An Efficient Method to Classify Brain Tumor using CNN and SVM

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***Abstract*— Brain Tumor is one of the most sophisticated diseases for the human body that happens when the brain cells start increasing unconditionally. Before giving treatment, the main challenge is to detect and classify tumors from brain MRI images. Researchers have been working really hard for ages to find the best method with higher accuracy for implementing them in real life medical image classification. The main problem is that when a classifier deals with huge amount of data it becomes difficult to classify them accurately. To solve this a CNN-SVM based method is proposed to classify brain tumor with higher accuracy. Firstly, a convolutional neural network having 19 layers is constructed using three convolutional 2D layers, three max-pooling layers, two fully-connected layers, three batch-normalization layers with activation functions reLu. Secondly softmax is used as a classifier and implemented over a dataset containing 3064 images on three class of tumor images (glioma tumors, meningioma tumors, and pituitary tumors). After that, another classifier named support vector machine is used to improve the accuracy of the CNN model using the features extracted from the model. The final accuracy of this proposed CNN-SVM based method is found 97.1%.**

Keywords*— *Convolutional neural network, Magnetic resonance imaging, Fully connected layer, Performance matrices, Support vector machine

I. Introduction

The irregular, uncontrollable growth of cells in the human brain is known as tumors that keeps multiplying with time. The abnormal cells damage the good ones and keeps growing and affects regular human body activity. Brain tumors are of four grades which mainly describes the growth rate of tumors. Two classes of brain tumor can be noticed, one is cancerous and another is non-cancerous. Cancerous tumors are of higher grade (three or four) and non-cancerous tumors are of lower grade (one or two). It is predicted that nearly 18,020 adults will pass on from primary cancer this year [1]. If formation of tumor is analyzed at the first stage, there's a high probability of improvement and these abnormal cells won't become cancerous cell. Magnetic resonance imaging is a safest way for analysis of brain tumor. It generates radio waves and strong magnetic field through which brief depiction of brain is captured [2]. Thus, precisely identifying the classes of brain tumors is regarded as most crucial job.

Convolutional neural network is considered as the feature extractor & also have weight sharing concept. Every neuron calculates their own weight products [3]. For classification purpose convolutional neural network is an efficient approach. Convolutional neural network is nothing but a normal neural network where instead of matrix multiplication, convolution operation is performed in its layers. The function of different layers is convolution, down-sampling, flattening, removing overfitting, mapping features etc.

This paper proposed, a combination of CNN and SVM model to accurately identify three classes (pituitary, glioma and meningioma) of brain tumors where significant features are extracted from the layer named fully connected and classification is performed with the help of CNN features using SVM.

The upcoming part of this proposed paper contains literature review described in part II, proposed methodology with theory in part III, result analysis and equation calculation in part IV and Conclusion and Future work in part V.

II. Literature Review

From the very early years when image processing started adding in the research field, researchers are working on brain tumors. The preceding researches on this topic from several papers are written below:

In [4], Parnian A. proposed a method where capsule network was used as a form of convolutional neural network. The proposed structure aims at focusing both the main area of tumors and their association with nearby tissues. This method got the accuracy of 90.89%. In [5], S. Deepak proposed to design a convolutional neural network for the extraction of features and then used support vector machine to work with those features and classification. Then compared proposed work using several datasets. The accuracy of the work was 95.82%. In [6], Zar N. K. S. proposed method of transfer learning where preprocessing was done before CNN training. Then used VGG-19 pretrained model for tunning. The proposed model got the accuracy of 94.82%. In [7], Sunanda D. proposed a classifier method using convolutional neural network where some morphological operation was used and resize, filtering, equalize, and histogram analysis were done. The average accuracy of the proposed work is 94.39%. In [8], Justin S. P. proposed a method where a lot of preprocessing algorithms like vanilla processing, zooming, resize, augmentation, locating were performed and then built a convolutional neural networking model and also random forest as classifier. Per image accuracy was 90.25% in this paper.

III. Propossed Brain tumor classification Methodology

This paper proposed, a CNN and SVM based classification method and Fig. 1 describes the whole working procedure in flowchart. A dataset of three different classes of images are taken at the beginning. After using 'Image Data Store' function the classes of different image types are labeled. Before training the network, the dataset is split into training and validation set.

