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CLASSIFICATION OF BRAIN TUMOR USING FINETUNED EFFICIENTNET

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Abstract: Brain tumor is the growth of abnormal cells in brain some of which may leads to cancer. The usual method to detect brain tumor is Magnetic Resonance Imaging (MRI) scans. From the MRI images information about the abnormal tissue growth in the brain is identified. In various research papers, the detection of brain tumor is done by applying Machine Learning and Deep Learning algorithms. When these algorithms are applied on the MRI images the prediction of brain tumor is done very fast and a higher accuracy helps in providing the treatment to the patients. These Prediction also helps the radiologist in making quick decisions. In the proposed work, a self-defined Convolution Neural Network (CNN) is applied in detecting the presence of brain tumor and their performance is analyzed Efficient Network is one of CNN models that proposes high accuracy and less computational. Accordingly, this study suggested using the Efficient Network architecture to classify the types of glioma, meningioma, and pituitary brain tumours. Efficient Network has eight levels of category, which are from EfficientNet-B0 to EfficientNet-B7. This study obtains accuracy for best results in EfficientNet-B3 which achieved a accuracy of 97.34%.

***Index Terms** - Image classification, Brain Tumor, EfficientNet.*

I. INTRODUCTION

Medical imaging refers to a number of techniques that can be used as non-invasive methods of looking inside the body. Medical image encompasses different image modalities and processes to image the human body for treatment and diagnostic purposes and hence plays a paramount and decisive role in taking actions for the betterment of the health of the people. Image segmentation is a crucial and essential step in image processing which determines the success of a higher level of image processing. The primary goal of image segmentation in medical image processing is mainly tumor or lesion detection, efficient machine vision and attaining satisfactory result for further diagnosis. Improving the sensitivity and specificity of tumor or lesion has become a core problem in medical images with the help of Computer Aided Diagnostic (CAD) systems. Brain and other nervous system cancer is the 10th leading cause of death, and the five-year survival rate for people with a cancerous brain is 34% for men and 36% for women. Moreover, the World Health Organization (WHO) states that around 400,000 people in the world are affected by the brain tumor and 120,000 people have died in the previous years. Moreover, an estimated 86,970 new cases of primary malignant and non-malignant brain and other Central Nervous System (CNS) tumors are expected to be diagnosed in the United States. Brain tumor occurs when abnormal cells form within the brain. There are two main types of tumors- Malignant and Benign. Malignant brain tumors originate in the brain, grows faster and aggressively invades the surrounding tissues. It can spread to other parts of the brain and affect the central nervous system. Cancerous tumors can be divided into primary tumors, which start within the brain, and secondary tumors, which have spread from elsewhere, are known as brain metastasis tumors. On the other hand, a benign brain tumor is a mass of cells that grow relatively slowly in the brain. Hence, early detection of brain tumors can play an indispensable role in improving the treatment possibilities, and a higher gain of survival possibility can be accomplished. But manual segmentation of tumors or lesions is a time consuming, challenging and burdensome task as a large number of MRI images are generated in medical routine. MRI, also known as Magnetic Resonance Imaging is mostly used for a brain tumor or lesion detection. Brain tumor segmentation from MRI is one of the most crucial tasks in medical image processing as it generally involves a considerable amount of data. Moreover, the tumors can be ill-defined with soft tissue boundaries. So, it is a very extensive task to obtain the accurate segmentation of tumors from the human brain. In this work, we proposed an efficient and skillful method which helps in the segmentation and detection of the brain tumor without any human assistance based on both traditional classifiers and Convolutional Neural Network. Efficient Network is a rethinking model scaling from the Convolutional Neural Network method. This method performs a compound scaling in 3 dimensions to magnify depth, width, and image resolution. An efficient Network is appropriate for image processing; it performs less computational than the other models. medical images.

