A Hybrid Model for Brain Tumor Detection using EfficientNet and Fuzzy C Means Clustering Algorithm

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Abstract

This paper describes the detection of brain tumors from Magnetic Resonance Images (MRI) using the deep learning EfficientNet model and the Fuzzy C means algorithm. The earlier detection of brain tumors can reduce the risk of death. Deep Learning is a highly adoptable technique for the detection of brain tumors at an early stage. It potentially lowers the fatality rate rather than machine learning as it allows the processing of large amounts of data to be more accurate in medical diagnosis. The existing EfficientNet model did not include a segmentation algorithm which is required for model training because it provides a clear image of the training model that is deployed in the EfficientNet model. It was reviewed that the Fuzzy C Means clustering algorithm is the best used for segmentation along with the enhancement of the existing EfficientNet model. This proposed system uses a transfer learning approach for training the model which was evaluated that led to an accuracy of 99.68%. The integrated Fuzzy C Means and EfficientNet model have been tested with various MRI images, and it outperforms the existing EfficientNet models in terms of accuracy.

Keywords: *MRI Scan Images; Transfer Learning; EfficientNet model; Fuzzy C Means clustering algorithm.*

I. Introduction

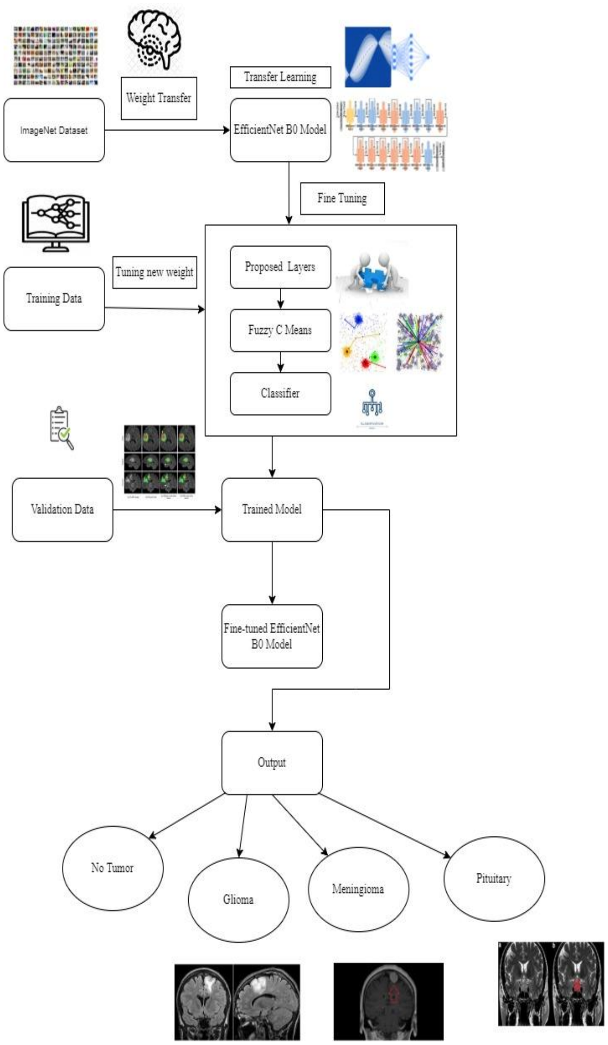
Brain tumors are basically of two types. They are primary brain tumors and secondary brain tumors. Primary brain tumors are classified into two categories based on how far the tumor has spread. They might be benign (noncancerous) or malignant (cancerous). The four grades of a brain tumor are I and II, which are low-level grade tumors referred to as Benign brain tumors, and III and IV, which are high-level grade tumors referred to as malignant brain tumors. Benign tumors are noncancerous because they do not spread to other regions of the body. Benign tumors are usually not hazardous because they can be surgically removed if caught early enough. However, if they are not detected early enough, they may mature and develop into a life-threatening malignant tumor. Malignant tumors can grow quickly and spread to distant locations, providing a life-threatening threat by spreading to other organs. Malignant tumors are harmful because they enter the cell and destroy the tissues within it, causing them to spread to other parts of the body. The annual incidence rate of malignant brain tumors decreased by 0.8 percent for all ages combined between 2008 and 2017 but increased by 0.5 percent to 0.7 percent for children and adolescents [8]. Males have the highest rate of malignant brain tumors, while females have the largest percentage of nonmalignant tumors. Malignant glioma tumor doubling periods ranged from 15.0 to 21.1 days, with an average of 17 to 20 days and no significant variances based on histopathologic differences [22]. Secondary brain tumors usually start in other places of the body and spread to the brain via metastasis. Lung, breast, skin (melanoma), colon, kidney, and thyroid cancers are the most prevalent types of cancer that can spread to the brain. Although the average survival time for individuals with brain metastases is less than 6 months, it is generally known that certain subgroups of patients have a higher chance of surviving longer [30]. As a result, the remedy to this dangerous situation is to diagnose a brain tumor early on. However, there's a chance you'll get an incorrect result after scanning.