The ratio of training and validation is 9:1 of the total dataset (3064 images). It means that 2758 and 306 images are used for training and validation respectively. Both the height and width of the input image is 512 pixels and for training purpose size is converted into 32*32 pixels. The After that proposed CNN model layers are constructed. At first, three convolutional 2D layer is taken and each of the layer has reLu activated and batch-normalization layers are attached with them. Here max-pooling layers are used after every convolutional layer. So, a total number of three max-pooling layers is used. Then two fully-connected layers are taken and between these two, a dropout layer is taken. After the ending fully-connected layer, softmax layer is taken as classifier. From the second fully connected layer model features are extracted and then using SVM classifier best accuracy is achieved. Here 'holdout method' is chosen for cross-validation.

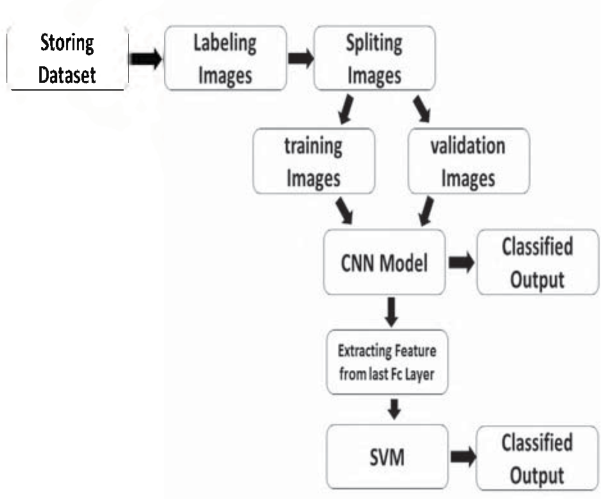

Fig. 1. working procedure flowchart

A. CNN Architecture

In the following Fig. 2, the full CNN architecture (19 layers) layer operation is described. Here is a short description of the used layers:

a. Convolutional Layer

The convolutional layer takes the input image and features are taken out from that and make a map of feature. In the proposed model, there are three convolution layers used and every convolutional layer has a batch normalization layer with activation reLu. The first convolutional 2D layer filter size is 7*7 and 32 number of channels are used to produce feature maps. In the second one, the filter size is kept 5*5 having 64 number of channels and in the last one 3*3 size filter is used and number of channels are 128.

b. Batch-normalization Layer

This layer is used after every convolutional 2D layer and this layer standardizes the input values of the previous layer.

c. Rectifier Activation Function (ReLu)

This activation function is used several times in proposed model. Every Convolutional 2D layer has this activation function and the first fully-connected layer has this activation function also. This is widely used because this function has no problem with removing the gradient. Because of this benefit, it is preferred over other activation functions.

d. Max-pooling Layer

This layer is mainly used for decreasing the number of samples taken from the upper layer. This also decreases the feature map area but keeps the region feature unchanged and that is what makes this layer unique and efficient. The reduction depends on the stride size used on the layer. Here in this method, the stride in all three max-pooling layers is 2 which means the calculation of pooling happens using a gap of two matrices from before and 2*2 pool size is chosen.

e. Fully Connected layer

This layer is known as doing classification and also does regression. This layer takes values from previous layer but not directly rather the values got flatten and then the values are taken. All the neurons in the layer is connected with each other and thus gives the decision of classification. In this method, two of these layers were used having 520 units and 3 units individually.

f. Dropout Layer

Normally dropout means removing something. This layer is mainly used for avoiding the overfitting problem of the proposed architecture. In this method, one dropout layer is used after the first fully connected layer. This layer change input values randomly.