II. LITERATURE REVIEW

In this the author proposed an optimized edge detection techniques based on genetic algorithm (GA). The performance of the proposed genetic algorithm-based cost minimization technique is compared to the classical edge detection techniques algorithms like canny, Prewitt, Roberts, Sobel and Laplacian of gaussian (LoG) edge detectors. Then the proposed GA edge detection method is employed, with the appropriate training dataset, to detect the fine edges. The study indicates that the proposed GA edge detection method performs well compared to classical edge detection methods. In this paper the author proposed a method based on brain tumor segmentation on multi cascaded convolutional neural network (MCCNN). In this they have used two ensemble predictions that is CNN and U-Net they are trained and tested they are combined the segmentation maps from these to give final prediction for tumor tissue type. The accuracy will be more because of cascading but complexity of network increases and requires larger space. In this the author introduced the brain tumor detection using deep learning model.

The proposed model is classified into 2parts they are classification with CNN (Convolution Neural Network), and segmentation with multi thresholding is done. In CNN model classification of images is done to find whether there is tumor or not. In segmentation they divided into two phases such as pre-processing and processing. In Pre-processing to remove noise several filters are used like median filter, Gaussian filter, Average filter are used. In P Processing Part, Otsu's multilevel thresholding is used to Extract Region of interest (ROI). In this article the author proposed the Image segmentation based on morphological operations and FCM algorithm (FUZZY C-means), This work is mainly proposed for detection of tumor and to diagnose brain tumor in its early stage. To classify whether the brain tumor in the image is benign or malignant.

The proposed method shows that the segmented images have a high accuracy while substantially reducing the computation time and diagnose brain tumor in patients with a high success rate. evaluation stage and outcomes as detects cancer with 92% and classifier has an accuracy of 86.6%. In this article the author worked on edge detection approaches he adopted the canny edge detection model accumulated with Adaptive thresholding to extract the ROI. The dataset contained 102 images. Images were first preprocessed, then for two sets of a neural network, for the first set canny edge detection was applied, and for the second set, adaptive thresholding was applied. The segmented image is then represented by a level number and characteristics features are extracted. Then two neural network is employed, first for the detection of healthy or tumor containing the brain and the second one is for detecting tumor type. Depicting the outcomes and comparing these two models, the canny edge detection method showed better results in terms of accuracy. In this the author introduced a model based on the Probabilistic Neural Network (PNN) model.

The model was evaluated on 64 MRI images, among which 18 MRI images were used as the test set, and the rest was used as a training set. The Gaussian filter smoothed the images. 79% of the processing time was reduced by the modified PNN method. A Probabilistic Neural Network based segmentation technique was implemented and Principal Component Analysis (PCA) was used for feature extraction and also to reduce the large dimensionality of the data. The MRI images are converted into matrices, and then Probabilistic Neural Network is used for classification. Finally, performance analysis is done.

III PROPOSED METHODOLOGY

The proposed model with multiple layers and pre-trained algorithms will be thoroughly discussed in the subsequent sections. Figure 1. depicts the stages of the brain tumor image preprocessing, augmentations, training, and evaluation. The proposed transfer learning and fine-tuning method are based on DL algorithms that use numerous hyperparameters for training and optimization. An optimizer is an algorithm that adjusts the neural network biases and learning rate. As a result, it aids in lowering total loss and improving accuracy. A loss function demonstrates how well a specific algorithm matches the given data for ML. With the help of an optimization function, the loss function gradually learns to decrease the prediction error. The binary cross-entropy and adam optimizer is used here to solve this specific problem.

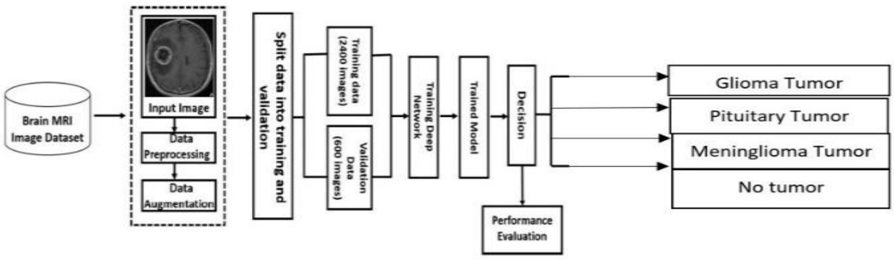


FIGURE1: Block Diagram of proposed methodology

A. Proposed Layers

This work is primarily related to implementing the EfficientNet-B3 model with the updated last layers inserted through layer freezing by fine-tuning and training to solve the problematic classification and detection of brain cancers in MR images. After performing data enhancement and augmentation to images measuring 224 × 224 × 3.

