Ensemble of Deep Learning approaches for Detection of Brain

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ABSTRACT

A tumor in the brain is defined as the unconventional growth of cells in the brain, a few of which can lead to cancer. Brain tumors can be detected by applying Machine Learning as well as Deep Learning algorithms. Deeper networks perform better than the classification models designed with fewer layers. To obtain better generalization performance individual models can be combined to achieve ensemble learning. In this work, several unique models are connected using the Max Voting algorithm to determine tumors in the brain from scans obtained by Magnetic Resonance Imaging (MRI). The prediction of tumors in the brain is made quickly and with higher accuracy, which assists in giving the treatment to the patients.

Keywords - **CNN, deep learning, Ensemble learning, machine learning, neural networks.**

I. INTRODUCTION

The brain is the center of our nervous system, which controls the whole activity of other body parts and supports decision-making. The spread of abnormal cells in our brain is referred to as brain tumor, see Fig. 1.

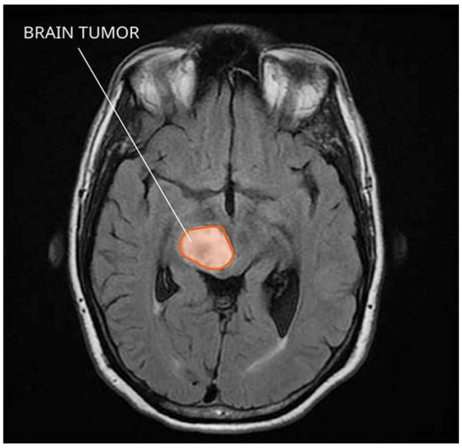

Figure 1: Brain Tumor in an MRI image [1]

Detection of which is necessary to save lives. Magnetic resonance imaging (MRI) is the primary step in detecting a brain tumor. The next step is to determine the type of brain tumor with a tissue biopsy or surgery. The result of the investigation conducted in this paper tells if the brain is normal or abnormal by implementing the deep ensemble techniques. In this paper, CNNs are used to classify normal and tumor brains. In CNN (Convolutional neural networks), convolution is a linear mathematical operation. The size of the image is decreased at every layer of the convolutional neural network without losing the information required for training. Different processes like convolve, max pooling, dropout, flatten, and dense are used to create the model. First, the models are built using individual CNN for the detection of tumors, and then max voting is used to ensemble the models together. \\The paper organization is as follows: The literature review is provided in Section II. Section III describes the methods used for the proposed ensemble model. Section IV explains the base models that have been used to build the ensemble model. Section V explains the voting mechanism implemented to generate a single final prediction from individual prediction of the three models.

II. LITERATURE REVIEW

Deep learning has been used in brain tumor detection because of its high reliability of results. Amin et al. [2] have used lightweight DNN technique for brain tumor segmentation. Gull et al. [3], Chahal et al. [4] and Soomro et al. [5] reviewed several works that use artificial intelligence and convolutional neural networks for detection of brain tumors. Rehman et al. [6] used 3D CNN for extracting features of tumor sections in the brain. Saba et al. [7] used hybrid features, traditional as well as features extracted from VGG-19, to segment brain tumors. Amin et al. [8] worked on lesion segmentation in brain MRI images using Weiner filter, local binary pattern, and Gabor features. Xiao et al. [9] describe the role of different CSF biomarkers for identifying types of tumors. Sadad et al. [10] attempted to segment brain tumors using Unet and ResNet 50 architectures. Toğaçar et al. [11] segmented brain tumors by developing a novel deep net architecture called BrainMRNet. Siar et al. [12] detected brain tumor using deep neural network and compared their results to radial basis function and decision trees. Rajinikanth et al. [13] detected brain tumors using a combination of features extracted from deep neural networks and handcrafted features. Hossain et al. [14] applied fuzzy c-means clustering algorithm for segmenting tumors in brain MRI scans. Amin et al. [15] also attempted to use a model based on long short term memory (LSTM) architecture for tumor segmentation in brain. Shakeel et al. [16] used wireless IR imaging and neural networks for brain tumor segmentation. Dhaundiyal et al. [17] fused information of biomedical images obtained from different modes using clustering. Praveen et al. [18] used particle swarm optimization based evolutionary approach to detect mesothelioma cancer using biomedical images of head and neck.