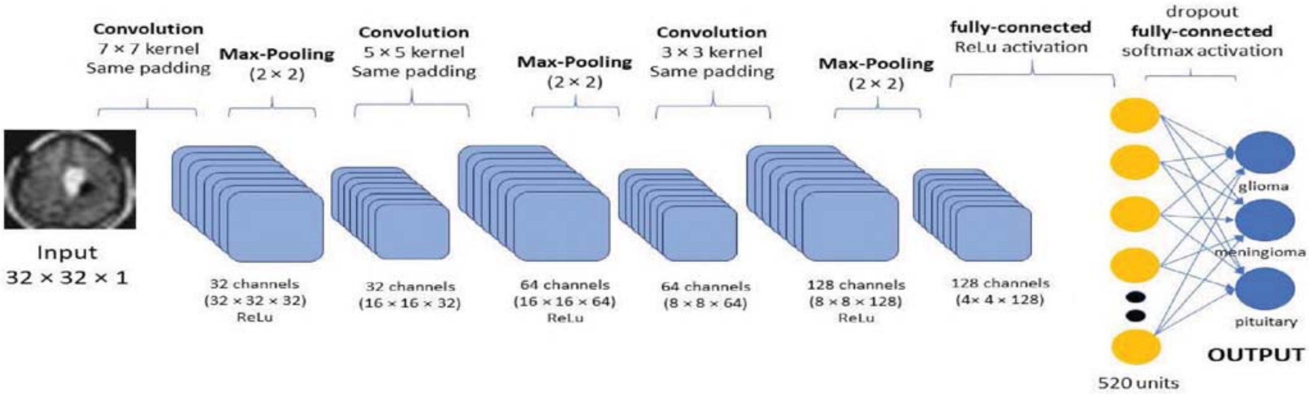

Fig. 2. Convolutional Neural Network Architecture

In TABLE 1 the parameters of each layer of CNN architecture is calculated. The calculation of the total number of parameters are done using filter size, number of channels, number of units in fully connected layer. The max-pooling and dropout layer has no parameters and the parameters of the batch-normalization layers are not learnable.

TABLE 1. Parameters of Different layers of CNN

Model Layers	Parameters
Convolutional Layer(conv1)	480
Batch Normalization Layer(batch_norm1)	128
Convolutional Layer(conv2)	51264
Batch Normalization Layer(batch_norm2)	256
Convolutional Layer(conv3)	73856
Batch Normalization Layer(batch_norm3)	512
Fully -Connected Layer(fc_1)	67080
Fully -Connected Layer(fc_2)	1563
Total	195139

g. Softmax Layer

This classifier layer takes values from the last fc layer and performs classification operation using the softmax function. Cross-entropy error or loss is the principal feature of this function. It determines the probabilities of the training network for validation of testing images. The equation is given bellow:

$$€(\mathrm{Ym}) = \frac{e^{\mathrm{Xm}}}{\sum_{n=1}^{X} e^{\mathrm{Xn}}} \tag{1}$$

Where € denotes softmax, Y is the input vector, e^{Xm} is the exponential function of input, X is the number of classifier & e^{Xn} is the output exponential function.

B. Support Vector Machine

To improve the accuracy of proposed CNN architecture this classifier is used. This is a classifier that works with supervised data like features or hyperplanes from images or deep neural network architecture. It can be used both in two-class classifier and multiclass classifier. In this proposed method, this is working as multiclass classifier to classify three different sorts of tumors using the features from convolutional neural network architecture.

IV. RESULT ANALYSIS

A. Dataset

To train up proposed model a dataset comprised of 3064 images of brain MRI is used which is available in figshare [9]. Dataset image numbers are glioma (1426), pituitary (930), meningioma (708).

B. Training Progress

In the training options an efficient optimization function used is ADAM. It updates some of the parameters from each batch and weight is one of them. The learning-coefficients also changes by using this function. To avoid disposal of some data during training period 'every-epoch' is set in shuffle option. At initial the learning rate is 0.001 but after certain period it is reduced by using 'LearnRateSchedule' option. The learn rate drop period and factors are used to control the learning drop of training. Maximum number of epochs are also told in this training option section.

In TABLE 2, the hyperparameters of CNN models that are discussed above are mentioned and these are taken as training options.

TABLE 2. Hyperparameters for train up model

Hyperparameters	Value
Optimization function	ADAM
InitialLearnRate	0.001
LearnRateDropPeriod	5
LearnRateDropFactor	0.2
MaxEpochs	15
ValidationFrequency	10

In Fig. 3, the training and validation accuracy is shown in accuracy vs iteration graph. The model is trained with different number of epochs but it has acquired 96.71 percent accuracy when maximum number of epochs are 15. Here the number of maximum iterations is 315 and per epoch 21 iterations have occurred.