The images were sent into the pre-trained EfficientNet-B3 model, which automatically extracted the features. These characteristics could be color and shape descriptors like edges, circularity, roundness, and compactness. Represents the proposed final layers for the EfficientNet-B3 composed of flattening, dropout, two fully connected (FC) layers, and a sigmoid classifier. We directed the feature sets from the sixth MBConv layer and converted them into a 1D array using a flattened layer. After flattening, it is passed to a dense layer with 128 hidden units. We used rectified linear unit ReLu as an activation function coupled to another dense layer with one neuron representing our provided labels before predicting the results.

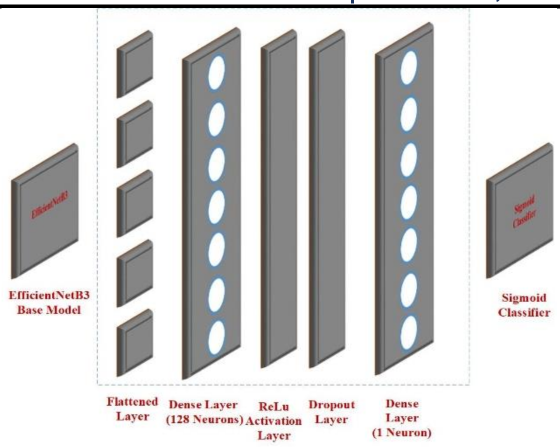


FIGURE2: Schematic Diagram of proposed layer

B. EfficientNet BASELINE MODEL:

EfficientNet is a CNN model developed by the Google Brain Team. These network scaling found that optimizing network depth, width, and resolution can boost performance. To create a new model, scaling a neural network to construct more DL models that yield much higher efficiency and accuracy compared to the previously used CNNs. For the ImageNet, EfficientNet performed large-scale visual recognition with accuracy and consistency. EfficientNet-B3 uses a composite scaling method that creates different models in the convolution neural network family. The number of layers in a network corresponds to the network depth. The convolutional layer width is proportional to the number of filters it contains. The height and width of the input image determine the resolution. The latest EfficientNet-B0 baseline model that accepts a 224 × 224 × 3 input image and scaling the depth, width, and resolution regarding ø.

$$d = \alpha\ \varphi \quad -(1)$$

$$w = \beta\ \varphi \quad -(2)$$

$$r = \gamma\ \varphi \quad - (3)$$

$$\alpha \geq 1,\ \beta \geq 1,\ \gamma \geq 1. \quad -(4)$$

where d, w, and r denote the network's depth, width, and resolution, respectively, and the constant terms α, β, and γ were determined using the grid search hyperparameter tuning technique. The coefficient is a user-defined variable that manages all model scaling resources. This technique adjusts network depth, width and resolution to optimize network accuracy and memory consumption based on available resources. Unlike other deep CNNs, EfficientNet-B0 adjusted each dimension using a predefined set of scaling coefficients, and trained on the ImageNet dataset. Even with the transfer learning technique, EfficientNet produced outstanding results and demonstrated its utility beyond the ImageNet dataset. The model was released with scales ranging from 0 to 7, indicating an increase in the parameter size and accuracy. This work is primarily related to implementing the EfficientNet-B3.

