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## Impact of Dimensionality Reduction Method in Brain Tumor Classification Using Transfer Learning



**Abstract:** - Neural networks and related algorithms and libraries are preferred these days for the analysis of brain tumor types and its classification/detection. The proposed method is a CNN-based DenseNet library model that uses dimension reductionality technique called Principal Component Analysis (PCA) to classify brain tumor MRI images into several classes having tumor and not having tumor. The proposed work is to understand and classify the brain MR images into glioma, meningioma, pituitary and no tumor class from the dataset comprising of MRI images. The tested CNN model described in this paper is a variant of DenseNet with PCA. The performance of the DenseNet model has been evaluated using four assessment indices namely, Precision, Recall, F-score, and Accuracy.

**Keywords:** Artificial Intelligence; Brain tumor; Brain tumor classification and Detection; CNN; Confusion matrix; Contrast enhancement; Augmentation; Deep learning; DenseNet; MRI images; Principal Component Analysis.

### I. INTRODUCTION

In recent times, the detection and classification of the tumor from the various images are playing vital role in deciding the type of tumor and the level of disease. Use of artificial intelligence and deep learning libraries is advancing in the medical applications and by using different training models, medical professionals can determine the type and intensity of the tumor with accuracy. Every tumor confine to parameters such as the size, type, shape and penetration in cells. In the manual diagnosis, the medical evaluation and conclusion about the tumor may vary from person to person which can be fatal for patient. To overcome the challenges, AI-based diagnosis is found to be very popular amongst researchers where neural networks and related algorithms and libraries are preferred for the analysis of brain tumor types and its classification/detection. The proposed method is a CNN-based DenseNet library model that uses dimension reductionality technique called Principal Component Analysis (PCA) to classify brain tumor MRI images into four class types called glioma, meningioma, pituitary, and no tumor. The proposed work is to understand and classify the brain MR images into the above-mentioned classification from the dataset comprising of thousands of images of high pixels.

The tested CNN model described in this paper is a variant of DenseNet with PCA and the results are found to be satisfactory. In this proposed model, the brain tumor MRI images are first pre-processed and then augmented for the good results and fast training of the models. The performance of the DenseNet model has been evaluated based on parameters namely, Accuracy, Precision, Recall, and F1-score. The experimental results indicate that the proposed model is 97% and 96% accurate during training and testing, respectively. The parameters of high accuracy and F1 score, makes the designed DenseNet training model with PCA more useful in the study of brain tumor diagnostic tests. Image pre-processing and augmentation are necessary for the brain tumor detection and classification to apply deep learning models [1]. The CNN model named LU-Net is used for the segmentation of tumors for two classes with tumor and no tumor. The performance parameters metrics, recall, precision and accuracy are within required range compare to VGG16 model [2]. A modified CNN model has been designed for the small datasets which takes less execution time and more efficiency in competition of well-known CNN models [3]. The modified architecture has been designed with the main CNN model VGG16 and it shows improvement in performance parameters of tumor detection and classification [4]. In CNN based models by using softmax better results of F1 score and accuracy can be achieved with several datasets [5].

The proposed model which uses AlexNet, GoogLeNet and ResNet18 architecture features with the several classifiers. The proposed model is trained on large dataset and having accuracy of 99% [6]. The proposed hybrid model uses AlexNet, GoogLeNet, VolumeNet, and CNN to reduce the minus points of the previously

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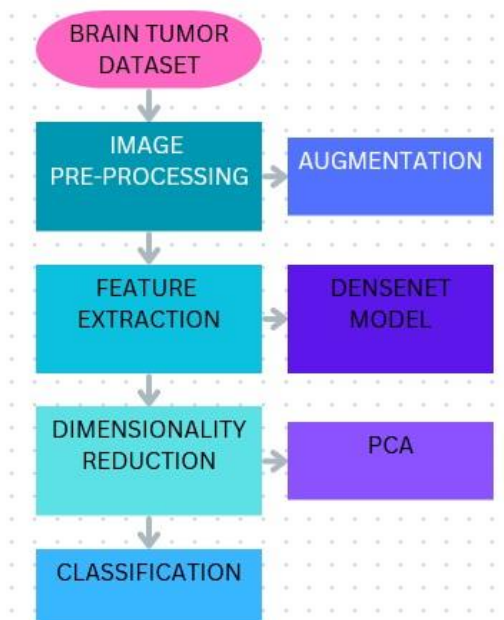
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conventional models [7]. The proposed model having CNN based diagnosis configuration is used for the tumor detection and classification. In this model we get good results by adding more layers of convolution towards CNN [8].

The proposed CNN model showing quick response for identification of images having tumor component [9]. The proposed model uses MobileNetV2 deep learning model compare to well-known CNN models. This model is showing high precision, accuracy and F1-score but the model is suitable for small size dataset [10]. In this article regular machine learning techniques as well as deep learning methods with the support of SVM classifier are used which show good performance results [11].

## II. PROPOSED METHODOLOGY

The proposed model uses ANN model and the analysis is trial and error based. This model produces efficiency less than 70% and it can be increased by applying more number of images [12]. In this article typical filtering methods are used like K-mean clustering, edge detection, Gaussian Filtering for the detection of the brain tumor [13]. In this article reader can know and understand the use of CNN for the segmentation of the brain tumor [14].