Saumya Chauhan et al. had taken up an MRI Image and had applied pre-processing techniques like median filtering, converting the image to RGB and also to the l*a*b color space. This pre-processed image is also given to the segmentation where it follows color-based segmentation. The segmented images undergo feature extraction by GLCM texture and finally with the help of the IBkLG classifier on the training dataset, the image would be classified into any one of the three classes Normal, Benign, Malignant [11]. Anikhet Sharma et al. had used the data mining approach for the detection of the brain tumor by pre-processing the image by performing gray scaling, edge detection, and skull removal. This pre-processed image is further segmented by threshold segmentation technique and then it got clustered with the help of k-means clustering and finally got classified with the naive Bayes algorithm [16]. Sunita et al. had reviewed different approaches in the data mining techniques. Among those papers, one of them had used three different algorithms for three different processes. Highlight extraction is performed using Discrete Wavelet Transform, dimensionality reduction using Principal Component Analysis algorithm, and finally, characterization using KNN classifier [21]. However, using all these algorithms would increase the complexity of the system and this could be resolved by using other approaches. All these data mining approaches help discover the knowledge from the input but data mining fails to perform when the given data is not up to the level. This greatly impacts the accuracy and sometimes results in false predictions. To overcome all those disadvantages, it is known that machine learning could perform better as data mining usually involves discovering the knowledge but it fails in making the decision. But Machine Learning succeeds in decision making as it teaches and trains the model to make decisions and make the machines act like humans in making decisions. Daksh Pruthi et al. had taken up the image pre-processed with median filter and then given for segmentation. Morphological and thresholding techniques are adopted for the process of segmentation. Here the author had fused the segmented image and then it is given to the SVM classifier to get the desired result [28]. Chadha Megha et al. had taken an MRI Image which is pre-processed and then skull stripped and further segmented with morphological operations and finally feature extracted and classified using SVM to give the desired results [25]. However, though machine learning algorithms could make machines make their own decision, it fails to work with the same accuracy for the larger dataset. Machine Learning should use an algorithm for performing the feature extraction and this can be overcome by the usage of deep learning. Deep Learning algorithms need not require feature extraction as they can perform feature extraction with the help of layers in the model. Yuehao Pan et al. discussed in their paper how the convolutional neural network outperforms the neural network [19]. Their experiments show a maximum improvement of 18% in grading performance of CNN based on specificity and sensitivity when compared to Neural Networks. Swaraja Kuraparthi et al. discussed the operation of the CNN Model. Swaraja Kuraparthi et al. goes into great detail about the layers that exist within the CNN. It is inferred from this paper that Batch Normalization is used to overcome generalization. For feature extraction, the Max pooling layer is used. A dropout layer is used to avoid overfitting. Different terminologies can be used to measure performance metrics. They are as follows: accuracy, prediction, recall, specificity, F1 score, and AUC. Classification can be classified using classification accuracy. The pre-trained models, on the other hand, are compared with AUC [13]. The Convolutional neural network's hidden layer was described by Abhishek Anil et al. This paper conducted some experiments or comparisons between AlexNet and VGGNet and concluded that VGGNet is superior to AlexNet [5]. Swaraja Kuraparthi et al. conducted experiments on Deep CNN architectures such as AlexNet, VGG16, and ResNet 50, and concluded that ResNet50 is far superior to other architectures. Shimaa E Nassar et al. compared the models UNet, VGG16, and DeepLabV3, and after conducting the experiments, the author discovered that DeepLabV3 is the best model because it has a higher dice similarity coefficient, which aids in determining accuracy. The author also stated that the DeepLabV3 model's efficiency is due to the presence of embedded, atrous, spatial, pyramid, and pooling [14]. Umit Atila et al. in their paper had discussed and proved how EfficientNet Model is far better compared to the other deep learning model in training and testing dataset [2]. As a result, it is concluded that the EfficientNet model should be used for this proposed system. Subhashis Banerjee et al. made some comparisons with VGGNet and ResNet. In addition, the author included a comparison of the approaches of using transfer learning with and without fine-tuning [7]. It is inferred from this that the performance with finetuning and transfer learning achieved greater accuracy when compared to transfer learning without fine-tuning. Fine-tuning is the process of using transfer learning, but it has an additional feature in that it is not only modifying the final layers of the pre-trained model and training them again for the model, but it is also training the modified model completely as this increases the model's efficiency. In this paper, Jaeyong Kang et al. discussed pre-processing and data augmentation techniques. Pre-processing is a process that is used to calculate the extreme point. The author also discussed thresholding, which is a method for converting MRI to binary format. The author described the bicubic interpolation technique, which is a part of the pre-processing technique. The author also stated that when compared to other interpolation techniques such as bilinear interpolation, bicubic interpolation produces a smooth curve. Finally, the author demonstrated that data augmentation improves classification accuracy when compared to the accuracy obtained from the dropout layer of the CNN Model. Even though both techniques have been shown to eliminate overfitting, the author claims that data augmentation outperforms the dropout layer in terms of accuracy [17]. Shreya Goshal et al. had discussed in their paper how a model with and without transfer learning performs. This paper had clearly illustrated the performance and accuracy difference between both approaches [15]. Ting Xiao et al. had developed the three transferred models InceptionV3, ResNet50, and Xception, a CNN model with three convolutional layers, and a traditional machine learning-based model with hand-crafted features were developed for differentiating benign and malignant tumors. Cross-Validation results have demonstrated the transfer learning method. Normally, Transfer learning is believed to be a powerful tool for training deeper networks without overfitting. As the transfer learning method outperformed the traditional machine learning model and the CNN model where InceptionV3 achieved the best performance with an accuracy of 85.13% and an AUC of 0.91. But there comes an issue where InceptionV3 will consume more memory which is not suitable for embedded devices [23]. From the above context, it is inferred how transfer learning could help in improving accuracy and performance. Image segmentation is one of the most effective deep learning algorithms, and it's employed in a variety of vision applications [9]. The objective of image segmentation is to group sections of a picture that belong to the same object class together. This method is also known as pixel-level categorization. To put it another way, it requires breaking down images into a variety of segments or objects. Various image segmentation algorithms, such as thresholding [27], region growing [26], histogram-based construction, and K means clustering [10], have been developed in the literature. Image segmentation, on the other hand, can be thought of as a problem of pixel classification with semantic labels or object division. Image segmentation is also commonly used in medical applications, such as tumor border extraction and tissue volume quantification. The utilization of how Fuzzy C means plays a significant part in clustering of segmentation is gathered from the above-mentioned paper. Thus, from the above different reference papers, it is inferred finally to make a hybrid brain tumor detection model by combining EfficientNet model with fine-tuning transfer learning approach using Fuzzy C Means clustering algorithm. This paper discusses the creation of a Deep Learning-based model using the Transfer Learning approach using EfficientNet and Fuzzy C-Means Clustering to aid in the earlier detection of brain tumors.