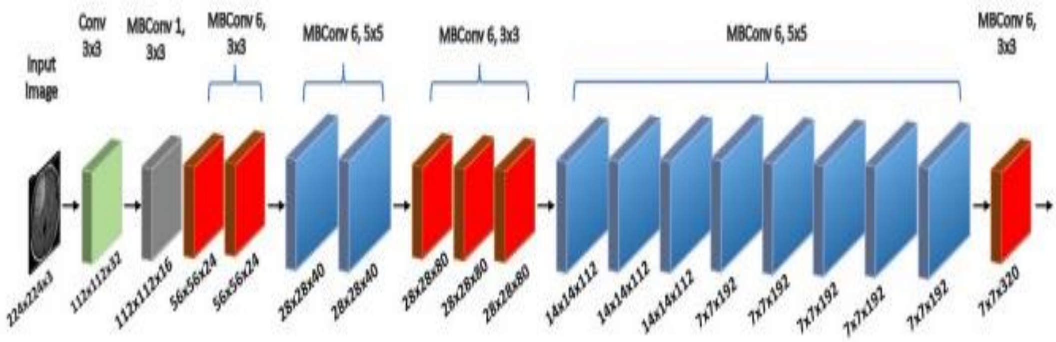


FIGURE3: Baseline EfficientNet model architecture

In this We used sigmoid as selected classifier. Equation .5 shows the mathematical function of a sigmoid classifier with a recognizable S-shaped curve. Sigmoid is a logistic function that performs a binary classification. It assigns values to 0 or 1 by setting up the threshold value of 0.5, where 0 represents non-tumor and 1 represents tumor images. The neuron at the last dense layer represents these classes

$$f(x) = Sigmoid(x) = \frac{1}{1+e^{-x}} \quad -(5)$$

C.FINE TUNING OF NETWORK:

The EfficientNet-B0 base model trained on the ImageNet data consisted of 1000 different classes and over 14 million images. Consequently, the current structure of EfficientNet-B3 could not be employed for our chosen task, and thus, fine-tuning was required. We then froze all layers of the base model before fine-tuning our proposed end layers with the brain tumor MR image training data. With this method, we were able to keep the feature extraction capability in the weights obtained by training with the ImageNet dataset within the extraction layers and prevent them from being overridden during the training iterations. After training both the classifier and our recommended layers, we unfroze the complete layers of our network with weights obtained from the brain tumor MR image dataset and the ImageNet dataset weights to combine and construct our final model. Next, we used our test data to validate the final model.

D. HYPERPARAMETERS AND LOSS FUNCTION:

The fundamental goal of a Deep Learning (DL) model is to achieve the absolute lowest rate of errors, considering that a model with a lower computed loss is more efficient.

We used cross-entropy (CE) to obtain the average measure of the difference between the expected and predicted values. The loss measurement for the binary classification is shown in Equation 6.

$$CE = -(y \log(p) + (1 - y) \log (1 - p)) \quad - (6)$$

IF y=1 then CE=-(1xlog(p))

IF y=0 then CE=-(0log(p)+1log(1-p))

where y represents binary values of 0 or 1, and p represents the probability.

Therefore, if probability is high the loss will be low, if probability is low the value of error will be high (bigger negative value).