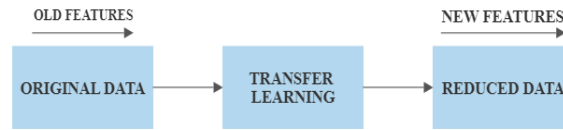
**Figure 1. Proposed Model**

In the proposed approach shown in figure 1 for classifying brain tumor MRI images into four categories called glioma, meningioma, pituitary, no tumor categories. The objective to apply this deep learning algorithms and a transfer learning technique is to calculate the impact of the proposed model by achieving remarkable accuracy in the classification and detection of tumor from brain MRI images. The applied procedure includes Brain Tumor MRI Dataset, preprocessing, Feature extraction, Dimensionality reduction (using PCA), Classification and basic system performance measures. To extract features, pre-trained CNN models are used followed by softmax layer to classify these features. The step wise flowchart of the proposed model is shown in figure 1. The brief description of each stage of the proposed system is described as follows.

Dataset description, The Kaggle Brain tumor detection dataset is used in this research work. The dataset contains few hundred samples. For proposed research work training and testing percentage are 81.3 and 18.7 respectively. This dataset is made publicly available for researchers. Free and paid datasets are available of various sizes. Image Preprocessing, Pre-processing and data augmentation steps are required before detection and classification of the tumor to apply to the model. The images in the dataset are to be filtered, transformed and resized into the size of 224 x 224 x 3 in the pre-processing step for this proposed model. Image augmentation is necessary for preparation of healthy dataset for training of the model. As we generate bigger dataset the proposed model's

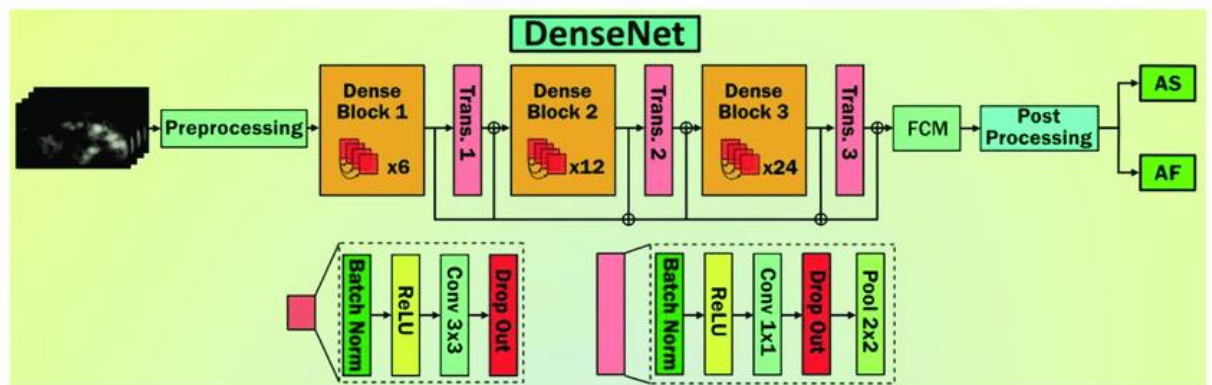
accuracy becomes better. To prepare healthy and balanced dataset from the taken one professional prefer these pre-processing and augmentation techniques before detection and classification.

Feature Extraction,



**Figure 2: Transfer Learning**

Using the deep learning pre-trained models, the system learns how to extract features on its own while being trained. Various CNN architectures of the deep learning network can extract features on their own, using convolutional filters or sometimes called kernels. To extract the required information from the input raw data using different tools is known as feature extraction. As the proposed model targets four different classes, feature extraction stage becomes important for detection and classification. In feature extraction we generate feature vectors from input MRI images. These feature vectors are used by classifiers to match the input unit to the desired output unit. By detailing these features, we can easily classify the desired classes. We have taken the DenseNet CNN model for the training purpose. In the case of Brain Tumor, transfer learning plays vital role to decide the accuracy of the taken CNN based pre-trained model. CNN is network having multiple layers for feature extraction and classification purpose. CNN uses several filters for extraction of features and learning which is used for classification of the tumors. All generated input image vector are passed through the series of ‘convolution layers with filters’, ‘Pooling layer’, ‘fully connected layers (FC)’, and the ‘Softmax function’ for the



**Figure 3: Architecture of DenseNet**

classification. DenseNet Model is one kind of pre-trained model having different versions. It is one type of Convolutional Neural Network architecture and used for the depth, width, resolution scaling. It has various versions of architectures which are used to generate a balanced efficiency and accuracy compare to existing CNN models. Transfer learning is the most required process for the proposed model for gaining knowledge taken from one event and applying it to another same type of event. It is the process of using the knowledge offered by a earlier trained network to train new models for different but same type of classified data. The basic idea of transfer learning is shown in Figure 2. If we gain the enough information like weights, features, resolution, tumor size from the earlier trained model during transfer learning, then having fewer data for the coming training of model we will not face major issues. In deep learning pre-trained models as well as frameworks are well structured for learning extracted features at different layers. To generate the targeted results all the layers of the framework must be linked or we can say fully connected layer must be required. In the proposed model we are approaching pre-trained CNN model DenseNet with and without fine tuning for the extraction of features. For brain tumor detection from MRI images, we extract features from a pre-final layer of a pre-trained model and train a separate learning model for classification in the proposed method.

Principal component analysis is a linear dimensionality reduction technique which is used for extraction of features from basic information and transforming the high dimensional to lower dimensional. It tries to maintain the main content of the information and tries to remove redundancy with fewer changes. Dimensions in our case are characteristics of the data like size, shape, pixels and some more. PCA is unsupervised reduction method. The process of transforming data from a high-dimensional space to a low-dimensional space while preserving essential information is known as dimensionality reduction. A dataset with a large number of input images or data which can complicate model prediction, making it probably more difficult to predict using a large number of features. In these kinds of circumstances, the dimensionality reduction technique is used. Here PCA (Principal Component Analysis) is used as a feature reduction method. It is a statistical method for determining feature correlations and reducing data dimensions. Using orthogonal transformation, it transforms the observation of correlated features into a set of linearly uncorrelated features. These new transformed features are Principal Components.