The proposed system description of A Hybrid Model for Brain Tumor Detection using EfficientNet and Fuzzy C Means Clustering Algorithm described in Section 2, Section 3 deals with the simulation and results of the proposed system and finally conclusion in section 4.

II. A HYBRID MODEL FOR BRAIN TUMOR DETECTION USING EFFICIENTNET AND FUZZY C MEANS CLUSTERING ALGORITHM

Fig.1. Architecture of the proposed system



The four major phases involved in the construction of a model are as follows:

- Pre-processing
- Data Augmentation
- Segmentation
- Classification

The architecture diagram for the proposed system is mentioned below in Fig.1. This architecture diagram would explain how this proposed system works right from getting input from the user as MRI Image to the model predicting the output as either no tumor or glioma or meningioma or pituitary tumor.

A. Dataset

This proposed system uses the "BRAIN TUMOR MRI DATASET" dataset from Kaggle to train the model. There are about 5712 training and 1311 testing photos in this dataset. Images from the pituitary, glioma, meningioma and no tumor classes will be included in this dataset. The key reason for choosing MRI Images as our dataset is that they provide a better image of the tissues, bones, and organs, as well as allow for a more in-depth examination of the organs. However, a brain tumor is identified, which is a collection of cells, MRI provides greater clarity and resolution than other forms of diagnosis.

