRI images has been proposed using DCNN based softmax Classifier. The proposed system has been compared with the existing ones. The results are really encouraging as the loss is reduced and accuracy is increased. The proposed system achieved the training accuracy of 98.9% and validation accuracy of 100%. The training loss is reduced up to 0.0230 and the validation loss reduced up to 0.0109.

Key-words: MRI, Pre-processing, Image Data, Deep Learning Transfer Learning, Deep Convolutional Neural Network, and Classification.

1. Introduction

Brain Tumor detection and early prevention is the need of the today's world. So, it is very important to diagnose it correctly. Brain tumor is classified as Benign and Malignant. Tumor expands due to unordinary growth of cells in different parts of the body [2].Brain tumor is caused due to uncontrollable growth of cancerous cells tissues, Benign tumor is initial stage of tumor which is not cancerous and can be treated properly while malignant tumor can spread to different tissues and this stage is dangerous. Human Brain Image can be classified by using two techniques. a) Supervised like Artificial neural network, Support vector machine, K-nearest neighbours (KNN). b) Unsupervised techniques like Self organization map & Fuzzy c-means [6].

The proposed technique implies an automatic deep convolution neural network based on VGG16 model for classification of Brain MRI image. DCNN directly extracts the features from the images with minimum pre-processing involved. VGG16 pre trained model is used to train the network because it required training on last layer so computational time is least and efficiency is more [13].

2. Related Work

Charfi et al, recommends a hybrid insightful machine learning method named Computer aided detection (CAD) for location of brain tumor. The proposed strategy presents histogram subordinate stringing for picture division, discrete wavelet transform (DWT) for include extraction principal component analysis (PCA) for dimensionality decrease and feed forward back propagation neural network to classify input into normal or abnormal. The classification precision accomplished through various training and test images will be 90% [1].

Babu et al, presented their study which involves a comparative analysis of brain tumor detection using machine learning methods. The two type of dataset is used, one is augmented and other is un-augmented. The result shows that convolution neural network (CNN) with augmented dataset gives more accurate result [2].

Siar et al, presented a hybrid technique of feature extraction algorithm and the convolution neural network (CNN) for tumor detection. A no. of images is used for training and testing and different types of classification are used with CNN to improve the accuracy. The result showed that CNN with softmax classifier gives the best result. Different types of benchmark are used for accuracy like sensitivity; specificity and precision evaluate network performance [3].

Hemanth et al, proposed an automatic segmentation method based on CNN. It involves collection of data, pre-processing of data after that average filtering and segmentation is done. Further steps involve feature extraction, classification & identification via CNN. The technique of machine learning is very useful for early detection & prevention [4].

Amin et al, proposed a hybrid technique of enhancement, segmentation and feature fusion process. Different types of classifiers are used for the classification purpose. The result shows that K Nearest Neighbours (KNN) classification accuracy is excellent [5].

Sharma et al, proposed a brain tumor detection system based on machine learning algorithm. Gray Level Co-occurrence Matrix (GLCM) is used to extract texture feature like energy, contrast, correlation and homogeneity. Two types of machine learning algorithm are used Multilayer Perception (MLP) and Naive Bayes. The result showed that MLP gives more accuracy [6].

sharif et al, presented a technique of extreme learning. The experiments are performed on different series of datasets. First, image enhancement is done using triangular fuzzy median filtering. Segmentation is done using unsupervised fuzzy set method. Gabor and texture features are extracted by using lesions method. These features are further applied to extreme learning machine and regression extreme learning machine for classification purpose. The results showed improvement and calculation time was very less [7].

Shree et al, proposed a brain tumor Detection Technique based on Discrete Wavelet Transform (DWT) and Probabilistic Neural Network (PNN). First, pre-processing is done to improve Signal to Noise Ratio (SNR) after that DWT is used for segmentation and Gray Level Co-occurrence Matrix (GLCM) is used for textural feature extraction followed by morphological operation. Classification is done by using PNN classifier. The result showed the accurate and early detection of tumor along with exact location of tumor [8].