The number of principal components generated may be equal to or less than the original features of the input feature vector. This new selected feature will be applied as an input to the coming phase of the proposed model so that we can reduce the learning time. Principal components rely on direction and magnitude.

### III. CLASSIFICATION

Classification is a process to separate the desired features from the applied input the stage based on their input features. In our case the classification technique is used to classify the MRI images of the brain into four categories 'glioma', 'meningioma', 'pituitary' and no tumor. The Softmax classifier has been used to classify the input feature vector into desired categories. In order to classify brain MRI images into glioma, meningioma, pituitary and no tumor, the pre-trained CNN DenseNet model is used for extraction of the features. The PCA is applied after the extraction of features from the model and then furthermore reduced feature set is generated for classification. In deep learning training models, hyper-parameters show a important role in achieving accurate results. Here we are using pre-trained CNN model DenseNet. The different hyper parameters considered such as the number of epochs, learning rate and batch size to provide an efficient trained model. The model is developed using Keras library and supported by Tensor flow. The pre-trained DenseNet CNN model followed by PCA achieved more than 95.00 % training accuracy and 96.00 % validation accuracy. We are using 80% for training and 20% for testing of the dataset. By taking various parameters like learning rate 0.1, 0.01, 0.001, the batch sizes of 32, 64 and the number of epochs 50, 75,100 results are to be taken. The confusion matrix is used to assess the performance of the proposed model. A confusion matrix is a tabular representation of correct and incorrect classifications. A confusion matrix can be used to extract various metrics that show the classifier's performance for each tumor class. Precision, Recall (or sensitivity), and F1-score, accuracy are all important evaluation metrics.

The proposed model evaluation focus will be on the accuracy as an evaluation parameter. The performance parameters' equations are mentioned below:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \dots\dots\dots (1)$$

$$Precision = TP / (TP + FP) \dots\dots\dots (2)$$

$$Recall = TP / (TP + FN) \dots\dots\dots (3)$$

$$F1- Score = 2 x [(Precision x Recall) / (Precision + Recall)] \dots\dots\dots (4)$$

Where TP is True Positive, FP is False Positive, TN is True Negative and FN is False Negative. During preparation of the transfer learning model there are some other performance parameters also we can include in the analysis of the proposed model.

IV. RESULTS AND DISCUSSION:

Overall classification results of the proposed model as the precision, recall, F1-score and accuracy are showing in given table below. Observation table shows the results with and without PCA. From the tables we can observe positive impact of dimension reduction technique in parameters measurements. We have used four parameters named Precision, Recall, F1-Score and Accuracy. In results section figure 4 to figure 17 shows the observations and impact of PCA on the classification result which we used for classification of the tumor. In the case of without PCA accuracy and loss is slightly higher as compare to the proposed method so it is clear from these experiments that PCA can reduce number of trainable parameters in the model without greater impact on accuracy so the execution time we can reduce and get the fast response.