B. Preparation of dataset

At the start, only a few constants were declared. Each variable represents the location of the training and testing datasets. Because it is an EfficientNetb0 model, the image size is set to 224. The batch size constant is then set to 32. The number of classes is recorded in a variable because there are four of them.

C. Pre-processing of the dataset

The step-by-step process of creating a deep learning model helps to change the image size because deep learning models use large data sets and it is not guaranteed that all images will be the same size [17]. There are a variety of other methods and processes to achieve pre-processing. The preparation phase in our proposed program begins by converting the image from BGR to RGB, which is necessary because the images may have different pixel configurations. In addition, some additional changes are applied to the given image. After converting to RGB, images are subject to toPILImage conversion, which helps to convert the input tensor into an image. Converting a new size is used to increase the size of the input image. As the image is used in the EfficientNet B0 model, the image size is set to 224. As a result, the previously analysed image will be used for another purpose.

D. Augmentation of the dataset

Data augmentation would be applied to both the training and testing datasets. Data Augmentation is a deep learning model approach that expands the available dataset by adding extra photos. This approach would make it easier to add new photographs that were made from old ones. Deep Learning would be more accurate if it was trained on a larger dataset. As a result, this strategy will aid in the improvement of accuracy [17]. The usage of data augmentation will reduce overfitting. When a model performs very well in the training dataset but not so well in the testing dataset, this is known as overfitting. On this dataset, only a few data augmentation techniques were used. The photos in the dataset were first scaled, and then they were flipped at random using horizontal and vertical orientations, both with a probability of 0.5. This would aid in the creation of new photos from old ones, boosting the number of images in the training and testing datasets. As more photos are used in training and testing, the model's accuracy improves, resulting in improved performance. Gaussian blur is applied to the photos after they have been flipped vertically and horizontally. This is done so that our model can recognize even blurred photos when they are sent in as input. The dataset is also subjected to the Random Adjust Sharpness transform. All of these data augmentation approaches are primarily used on dataset photos to avoid model overfitting and to increase the total number of images in the dataset.

E. EfficientNet B0 Model

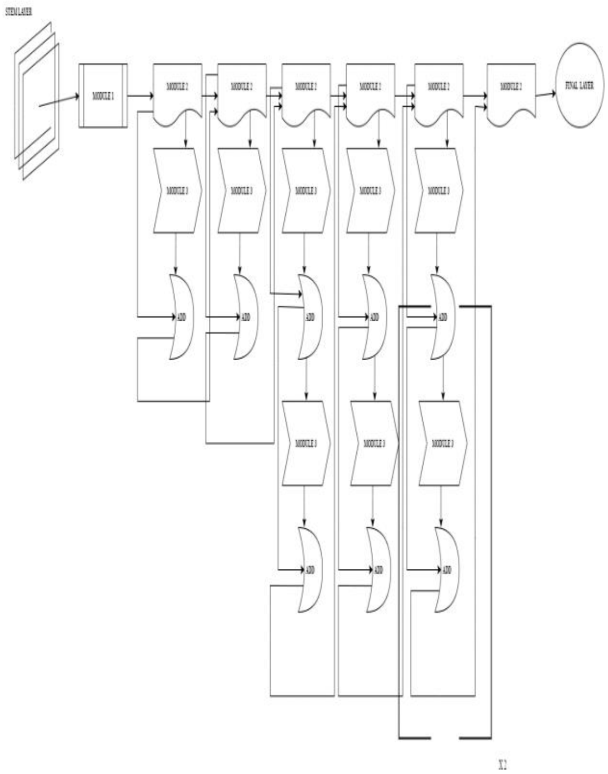
The above pre-processed image was made to be given as an input to this model. The CNN model requires development because it has drawbacks such as Vanishing Gradient [4]. In the year 2019, Google Brain Team proposed the EfficientNet Model. MobileNet served as the foundation for EfficientNet. MobileNet was created to make the deep learning model to make [1]. MobileNet employs both depth and point scaling. The base model EfficientNet B0, on the other hand, is based on the inverted bottleneck residual blocks MobileNetV2, as well as squeeze and excitation blocks. The EfficientNet model is also said to have nearly 20 layers in it. The EfficientNet model was created to carefully study model scalability while also balancing network depth, width, and resolution. To balance the scalability of depth, width, and resolution, the EfficientNet model was brought up. The EfficientNet model's objective also involves maximizing model accuracy under the given restrictions. The EfficientNet's baseline model is built up of convolutional layer blocks and inverted residual blocks (MbConv), both of which were previously employed in the MobileNetV2 model. The convolution layer would be followed by the batch normalization layer [18] and the activation layer in the Convolutional Layer Block. In addition to these layers, this effective net model contains a squeeze and excitation block. The fundamental aim of the squeeze and excitation blocks in the EfficientNet model is that they will play a critical part in the model's performance gain [3].