Das et al, described a Convolution Neural Network (CNN) classifier based technique which classifies three types of tumor classes which are Glioma, Meningioma and Pituitary, as part of the process, first pre-processing is done using Gaussian filter and then histogram equalization is done and the classification is done using CNN model. The result showed accuracy of 94.39%. CNN classifier plays as important role in medical field [9].

Amin et al, proposed a new system for brain tumor classification. First, fusion of different images are done after the noise removal and then segmentation is done by using global threshold. Finally, the segmented images are given to CNN model for classification. In CNN model, there are different layers convolution, batch normalization, RELU, max pooling, fully connected and softmax layer. The result showed the highest accuracy of 98% [10].

Kharat et al, described a brain tumor classification technique based on neural network. The first technique is feed forward artificial neural network (FF-ANN) and other is back propagation neural network. First image segmentation is done following feature extraction and then model learning. The result showed higher accuracy and less time [11].

Iqbal et al, described an effective brain tumor segmentation technique based on deep convolutional neural network. Brain Tumor Segmentation (BraTS) dataset is used for segmentation. Three different deep learning models are used

a.) Interpolated Network (IntNet)

b.) SkipNet

c.) SE-Net

Deep neural network technique gives better results as compared to other technique in this area of research [12]

Seetha et al, suggested a technique to reduce complexity and to enhance accuracy of brain tumor classification. CNN is introduced in the proposed system. It is a pre-trained model; training is done only at the last layer. Implementation is done through python programming language. The proposed system achieves the accuracy of 97.5% [13].

Sawant et al, suggested a machine learning approach for detection of brain tumor. The authors have done the comparison of different segmentation & classification and it was concluded that in order to achieve higher accuracy using less calculation time, CNN techniques are best [14].

Usmal et al, presented a technique of brain tumor classification. Different features like intensity, intensity difference & wavelet features are extracted and four different types of classifiers are used which are:

a.) K- Nearest neighbor

b.) Random Forest

c.) Adaptive boosting

d.) Random under sampling

The combination of wavelet based texture feature & RF classifier gives the best accuracy as compared with others [15].

Zaw et al, proposed a method for diagnosing brain tumor in an effective manner. Segmentation is done through maximum entropy threshold and classification is done through Naive bayes supervised machine learning technique. It can detect the tumor at every possible location and gives the accuracy of 94% [16].

Polly et al, proposed an automatic segmentation technique to classify high grade tumor and low grade tumor. A dataset of 440 images were taken and achieved the accuracy of 99%, sensitivity 100 % and specificity as 98.03%. The reliability of a system can be increased by using a large amount of dataset [17].

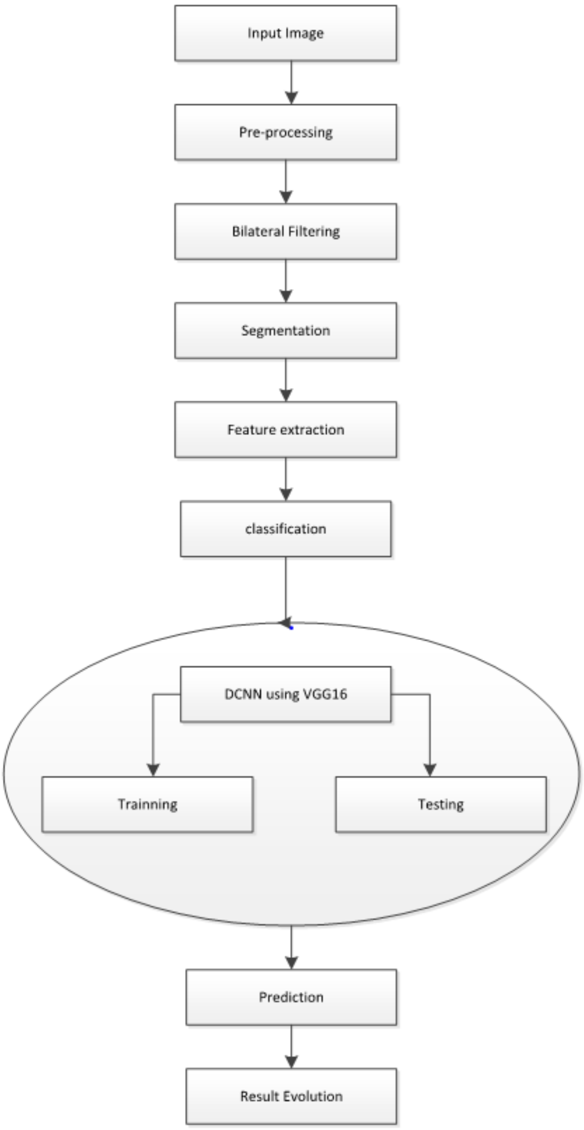
Mittal et al, suggested a model for brain tumor detection and comparison of different convolution neural network on a large amount of dataset. Five different models are used mainly simple CNN, CNN with data augmentation, Exception model, VGG 16& 19 model. It achieved a maximum accuracy of 99.2% over a dataset of 350 images [18],