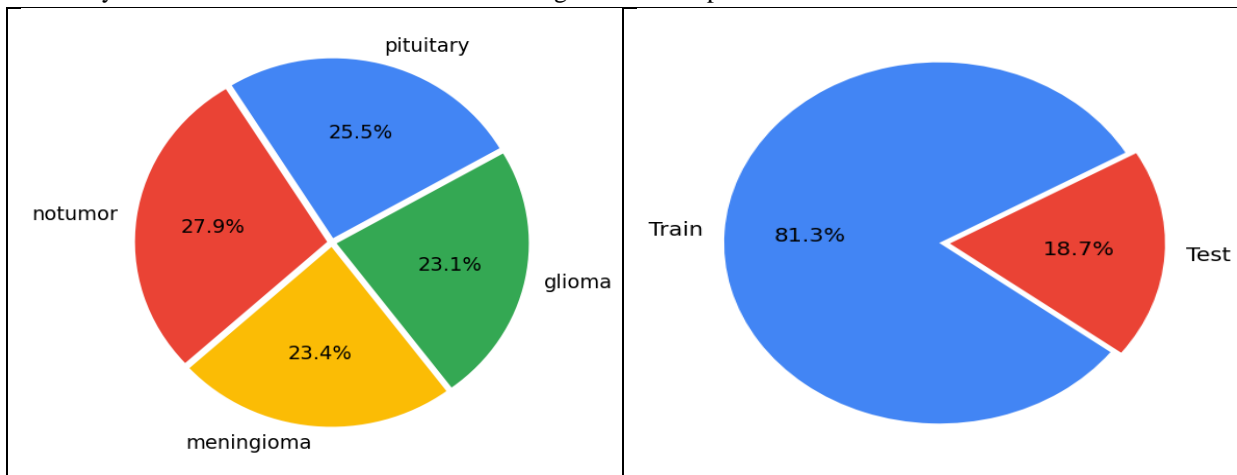


Figure 4: Classwise Dataset distribution for training and testing

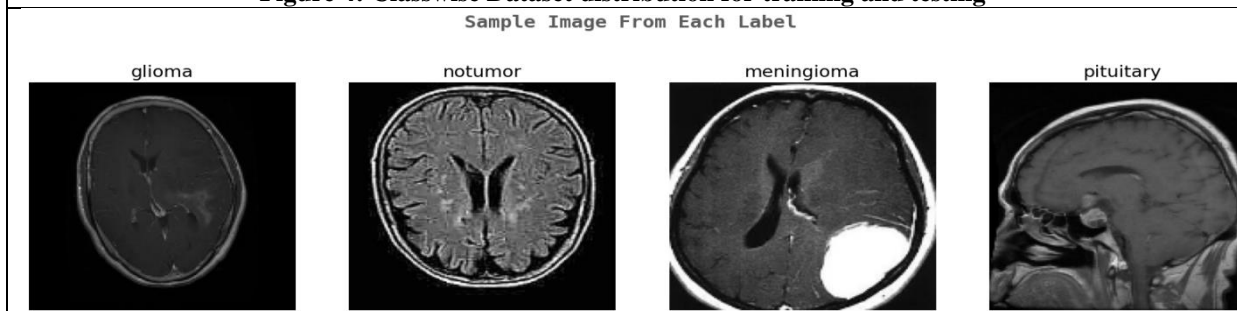


Figure 5: Sample image from each class

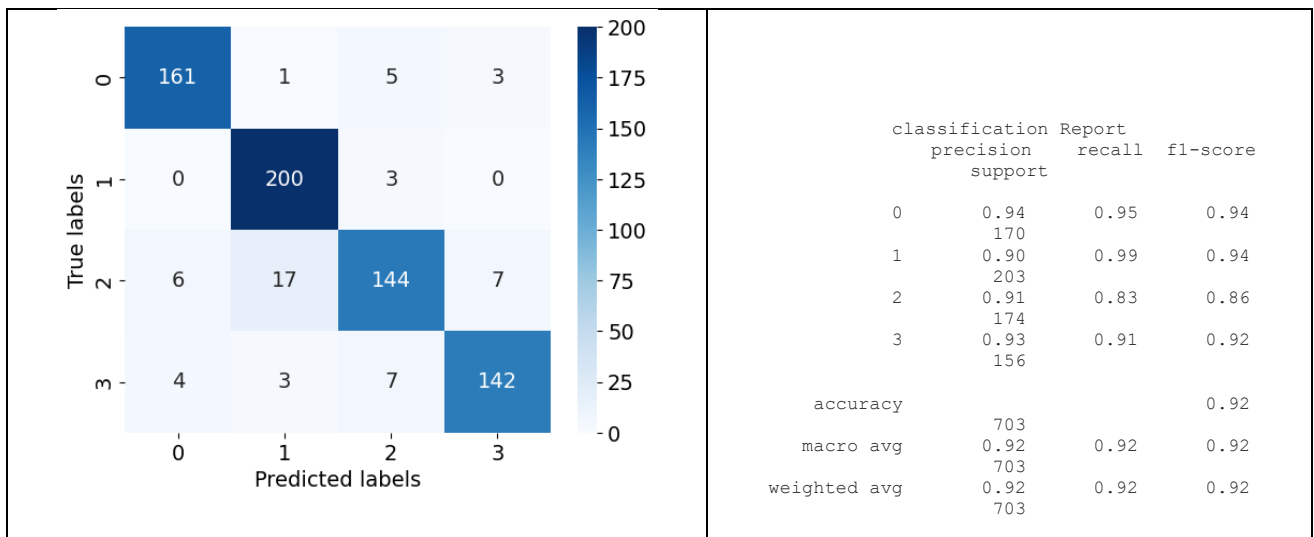


Figure 6: Confusion matrix and classification report