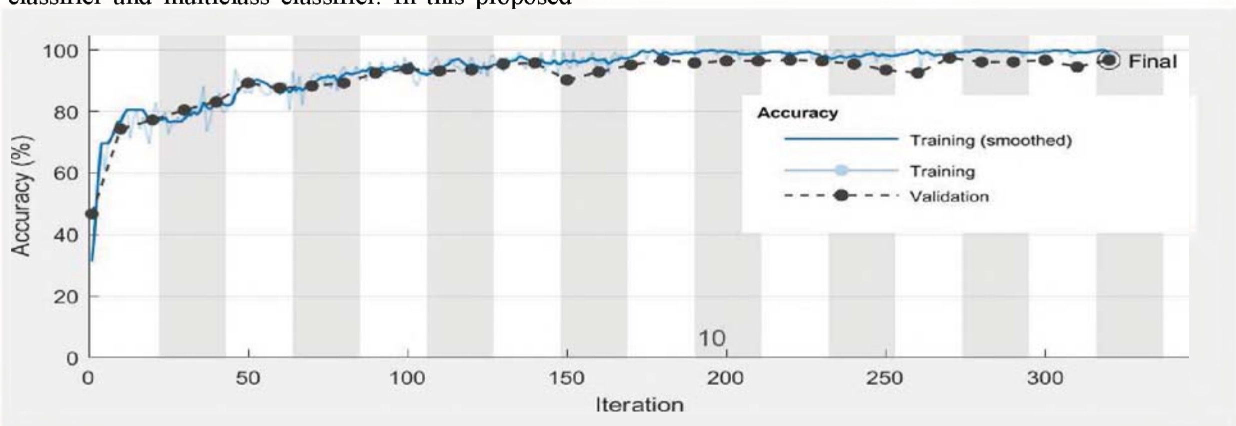

Fig. 3. Accuracy for training & validation

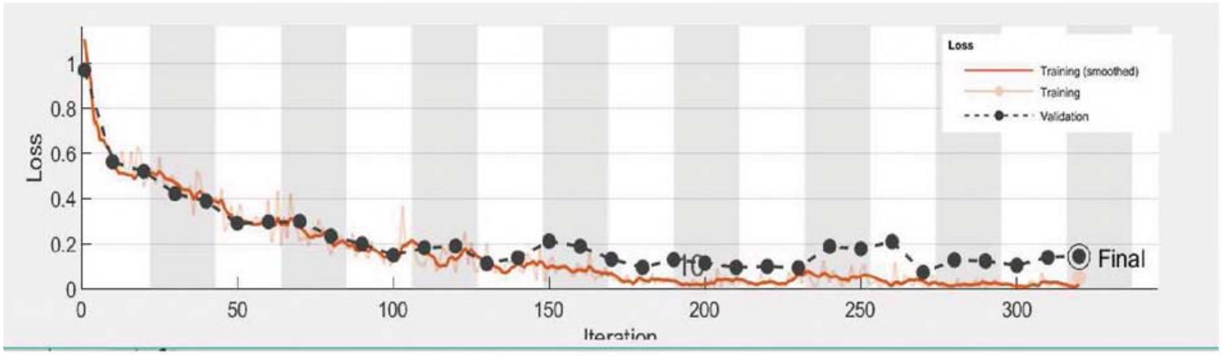

Fig. 4. Loss for training and validation

In Fig. 4, the training and validation loss are shown until 15 epochs and the loss is about 0.2%.

C. Performance Evaluation

Confusion matrix is an approach which can summarize overall classifier performance. Some equations are used for measuring the performance of classifiers from an observation of confusion matrices and their mathematical expressions are given bellow:

$$S.S_{(Sensitivity)} = \frac{TP_{(True\ Positive)}}{TP_{(True\ Positive)}+FN_{(False\ Negative)}} \quad (2)$$

$$P.C_{(Precision)} = \frac{TP_{(True\ Positive)}}{TP_{(True\ Positive)}+FP_{(False\ Positive)}} \quad (3)$$

$$S.F_{(Specificity)} = \frac{TN_{(True\ Negative)}}{TN_{(True\ Negative)}+FP_{(False\ Positive)}} \quad (4)$$

$$F1\ Score = 2 * \frac{P.C*S.S}{P.C+S.S} \quad (5)$$

Using the above equations, the sensitivity, precision, recall and f1 score of both CNN model and CNN+ SVM is shown in TABLE 3 and TABLE 4.

TABLE 3. CNN model Performance

Tumor Types	Sensitivity	Precision	Specificity	F1 Score
Glioma Tumor	95.9%	98.6%	96.9%	97.2%
Meningioma Tumor	98.4%	88.7%	99.6%	93.3%
Pituitary Tumor	96.9%	100%	98.6%	98.4%

TABLE 4. CNN+SVM Performance

Tumor Types	Sensitivity	Precision	Specificity	F1 Score
Glioma Tumor	98.6%	97.2%	98.8%	97.9%
Meningioma Tumor	91.9%	95.8%	97.5%	93.8%
Pituitary Tumor	98.9%	97.8%	99.5%	99.5%