F. Linear BottleNeck

The basic goal of nonlinear activation in neural networks is to avoid reducing numerous matrix multiplication to a single numerical operation. The use of a linear bottleneck allows the creation of several layers. The Linear Bottleneck is the last convolution of the residual block, which has a linear output before being added to the first convolution. The attention layer is not present in Linear Bottleneck. In the EfficientNet model, layer squeeze and excitation blocks are used for the goal of attention [12].

G. EfficientNet B0 Model Architecture

Fig.2. EfficientNet B0 Model

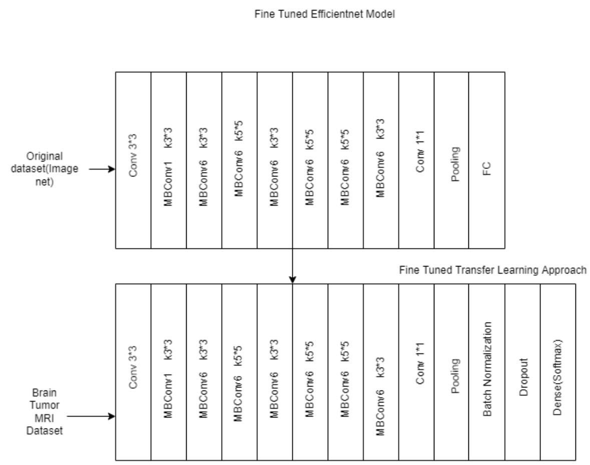


The EfficientNet B0 model is designed with 7 blocks in them is displayed in Fig.2. Each block is said to be divided into sub-block and they are present inside the block. Each sub-block would consist of the module in which each module consists of several layers arranged in them.

H. Transfer Learning

Transfer learning is a method that is commonly used in deep learning models to improve model accuracy. It is nothing more than reusing the pre-trained model for implementation. Transfer learning with fine-tuning is nothing more than completely retraining the model from the start, even after replacing the final or output layer [24]. However, in the case of transfer learning without fine-tuning, the model is only retrained at the final layers. As a result, the accuracy obtained by transfer learning with fine-tuning is far superior to that obtained by transfer learning without fine tuning [20]. Fig.3 shows the process involved in Fine Tuned EfficientNet Model which transforms into Fine Tuned Transfer Learning Approach.

Fig.3. Fine Tuned EfficientNet model

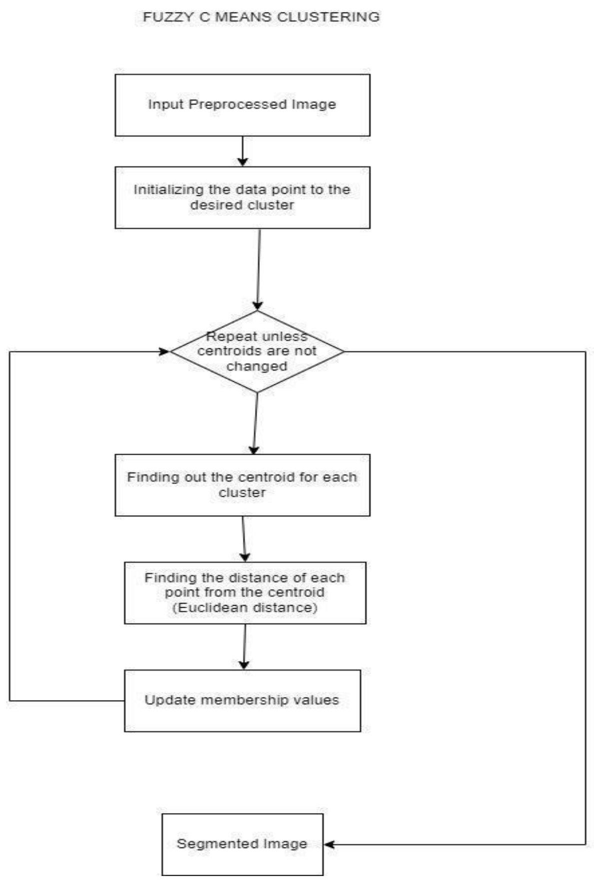


Hence the model for this proposed system is constructed in such a way like in addition to the pre-trained EfficientNet model it has included a batch normalization layer which is useful in normalizing and helpful in preventing the overfitting in the model. In addition to that, a dropout layer, as well as a dense layer, is also being added to the proposed model. The dense layer would act as a classification layer and this was made as a classifier due to the presence of the 'Softmax' Activation Function. The softmax activation function is highly useful in giving the prediction for the multiclass classification [6].