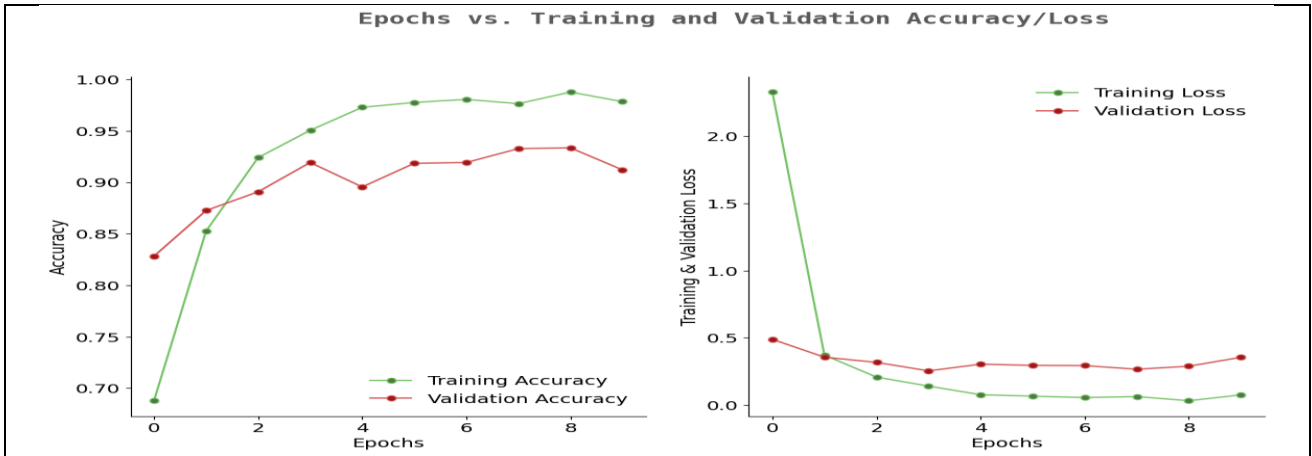


Figure 7: Epochs vs Training and Validation Accuracy/Loss

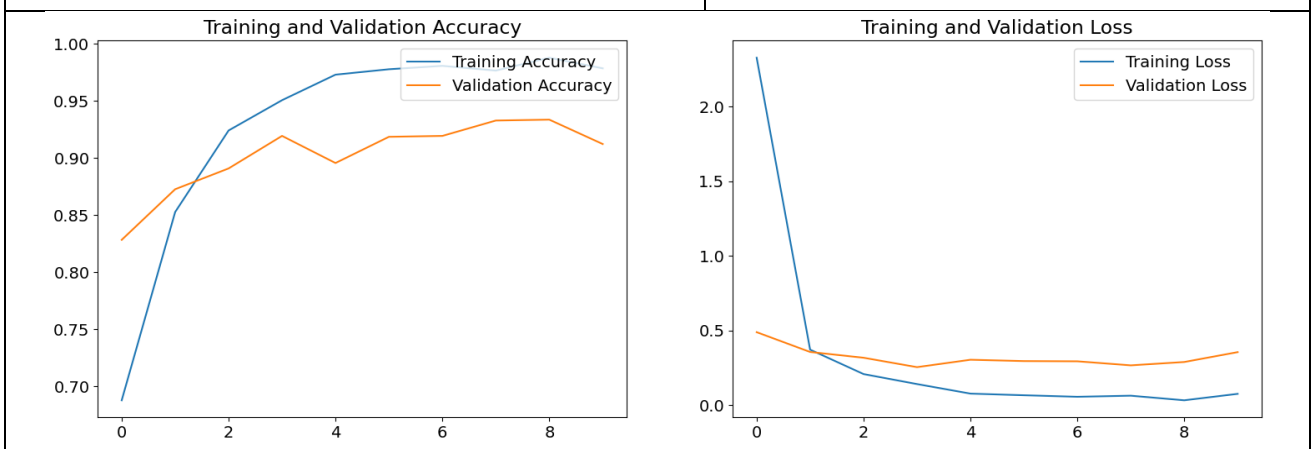


Figure 8: Training and Validation Accuracy/Loss

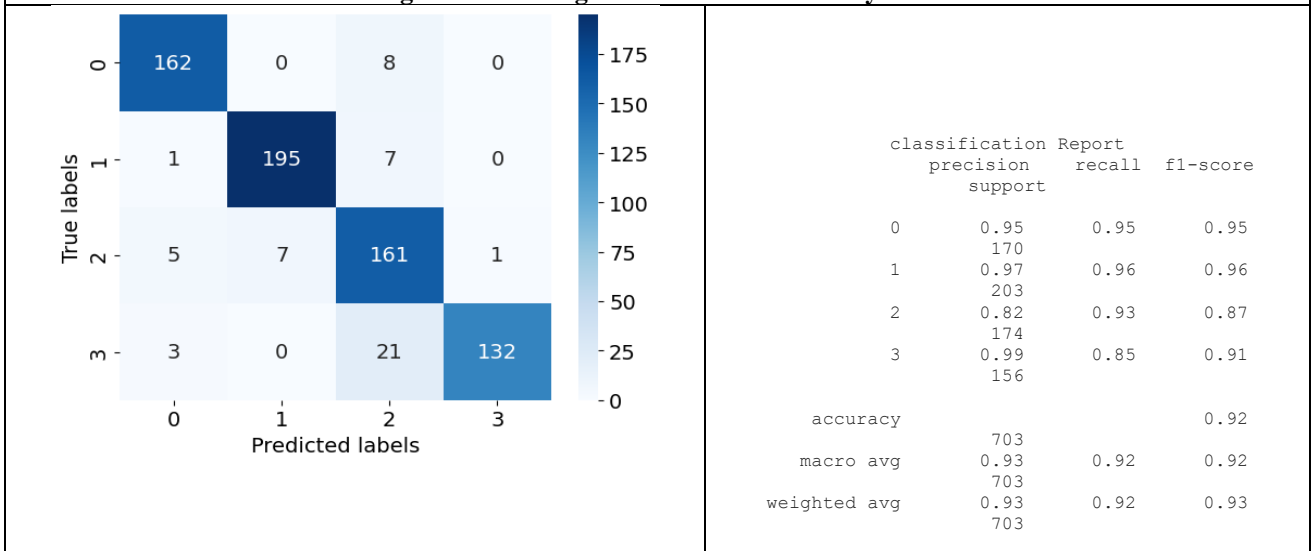
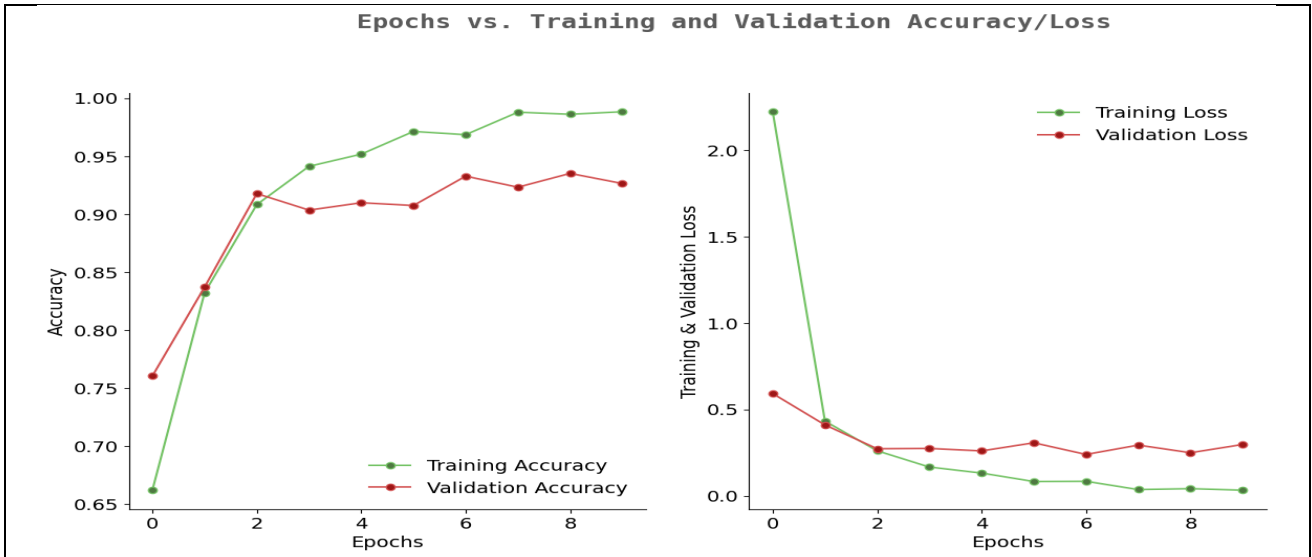
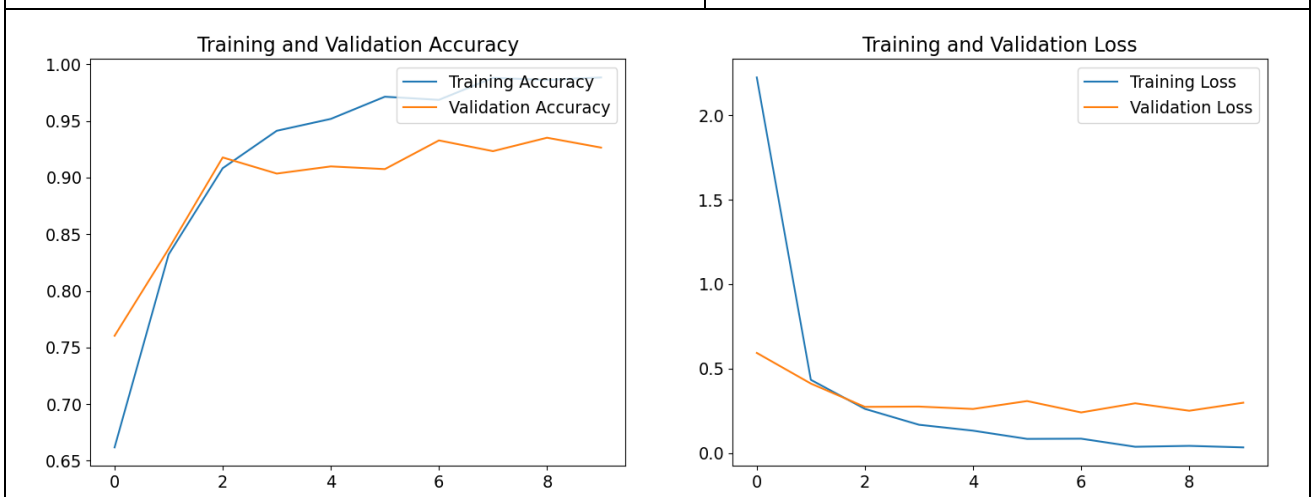