In this paper, three different models have been ensembled to generate prediction using voting algorithm.

III. METHODS AND PROPOSED ENSEMBLE MODEL

CNN is applied to the brain tumor dataset, and their performance in the classification of images is observed. The steps are as follows:

- Import the required packages
- Import the dataset.
- Read images, create a data frame, and set the target variable of images to 0 and 1, which are in the Yes and No folder, respectively.
- Divide the dataset into a train, test, and validation set with a ratio of 7:2:1.
- Preprocess the images.
- Create the model.
- Compile the model.
- Train the model on the train and validation set.
- Assess the model by trying it on a test set.
- Ensemble the test results from different models to get the final prediction.

A commonly used architecture of a deep learning model is shown in Fig. 2.

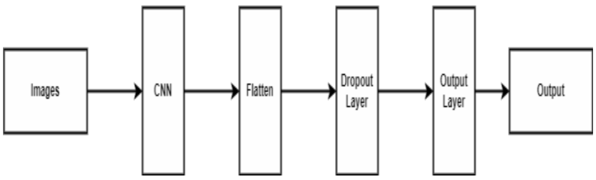

Figure 2: General architecture of a deep learning model

The models are compiled using "adam" optimization and binary cross entropy loss function. The models are trained by giving training and validation sets. When a trained model is obtained, testing is done on a test set; after getting results from three base deep learning models, we ensemble this result using the max voting technique to get better prediction results.

IV. BASE DEEP LEARNING MODELS

In this paper, three CNNs are used to build three individual models. The architectures of models are ResNet101, VGG-19, and, DenseNet121.

A. *ResNet101*

ResNet-101 [19] is a CNN that is 101 layers deep. A pre- trained version of the network trained on ImageNet database is used. The ImageNet database has 1000 item classes, such as goldfish, hen, ostrich, and numerous entities. ResNet depicts the residual network, and it has a notable role in machine viewing cases. ResNet101 involves more than 100 convolutional layers comprising more than 30 blocks of layers, and most of these are made use of in preceding blocks. The input dimensions of the model are 224 ×224 ×3.

B. *VGG19*

VGG-19 [20] is a CNN with 19 layers. VGG 19 is also pre- trained on ImageNet database. It has six principal structures, each of which is mainly composed of multiple connected convolutional layers and full-connected layers. The convolutional kernel size is 3 x3, and the input size is 224x224 x3.

C. *DenseNet121*

The initial layers in DenseNet [21] starts are basic convolution and pooling. This is followed by a dense block and a transition layer. DenseNet-121 has 120 Convolutions and 4 Average Pooling layers. Every layer inside the same dense block and transition layers, distribute their weights over different inputs. This lets deeper layers to make use of features extracted previously.

V. PROPOSED ENSEMBLE METHOD

A voting ensemble is an artificial intelligence ensemble model which merges the forecasts obtained from different frameworks. This approach may be used to upgrade the performance of the model, preferably attaining superior results compared to individual models involved in the ensemble. Ensembling may be employed for classification or regression. For regression, this requires computing the mean of the predictions generated by individual models. For classification, the results for each class are aggregated, and the class with the larger vote is selected. In classification, a complicated voting mechanism demands counting the votes for traditional nominal class labels from each individual model and predicting the class with the maximum number of votes.

A soft voting ensemble implies adding the predicted probabilities for class labels and predicting the class label with the greatest sum probability. In this work hard voting is used to ensemble three base deep learning models. The schematic diagram is shown in Fig. 3.