E. DETAILED ARCHITECTURE OF PROPOSED MODEL:

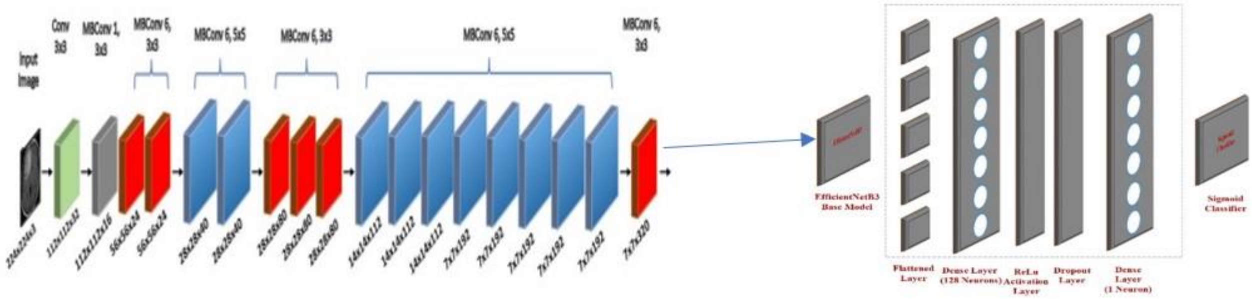
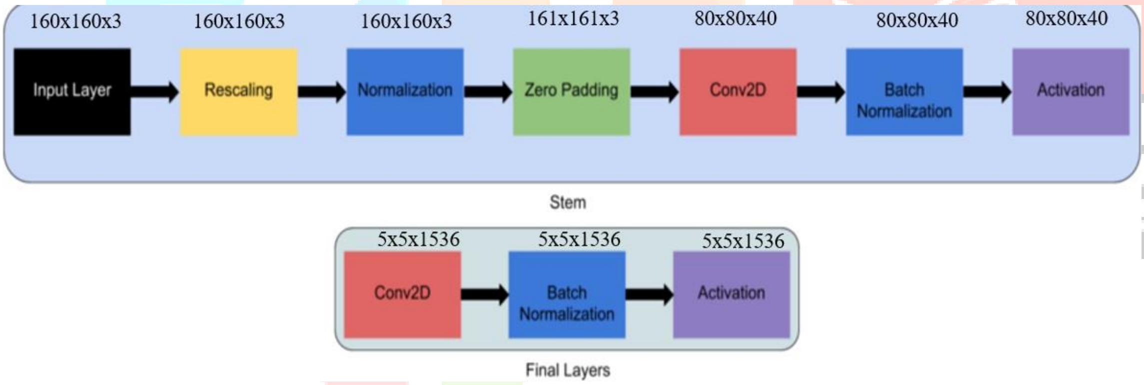


FIGURE4: Finetuned EfficientNet-B3

F. PROPOSED MODEL EfficientNet -B3:



G. EFFICIENTNET -B3:

1.Input layer: In input layer the images are taken as the input.

2.Reshape: In this block firstly most of the convolutional neural networks (CNN) are designed in a way that only accept images of fixed size. After reshaping the input images can fed into the networks.

3.Normalization: Normalization can help training of our neural networks as the different features are on a similar scale.

4.Zero padding: In convolutional neural networks, zero-padding refers to surrounding a matrix with zeroes. This can help preserve features that exist at the edges of the original matrix and control the size of the output feature map.

5.Conv2D: A filter or a kernel in a conv2D layer "slides" over the 2D input data, performing an elementwise multiplication. As a result, it will be summing up the results into a single output pixel.

6.Batch normalization: This allows every layer of the network to learn more independently and it is use to normalize the output of the previous layer.

It is inserted between a hidden layer and next hidden layer it normalizes the output of first hidden layer before sending to the next layer.