3. Proposed Methodology

3.1 Project Outline

The proposed technique uses a deep convolution neural network (DCNN) to classify the tumor image. DCNN consist of multiple layers input layer, convolution layer, Relu layer, pooling layer. Finally fully connected layer is applied to produce a label score between 0 & 1. The block diagram of proposed technology is represented in Figure1:

Figure 1 - Different Stages of Proposed Methodology



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3.2 Pre-processing

MR Images get influenced due to noise disturbance. To eliminate or reduce noise pre-processing is necessary. The strategy of pre-processing includes data cleaning, transformation, integration, resizing and reduction of data. This technique wipes out superfluous information and smooth up the loud or noisy information, recognize and table out exception and modify the data irregularities. Finally normalization is performed, this is useful stage to reduce the noise and enhance the quality of image [4].

3.3 Average Filtering

Subsequently the Average channel settles this issue by giving satisfactory and smooth picture. The Average channel takes after a non-direct channel not at all like straight channels. The Average channel supplant the pixel regards with an Average regard that being almost open (like, 3x3 or 5x5 or pixels close to the central pixel regard). In addition, Average channel tends to be edge protecting. It helps in surrendering salt and pepper issue [4, 13].

3.4 Image Segmentation

It is a process of dividing an image into small segments. The basic aim of segmentation is to modify the image in to simpler form to analyse. There are different types of image segmentation techniques.

- Threshold Method
- Edge based segmentation
- Region based segmentation
- Clustering based segmentation
- Watershed based method
- Artificial Neural Network based Segmentation

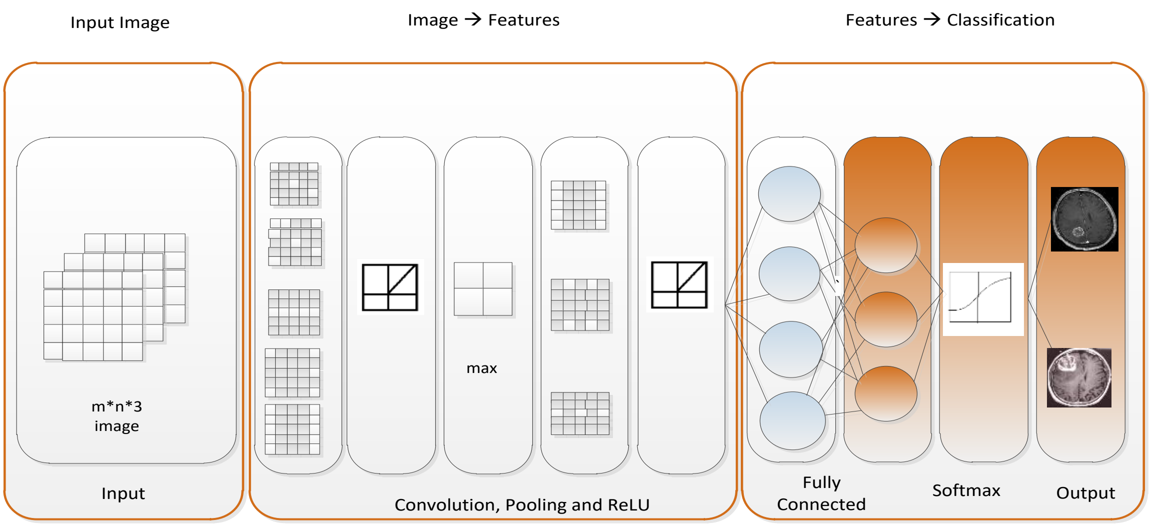
3.5 Feature Extraction

Feature extraction is basically used to reduce the large dataset into smaller groups while keeping the most important characteristics remains same. This process requires less no of computing resources. These techniques depict the real information with the precision and originality [6, 13].