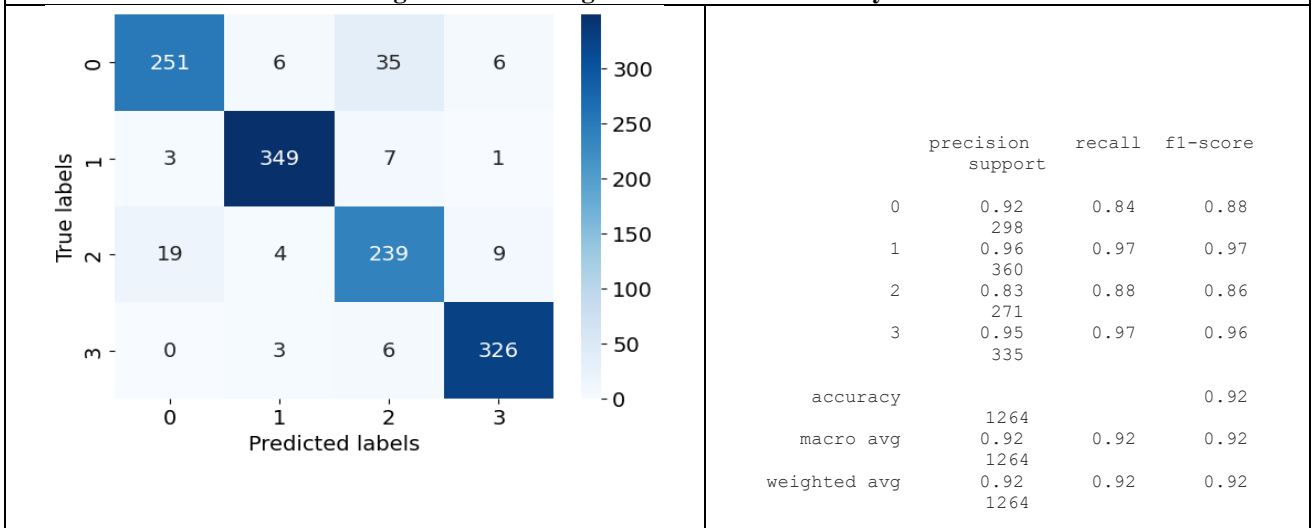
Figure 9: Confusion matrix and classification report