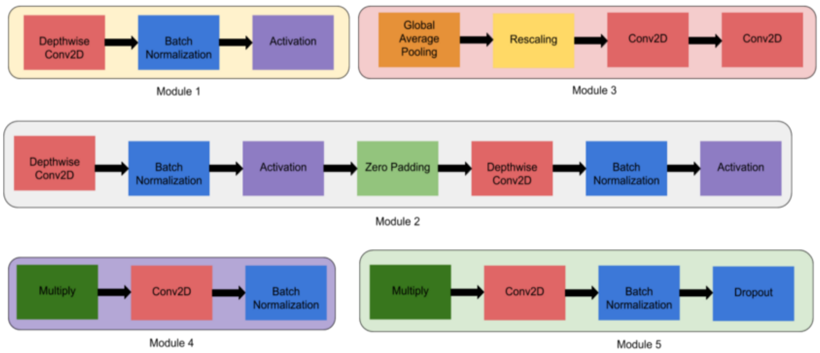


FIGURE6: Represents the overview of EfficientNet-B3 with 5 modules

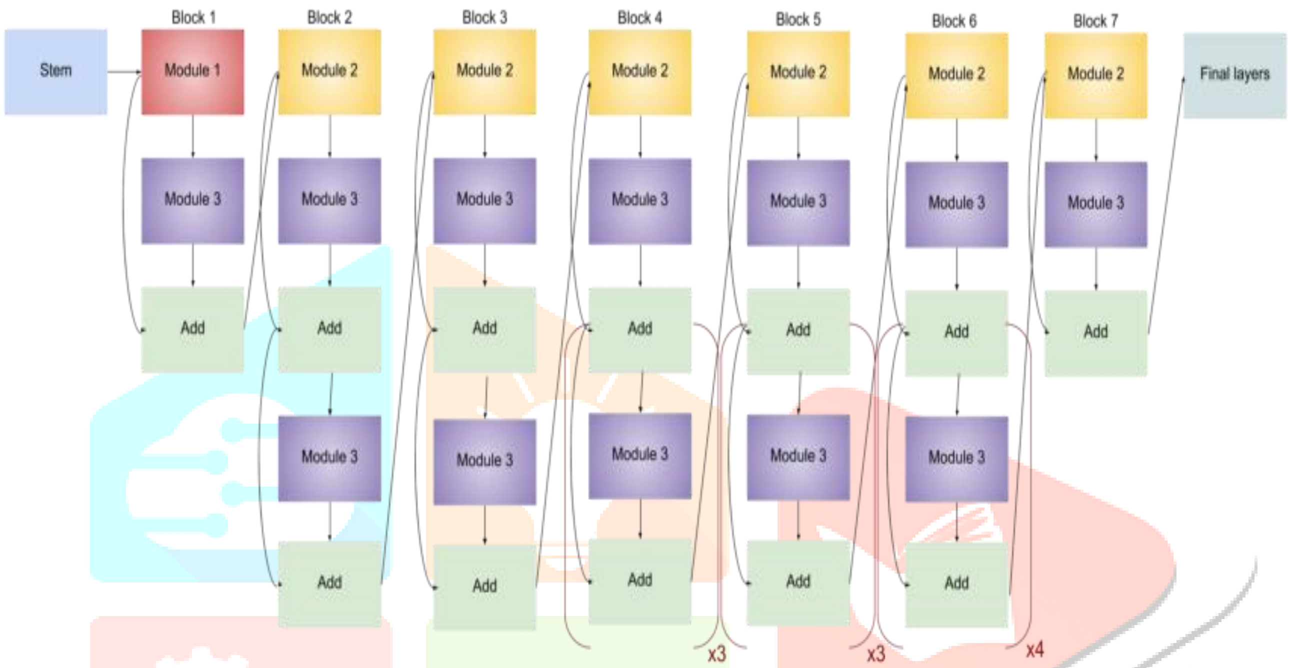


FIGURE7: shows Total Blocks with Modules

- **Module 1** — This is used as a starting point for the sub-blocks.
- **Module 2** — This is used as a starting point for the first sub-block of all the 7 main blocks except the 1st one.
- **Module 3** — This is connected as a skip connection to all the sub-blocks.
- **Module 4** — This is used for combining the skip connection in the first sub-blocks.
- **Module 5**— Each sub-block is connected to its previous sub-block in a skip connection, and they are combined using this Module.

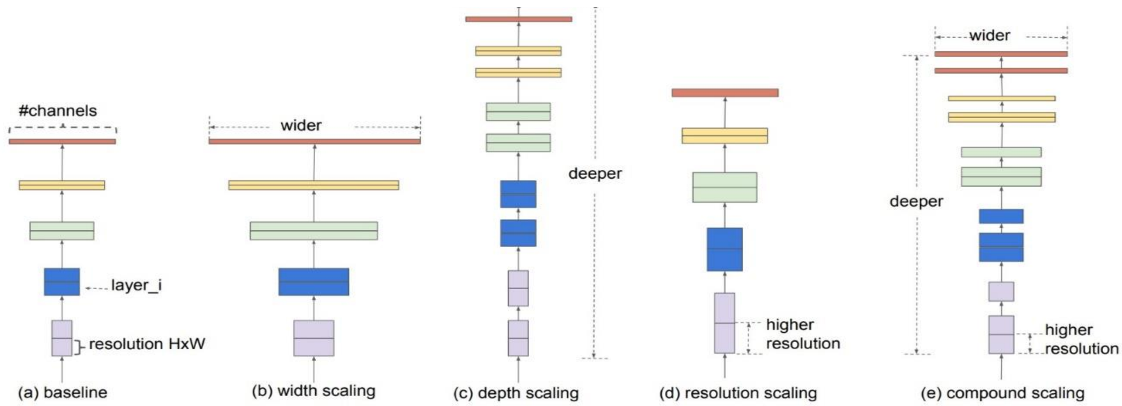


FIGURE8: EfficientNet-B3 Model scaling for CNN

Model scaling (a) is a baseline network example;(b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution (e) Proposed compound scaling method uniformly scales all the three dimensions with a fixed ratio.
There are three scaling dimensions of a CNN: Depth, width, Resolution.