3.6 Deep Convolution Neural Network (DCNN)

DCNN is utilized for automatic brain tumor classification. It directly extract the features from the images with minimum pre-processing involved. VGG16 pre-trained models is used to train the network because it requires training on last layer, so, the computational time is least and efficiency is more [13]. The block diagram of DCNN is shown in Figure 2:

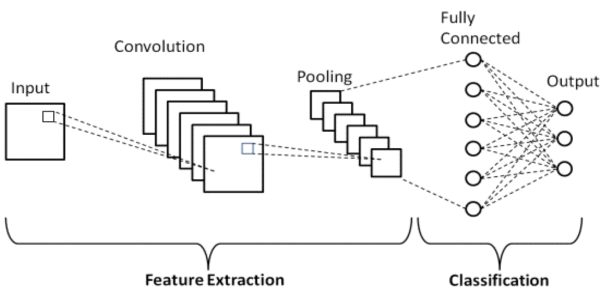
Figure 2 - Block Diagram of DCNN Network



The process starts with applying Convolution filter in principal layer, the channel affectability is limited by smoothing the convolution channel which is achieved by sub sampling. The activation layer is used to control the signal transfer between corresponding layers. The training time is improved using RELU activation function. The neurons in continuing layer is related with each neuron in following layer. Finally during training, loss layer is added in the end to provide the feedback to neural network

The different stages of DCNN network are shown in Figure 3:

Figure 3 - Different Stages of DCNN Network



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DCNN Architecture is comprised of three different types of layers convolution layers, pooling layers and fully-connected (FC) layers. Including these layers two necessary parameter i.e. dropout layer and the activation function [2,3]. The functioning of each layer is explained below:

3.6.1 Convolutional Layer

This layer is the principal layer that is utilized to separate the different features from the input image. In this layer, convolution operation is executed between input image and a filter of size m*m. The output of convolution layer is known as feature map it tells the image information like corner and edges. After that, this feature map is applied to other layers to learn various other features of the image [2,3].

3.6.2 Pooling Layer

Generally, after convolution layer pooling layer is applied. This layer reduced the size of convolved feature map to lessen the computational costs. This layer act as an interface between convolution layer and fully connected layer. There are various types of pooling operation which include max pooling, average pooling and sum pooling[2,13].

3.6.3 Fully Connected Layer

This layer comprises of weights and biases and neurons. The fully connected layer is generally applied before output layer. In this layer, classification process begins to start. Based on the different features extracted from the previous layers, it determines the class of the image [2, 3].

3.6.4 Dropout

Sometimes, over fitting occurs in training dataset. It causes a negative impact on the model performance. To avoid the problem of over fitting, dropout layer is used where some of the neurons are dropped during training process resulting in decreased size of model. For example, a dropout of 0.2 means 20% of nodes is dropped randomly from the convolution neural network [2, 9].