I. Fuzzy C Means Clustering Algorithm

Fuzzy c means is a type of clustering that falls within the soft clustering group. Soft clustering is nothing more than indicating the likelihood of how much data belongs to the cluster. Hard clustering, on the other hand, would provide the actual cluster name to which this data item would belong. By calculating the Euclidean distance, Fuzzy C Means would provide the prediction. As Fig.4 explains the steps involved in Fuzzy C means Clustering. The image which had got pre-processed as well as data augmented is given as an input to the segmentation part. The Fuzzy C Means Algorithm would help by performing the following steps. After given the image as input the data point for the cluster would get initialized and then the below steps would get repeated until the centroids are not changed. After initializing the data point for the cluster, this algorithm would find the centroid for each cluster, and from them, the Euclidean distance would be calculated which results in updating the membership value and when the centroids started to get changed then the algorithm stops and finally gives the segmented image [29].

Fig.4. Fuzzy C means Clustering workflow



III. SIMULATION AND RESULTS

The image which has been taken as an input is displayed in Fig.5. This image had not undergone any of the processing techniques.

Fig.5. Image before applying Fuzzy C Means algorithm

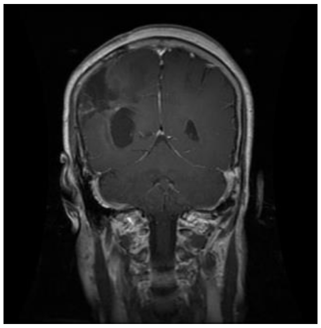


Fig.6. Image after applying Fuzzy C Means algorithm

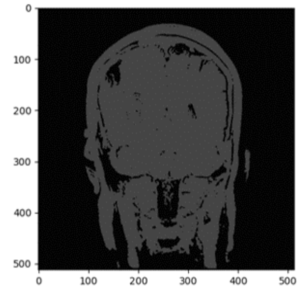


Fig.7a. Graph before applying Fuzzy C Means

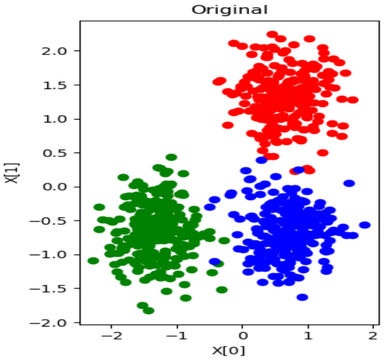


Fig.7b. Graph after applying Fuzzy C Means

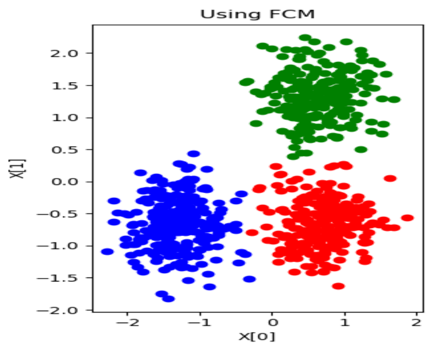


Fig.8. Image showing the predicted results of the model

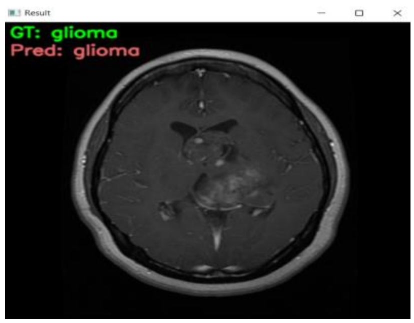


Fig.9. Graph showing accuracy of the model

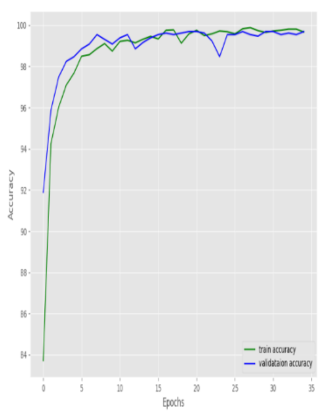
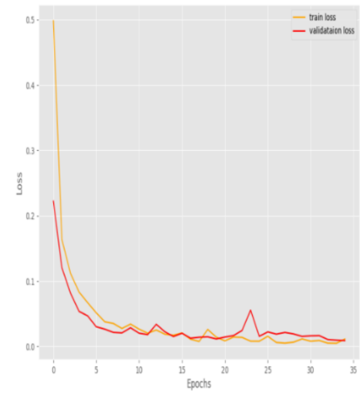