Depth simply means how deep the networks is which is equivalent to the number of layers in it.
Width simply means how wide the network is. One measure of width, for example, is the number of channels in a Conv layer.
Resolution is simply the image resolution that is being passed to a CNN.

Depth Scaling (d):
Scaling a network by depth is the most common way of scaling. Depth can be scaled up as well as scaled down by adding/removing layers respectively. For example, ResNets can be scaled up from ResNet-50 to ResNet-200 as well as they can be scaled down from ResNet-50 to ResNet-18. Easier said than done! Theoretically, with more layers, the network performance should improve but practically it doesn't follow. Vanishing gradients is one of the most common problems that arises as we go deep. Even if you avoid the gradients to vanish, as well as use some techniques to make the training smooth, adding more layers doesn't always help. For example, ResNet-1000 has similar accuracy as ResNet-101.
Width Scaling (w):
This is commonly used when we want to keep our model small. Wider networks tend to be able to capture more fine-grained features. Also, smaller models are easier to train. The problem is that even though you can make your network extremely wide, with shallow models (less deep but wider) accuracy saturates quickly with larger width.
Resolution (r):
Intuitively, we can say that in a high-resolution image, the features are more fine-grained and hence high-res images should work better. This is also one of the reasons that in complex tasks, like Object detection, we use image resolutions like 300x300, or 512x512, or 600x600. But this doesn't scale linearly. The accuracy gain diminishes very quickly. For example, increasing resolution from 500x500 to 560x560 doesn't yield significant improvements.

H. PERFORMANCE EVALUATION METRICS:

$$Precision = \frac{TP}{TP+FP} \qquad (1)$$

$$Recall = \frac{TP}{TP+FN} \qquad (2)$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \qquad (3)$$

$$Accuracy = \frac{TP+TN}{TP+FP+FN+FP} \qquad (4)$$

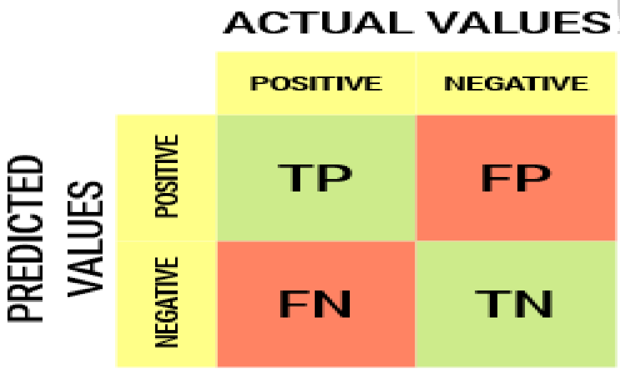


FIGURE9:Predicted values vs Actual values

1.**TRUE POSITIVE(TP):** True positives are the cases when the actual class of the datapoint was 1(True)and the predicted is also 1(True).
2.**TRUE NEGATIVE(TN):** True negatives are the cases when the actual class of the datapoint was 0(False)and the predicted is also 0(False).
3.**FALSE POSITIVES(FP):** False positives are the cases when the actual class of the datapoint was 0(False)and the predicted is also 1(True).
4.**FALSE NEGATIVE(FN):** False negatives are the cases when the actual class of the datapoint was 1(True)and the predicted is also 0(False).