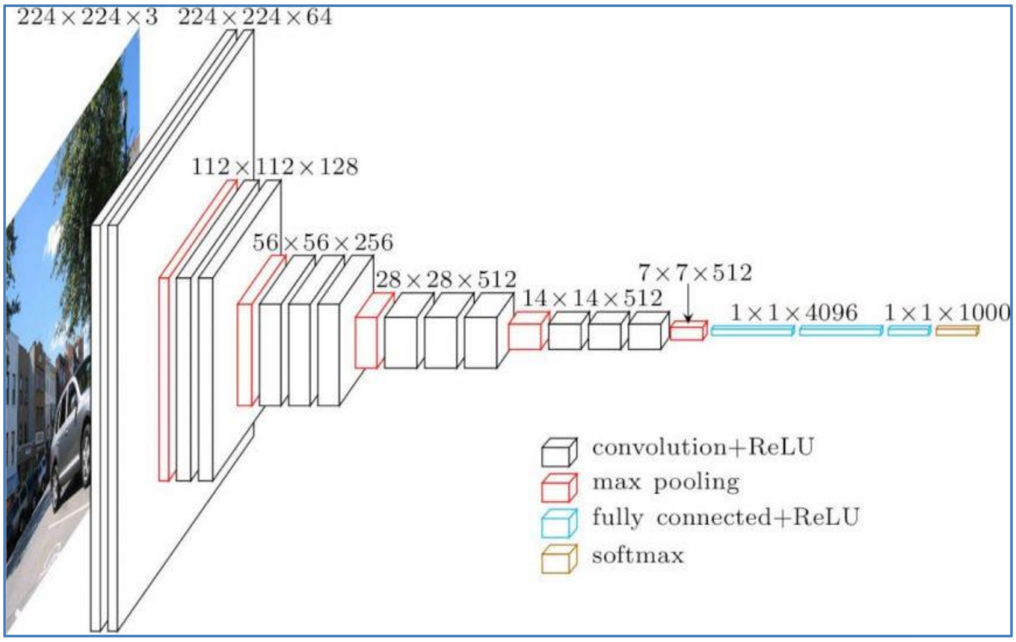
3.6.5 Activation Functions

Activation function is one of the important parameter of convolution neural network. It determines the information which should be fired in the forward direction. It adds nonlinearity to the neural network. There are various types of activation functions like Relu, tanh, softmax and sigmoid. Sigmoid and softmax function is generally used for binary classification and softmax is preferred for multiclass classification [3].

4. VGG 16 Architecture

The VGG-16 is pre trained model for image classification. It gives good results in image classification over other techniques like Alexnet[18]. Figure 4 shows the VGG16 architecture and Figure 5 shows the more intuitive layout of VGG16.

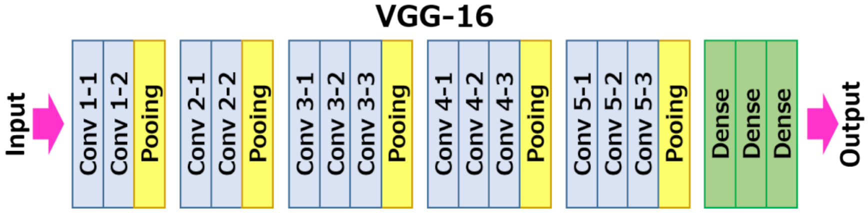
Figure 4 - VGG16 Architecture



The following are the layers of the model:

- Convolutional Layers = 13
- Pooling Layers = 5
- Dense Layers = 3

Figure 5 - More Intuitive Layout of VGG16



4.1 Input: Image of dimensions (224, 224, 3).

4.2 Convolution Layer Conv1:

- Conv1-1: 64 filters
- Conv1-2: 64 filters and Max Pooling
- Image dimensions: (224, 224)

4.3 Convolution layer Conv2: Now, filter size is 128

- Input Image dimensions: (112,112)
- Conv2-1: 128 filters
- Conv2-2: 128 filters and Max Pooling

4.4 Convolution Layer Conv3: In conv.3 filter size is doubled i.e. 256, and one more convolution layer is added.

- Input Image dimensions: (56,56)
- Conv3-1: 256 filters
- Conv3-2: 256 filters
- Conv3-3: 256 filters and Max Pooling

4.5 Convolution Layer Conv4: Similar to Conv3, but filter size is 512 now.

- Input Image dimensions: (28, 28)
- Conv4-1: 512 filters
- Conv4-2: 512 filters
- Conv4-3: 512 filters and Max Pooling

4.6 Convolution Layer Conv5: This layer is similar to Conv4.

- Input Image dimensions: (14, 14)
- Conv5-1: 512 filters
- Conv5-2: 512 filters
- Conv5-3: 512 filters and Max Pooling
- The output dimensions here are (7, 7). The output of this layer is flattened to get a feature vector.