Fig.10. Graph showing the loss of the model



The image after taken as input for the model, the image will be pre-processed as pre-processing is an important step to make the size of all the images in the dataset to get uniform. After pre-processing the image since the deep learning model could exhibit performance extremely well when they have a huge dataset the augmentation of the dataset is performed. After the process of augmentation, their output is given as input to the segmentation module. This segmentation module would function with the help of the Fuzzy C Means algorithm and this has been displayed in Fig.6 showing as the image obtained after the segmentation. The image which had got segmented is known to improve the accuracy of the model. However, if an image had got segmented then this would be beneficial for the model to undergo training and finally result in the classification of the model. The proposed system would also display the graph in Fig.7 a and Fig.7 b which shows the distribution of the data points over the cluster. And finally, after completing all the preliminary phases like pre-processing, data augmentation, and segmentation the model would involve in training, and here the training is performed with the help of cross-entropy loss function and adam optimizer and also with the learning rate of 0.0001. This training phase would give the accuracy of both the training and the validation dataset in which their comparison graph is listed in Fig.9 shows how the model had got trained with the different datasets for 35 epochs plotted with an equal interval of 5 epochs. This model would also give the loss of both the training and the testing dataset in which comparison has been made represented in the form of the graph shown in Fig.10. Similar to the graph of the accuracy of the model this graph would also take 5 epochs as its regular interval. Classification is considered to be the major part of the model. Classification is performed with the help of activation function('softmax') which is used in the dense layer. This classification would result in giving the output categorized into 4 classes. They are glioma, pituitary, meningioma, no tumor. The sample output of the proposed system is shown in Fig.8. Here in this output for the testing purpose an already known glioma tumor MRI Image is given as an input to the proposed model and this model predicted the same MRI Image as Glioma tumor.

A. Measuring Metrics

It is important to measure the performance and accuracy of the model to know or it is used to compare the performance with the other model. Hence to measure the accuracy confusion matrix is found. A confusion matrix is a metric that is used to measure the accuracy of the classification of the model. The confusion matrix would use parameters like a false positive, true negative, true positive, and false negative. With the help of these parameters, the confusion matrix would help in knowing how accurate the proposed model would help in predicting the target class. Fig.11 and Fig.12 below would give the confusion matrix of both the existing and the proposed model.

Fig.11. Confusion matrix of EfficientNet model

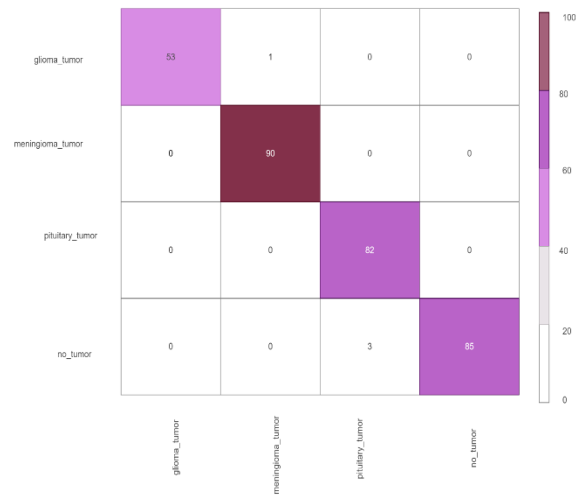
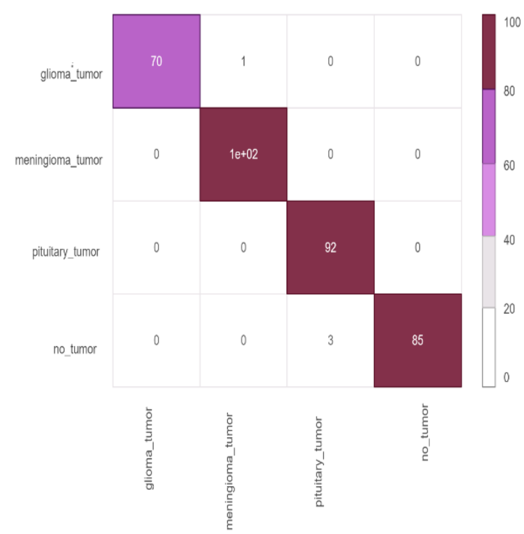


Fig.12.Confusion matrix for Fuzzy-based EfficientNet model



Accuracy is nothing but the measure of the performance of the model across all the other classes.