**Figure 10: Epochs vs Training and Validation Accuracy/Loss**



**Figure 11: Training and Validation Accuracy/Loss**



**Figure 12: Confusion matrix and classification report with PCA**

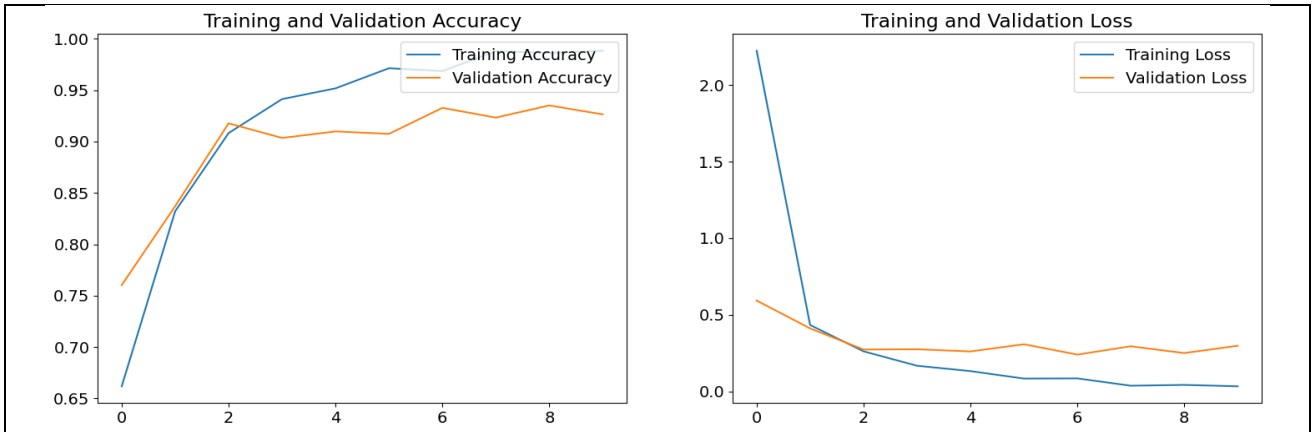


Figure 13: Training and Validation Accuracy/Loss with PCA

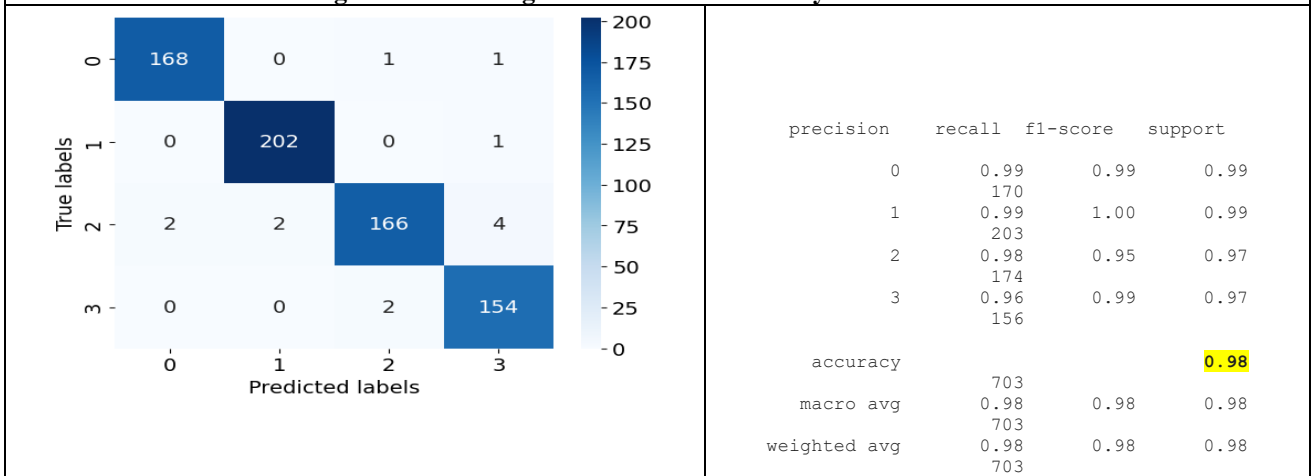


Figure 14: Confusion matrix and classification report with PCA with tuning

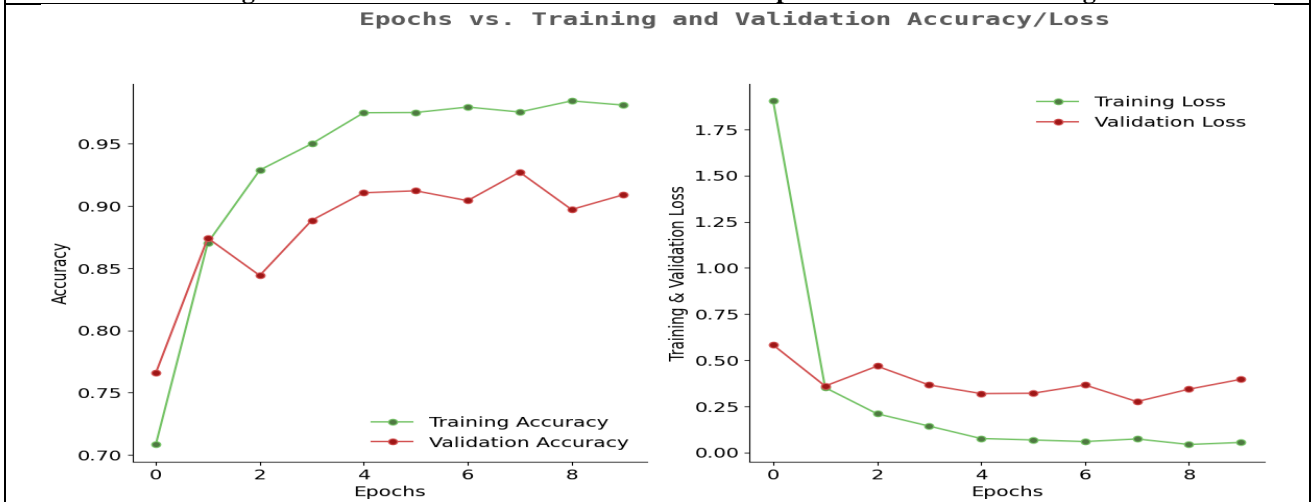


Figure 15: Epochs vs Training and Validation Accuracy/Loss with PCA



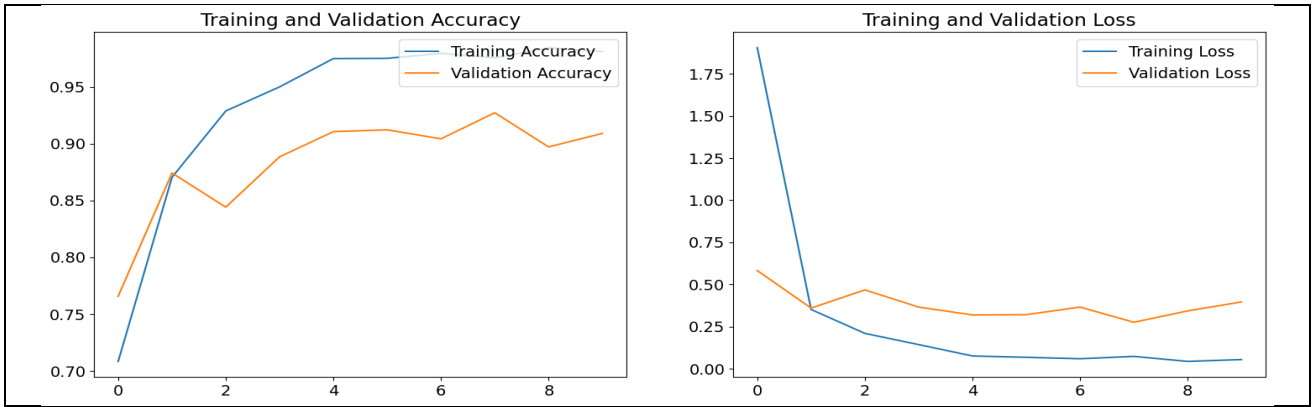


Figure 16: Training and Validation Accuracy/Loss with PCA with tuning

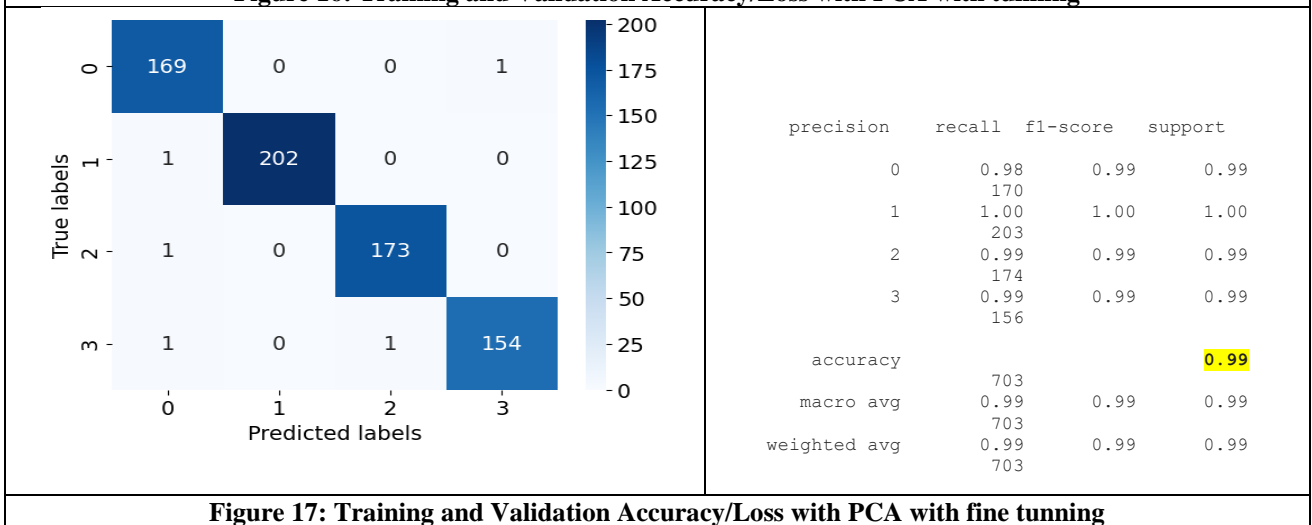


Figure 17: Training and Validation Accuracy/Loss with PCA with fine tuning

V. CONCLUSION:

In this work we first execute the effect of the pre-trained model DenseNet as the feature extractors for the detection and classification of the Brain Tumor from MRI images. Initially we took the result without any kind of dimensionality reduction technique application. In this experiment we got good result but the time taken and no of parameters are very high. Then applying the dimensionality reduction technique called PCA we got good results. In both the cases results are almost same type but we see some other aspects then this proposed model is useful. In the proposed model we got the result up to 97% which is higher compare to the model which does not use any dimension reduction concept. Here we use publically available small dataset; we can apply on bigger dataset also which gives positive results. As the PCA is beneficial with DenseNet, we can also use some other dimensionality reduction techniques with several other training models and analyze the impact on accuracy and precision.

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