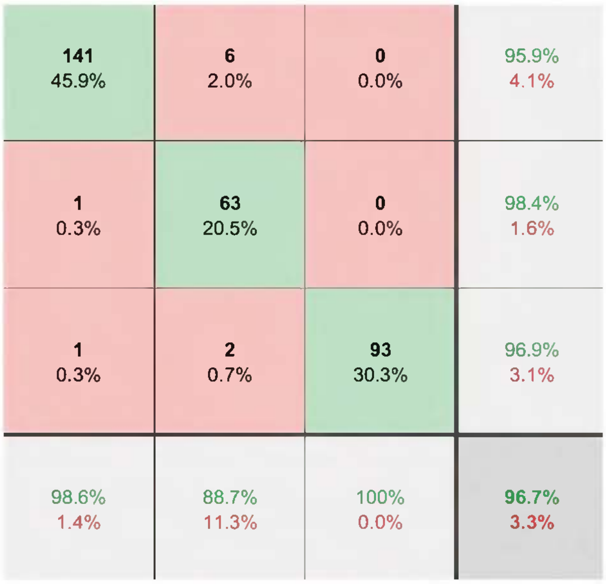

Fig. 5. Confusion matrix (CNN model)

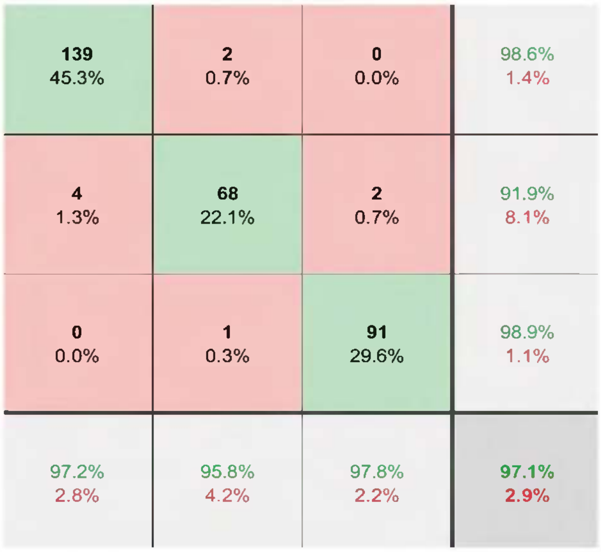

Fig. 6. Confusion matrix (CNN+SVM)

The Fig. 5 and Fig. 6 represents the confusion matrix of CNN model and CNN+SVM model respectively. It can clearly be noticed from the confusion matrices that the CNN model has achieved 96.74 percent accuracy where combination of CNN & SVM has achieved 97.1 percent accuracy. These confusion matrices show individual and average accuracy of correct predictions of each tumor dataset.

D. Comparison with existing methods

There are a lot of work done by using the same dataset which is used in this proposed methodology. In TABLE 5, here is a quick comparison between those and the proposed one:

TABLE 5. Comparison with existing methods those used Figshare dataset

Author	Method	Accuracy
Abiwinanda [10]	CNN	84.19 %
Ismael [11]	DWT,Gabor	91.90 %
Sunanda [7]	CNN	94.39 %
Deepak [5]	CNN, SVM	95.82 %
Afshar [4]	Caps-Net	90.89 %
Swati [6]	CNN (transfer learning)	94.80 %
Yang [12]	CBIR	89.30 %
Paul [8]	CNN	90.25 %
Cheng [13]	BoW+SVM	91.28 %
Afshar [14]	Caps-Net	86.56 %
Proposed-model	**CNN+SVM**	**97.1%**

From the above comparison, it is seen that this proposed CNN and SVM based classification method is better than other conventional method. Because here the features of the images are classified first in CNN and features of the last layer of CNN are used for further classification in SVM. The combination of the two different classifiers made this proposed method to get better accuracy. The method proposed in [5] also used CNN- SVM but despite of having less layers and parameters than that this method performs better as the model architecture seems more accurate.

V. CONCLUSION AND FUTURE WORK

The purpose of the proposed method is achieving maximum accuracy in image classification and minimum number of error rate. In this proposed paper, a custom convolutional neural networking architecture and SVM are applied to find better accuracy over the used dataset. Here, the images which are acquired from dataset are raw and only just resizing the images the whole dataset is used for the convolutional neural network training. The training accuracy is very high at 96.74%. Then a multiclass support vector machine classifier is used which shows better accuracy of 97.1%. This method is robust one because there is no use of major preprocessing of the input data that makes this model efficient. This method can be further developed using some preprocessing functions or segmenting or masking input images before taking them in the network for training and testing. Other classifiers can also be used to observe if they are good enough compared to support vector machine.

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