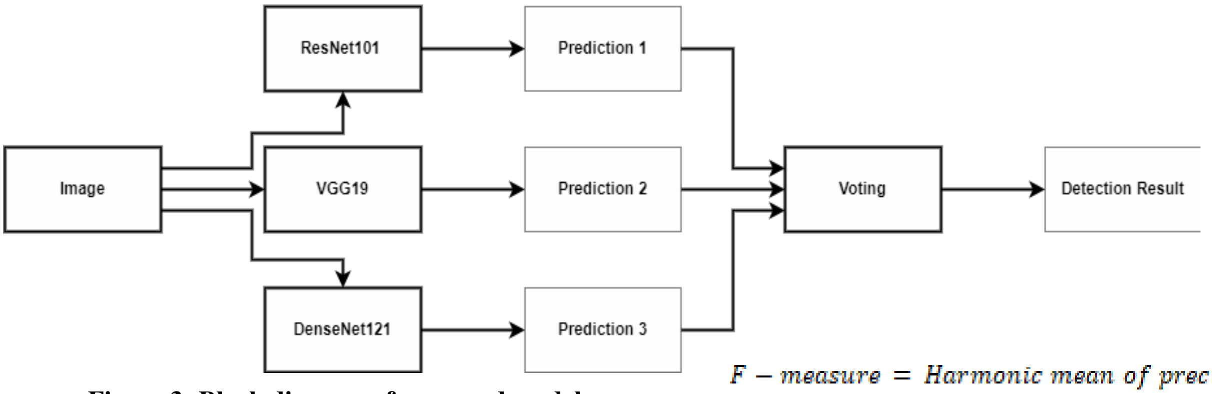

Figure 3: Block diagram of proposed model

I. Result Analysis and Discussion

A. Dataset

$$Recall = \frac{Correctly\ predicted\ positives}{Actual\ number\ of\ positives}$$

The dataset is obtained fom Kaggle. The dataset comprises of MRI scans of the brain. There are two folders; one includes images of a brain with a tumor, and the other contains normal brain images. The dataset contains 253 images, i.e., 98 with tumors and 155 without tumors. In Fig.
6, the first image is a normal brain, and the second image is a brain with a tumor. 176 images are used in training dataset, 51 in test dataset, and 26 in validation set. Sample images of brain with and without tumor from the dataset is shown in Fig. 4.

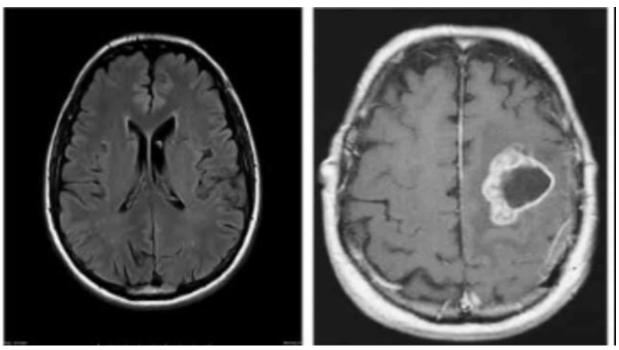

Figure 4: Sample normal (left) and abnormal (right) images from the dataset.

$$F - measure = Harmonic\ mean\ of\ precision\ and\ recall$$

B. Evaluation Metrics

Accuracy directly measures how often the classifier correctly predicts. We can define accuracy as the fraction of right predictions and the entire predictions.

$$Accuracy = \frac{Sum\ of\ true\ positives\ and\ negatives}{Total\ number\ of\ predictions}$$

Other evaluation metrics like precision, recall and F- measure can be similarly calculated.

A confusion matrix is a chart which is frequently utilized to report how well the model performed in case of test inputs for which correct outputs are already known. The general representation of a confusion matrix is shown in Fig. 5.

		Predicted	
		Positive	Negative
Actual	True	TP	TN
	False	FP	FN

Figure 5: Confusion Matrix

Confusion matrix generated for each of the individual as well as ensemble models are shown in Fig. 6, Fig. 7, Fig. 8 and Fig. 9.