4.7 Fully Connected/Dense FC1: 4096 nodes, generating a feature vector of size(1, 4096)

4.8 Fully Connected/Dense FC2: 4096 nodes generating a feature vector of size(1, 4096)

4.9 Fully Connected /Dense FC3: 4096 nodes, generating 1000 channels for 1000 classes. The activation function used here is Softmax.

4.10 Output layer

Following steps are involved in VGG16 model to train a dataset

Step 1: Image Augmentation

Step 2: Training and Validation Sets

Step 3: Loading the Base Model

Step 4: Compile and Fit

5. Results & Discussion

Figure 6 shows the accuracy and loss curves of the proposed method. A dataset of 570 images were taken and it is divided into two parts, set 1(training) and set2 (validate). Set1 contains 255 images of tumor patient and 255 images of non tumor patient. Set 2 contains 60 images of both. Set1 is used to train the model and set2 to validate (test) it. The proposed model achieved the training accuracy of **98.97%** and validation accuracy of **100%.**The training loss is reduced up to **0.0230** and the validation loss reduced up to **0.0109.**The reliability of a system can be increased by using a large amount of dataset. Figure 7 represents the various performance measures like training and testing accuracy with their losses w.r.t. no. of epochs. As the no of epochs increases, the accuracy increases and loss decreases.

Figure 6 - Performance of VGG16 DCNN Model

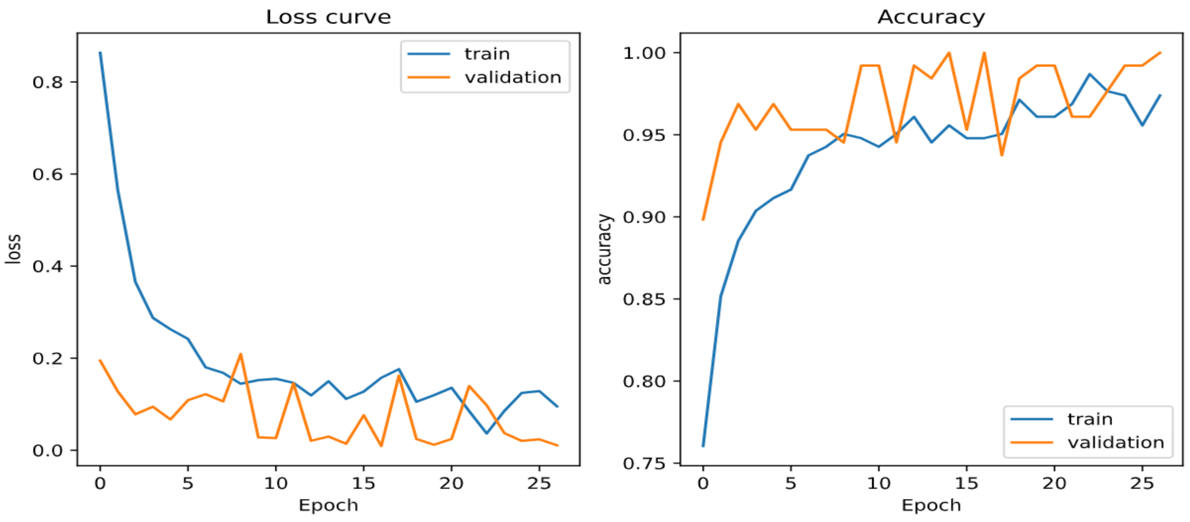


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Figure 7 - Performance of DCNN