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad . \qquad (1)$$

Precision is nothing but the measure of the ratio between the number of positive samples correctly classified to the total number of positive samples which are either classified correctly or incorrectly.

$$Precision = \frac{(TP)}{(TP+FP)} . \qquad (2)$$

Recall is more similar to precision but it is different from precision in such a way that recall would take up the ratio between the number of positive samples to the number of correctly classified positive and incorrectly classified negative samples.

$$Recall = \frac{(TP)}{(TP+FN)} . \qquad (3)$$

F1 score is nothing but the evaluation metric which is used to measure the accuracy of the model on the dataset.

$$F1\ score = \frac{(2\times(precision \times recall))}{(precision + recall)} . \qquad (4)$$

Table 1 Accuracy, Precision, Recall and F1 score of EfficientNet model

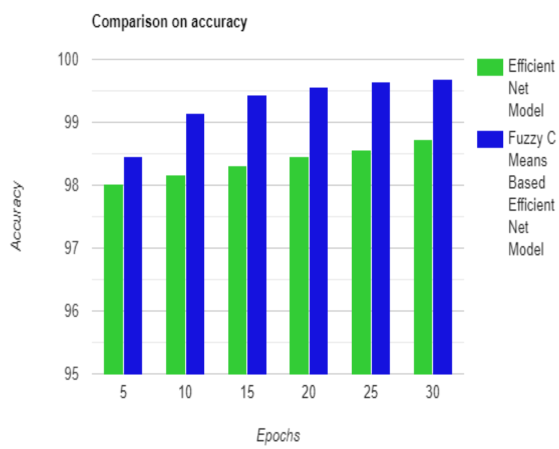
Class	n(truth)	n(classified)	Accuracy	Precision	Recall	F1 Score
Glioma	53	54	99.68%	0.98	1.0	0.99
Menin gioma	91	90	99.68%	1.0	0.99	0.99
Pituitar y	85	82	99.04%	1.0	0.96	0.98
No Tumor	85	88	99.04%	0.97	1.0	0.98

Table 2 Accuracy, Precision, Recall and F1 score of Fuzzy C Means-based EfficientNet model

Class	n(truth)	n(classified)	Accuracy	Precision	Recall	F1 Score
Glioma	70	71	99.92%	0.99	1.0	0.99
Menin gioma	1e+02	1e+01	99.92%	1.0	1.0	1.0
Pituitar y	92	89	99.76%	1.0	0.97	0.98
No Tumor	85	88	99.76%	0.97	1.0	0.98

Thus, from the above Table 1 and Table 2 since this proposed model has higher precision, recall, and F1 score it is evident that this proposed model gives far better accuracy compared to the existing model.

Fig.13. Image showing the comparison graph of accuracies obtained over every 5 epochs.



Thus, from the above, both the graph in Fig.13 this proposed system proves to give better accuracy and performance compared with the other existing models.

IV. CONCLUSION

Brain tumors are regarded as one of the deadliest diseases, with a high fatality rate as the tumor's stage advances. As a result, it is critical to detect tumors at an early stage to avoid death. This proposed system will aid in determining the type of tumor based on the MRI data provided as input to this model. However, it is equally important for a model to perform with the highest level of accuracy with a very small number of parameters compared to the other models. This proposed model is more accurate than all other existing models. This is due to the EfficientNet model, which is used in conjunction with a fine-tuned transfer learning approach. The Fuzzy C Means Clustering procedure, which is used to follow up on soft clustering, gives up the likelihood of how much a data item belongs to a given cluster. It is obvious from the experiment that early detection would aid in the earliest diagnosis. This proposed technique can also be used to verify a doctor's findings. This proposed system is known to be inexpensive to implement. Thus, this proposed model would help in inferring how far the use of segmentation using Fuzzy C Means had played a major role in improving the accuracy of the model.

ACKNOWLEDGMENT

This research has received no external funding.

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