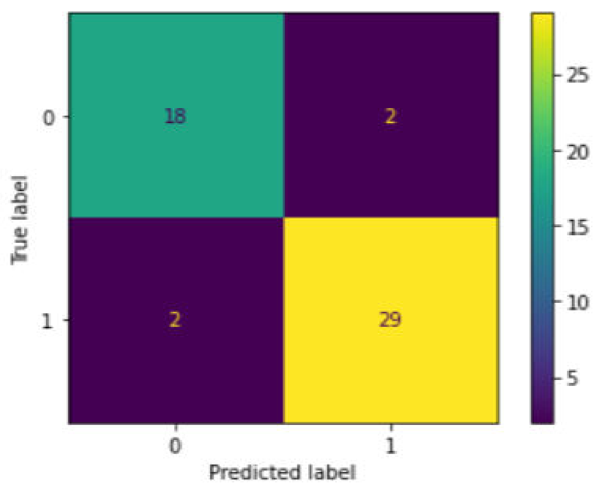

Figure 6: Confusion matrix for ResNet 101

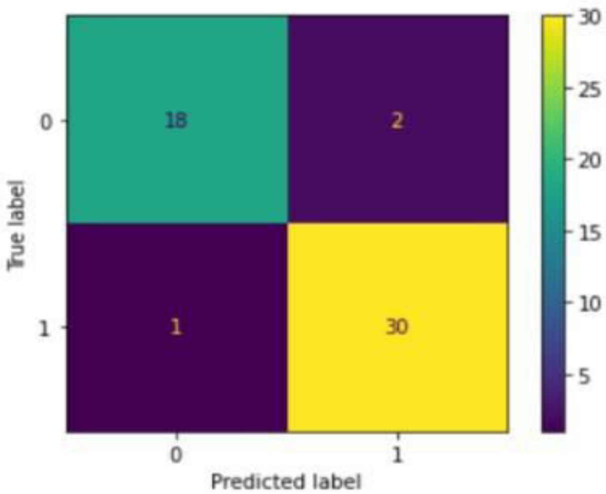

Figure 7: Confusion matrix for VGG 19

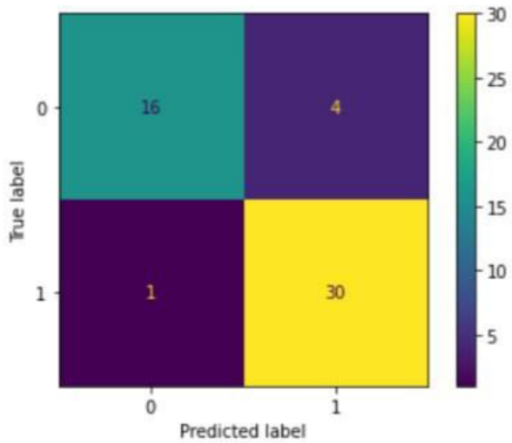

Figure 8: Confusion matrix for DenseNet 121

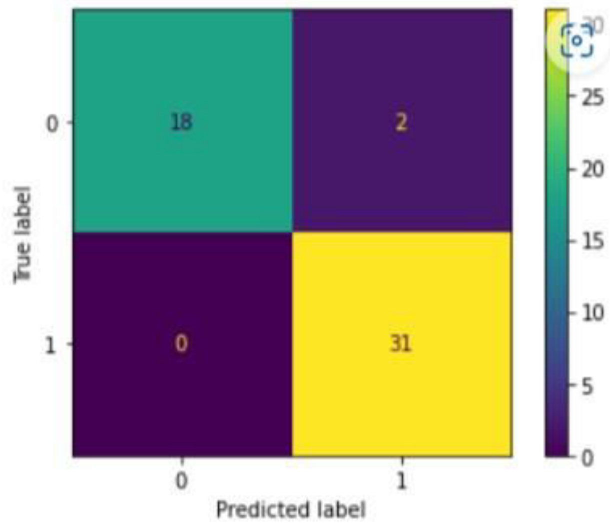

Figure 9: Confusion matrix for Ensemble model

C. Discussion

First, the three base models are evaluated individually, and then ensembling is done with max voting. The first base model is built using ResNet101, the second using VGG-19, and the third using DenseNet121. The accuracy of the testing set obtained from the base model and ensemble models is shown in the Table 1.

Model	**Accuracy**	**Precision**	**Recall**	**F-Measure**
ResNet101	0.92	0.94	0.94	0.94
VGG19	0.94	0.94	0.97	0.95
DenseNet121	0.90	0.88	0.97	0.92
Ensemble	**0.96**	**0.94**	**1.00**	**0.97**

Table 1: Results of Base and Ensemble models

II. CONCLUSION

An ensemble can make superior predictions and attain better performance than any single contributing model. In classification problem ensemble using the max voting algorithm of base deep learning models performs better than any single CNN-based model.In this paper testing accuracy of 96\% is obtained on ensemble of three CNN based models that are ResNet-101 (testing accuracy= 92%), VGG-19(testing accuracy = 94%) and DenseNet121 (testing accuracy= 90%). An ensemble lowers the span or scattering of the predictions and improves the performance of the model. The ensemble performs better than a single model. In future, efforts will be made to improve the accuracy of the algorithm.

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Biographies and Photographs

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