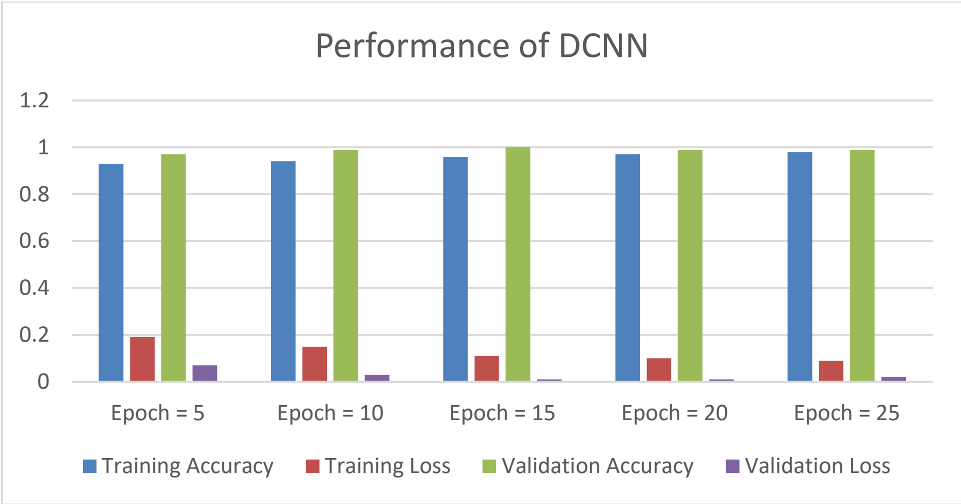
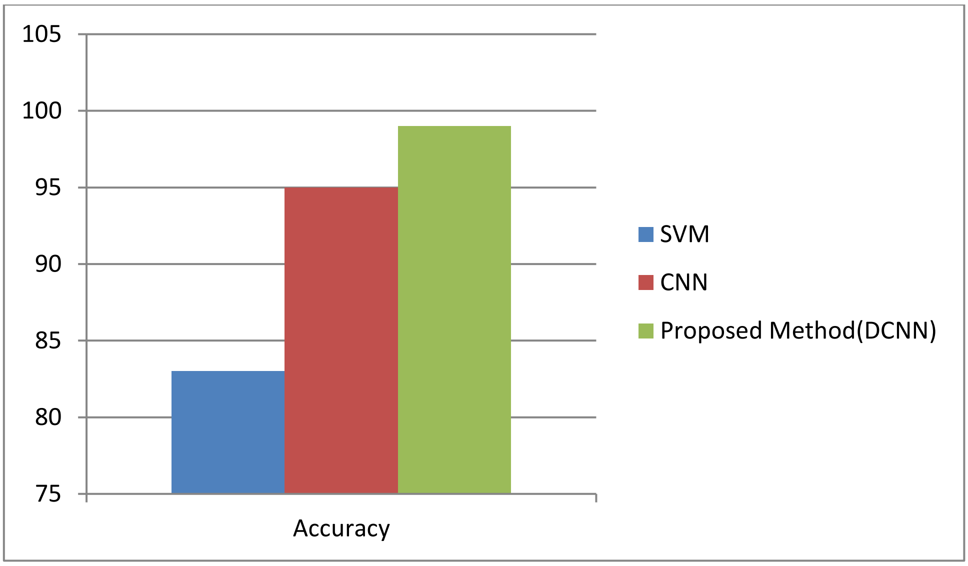


Figure 8 - Accuracy of Brain Tumor Classification



The proposed DCNN Network is compared with Support Vector Machine (SVM) & Convolution Neural Network (CNN). In SVM based classification, both the accuracy and computation time is low while in DNN & CNN complexity and computational time is low and accuracy is highest in DCNN. Figure 8 represents the comparison chart between proposed method and existing methods.

6. Conclusion

For automatic tumor segmentation, deep convolutional neural network (DCNN) stays a developing area of research in medical science. The proposed method enhanced the accuracy and reduced the loss as compared to other already exiting methods. Loss is basically the difference between true value and predicted value. If the model prediction is accurate then loss is zero and method to calculate loss is called loss function. For binary classification the loss function used is cross entropy. Loss can be decreased by adding more dropout layers and by increase no of epochs. Figure 6 shows the loss curve and accuracy curve. The training loss is reduced up to **0.0230** and the validation loss reduced up to **0.0109.** The proposed model achieved the training accuracy of **98.97%** and validation accuracy of **100%.** During testing system, it gives highest accuracy. The significant contribution of this research is thoroughly focused on segmentation, feature extraction and classification based on DCNN.

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