I.EXPERIMENTAL RESULTS AND ANALYSIS

A. EXISTING MODEL RESULTS:

This section discusses the results generated during the training and the validation of the proposed fine-tuned EfficientNet-B3 model trained on the MR images taken from open access from Kaggle. 3

Several preprocessing and data augmentation techniques were applied to enhance this particular dataset's quality and size. For better training, we used a variety of hyperparameters to train our proposed model. We used Adam optimizer batch size of 32, and CE loss function. A sigmoid classifier was employed as our final selected classifier. Meanwhile, the Keras API with a backend TensorFlow was used to train our fine-tuned EfficientNet architecture. The proposed model was trained to use 80% data for training and 20% for validation. Figure represents the training results and validation results curves with training epochs. For the proposed model, the graph illustrates that the accuracy of the validation and training sets steadily grew in a shorter period with the given hyperparameters as the number of epochs increased until it reached a point of stability.

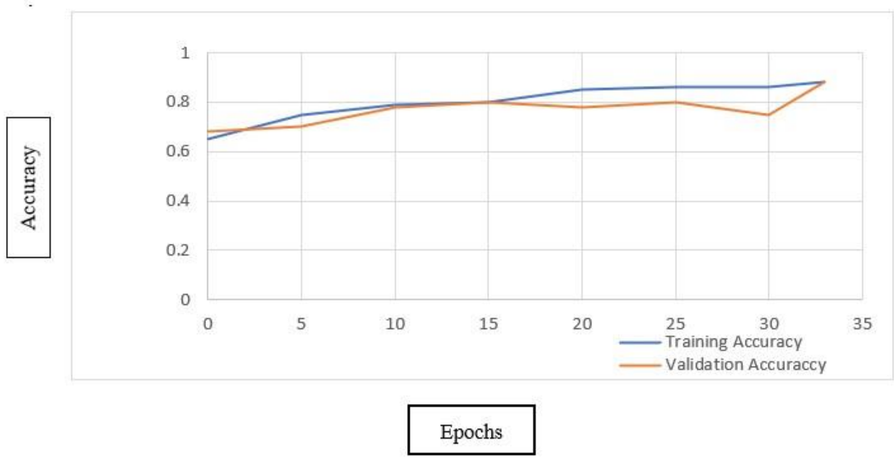


FIGURE10: Shows the graph between Accuracy vs Epochs for Existing model Before Finetuning

J. RESULTS OF PROPOSED MODEL:

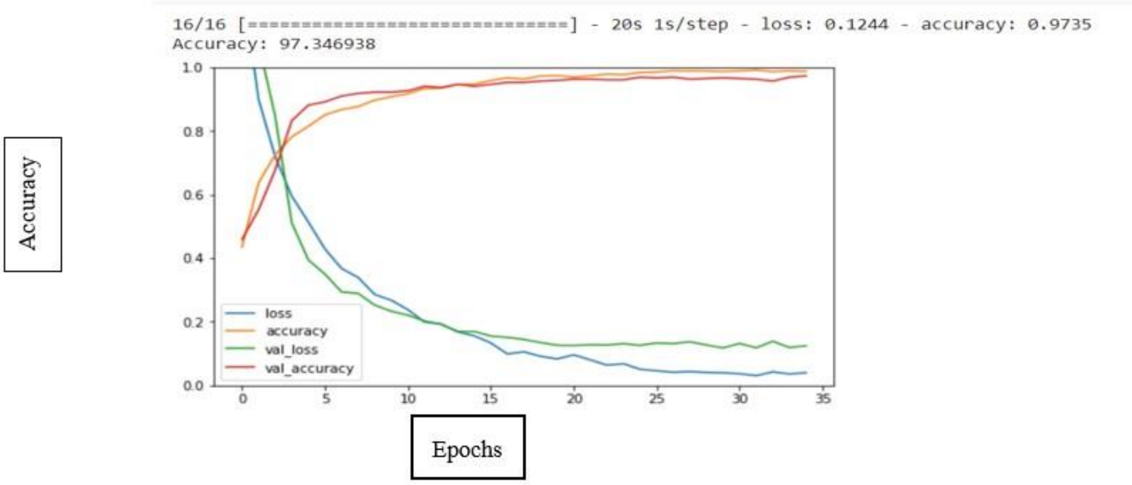


FIGURE11: Shows the graph Between Accuracy vs Epochs for Proposed model After Finetuning

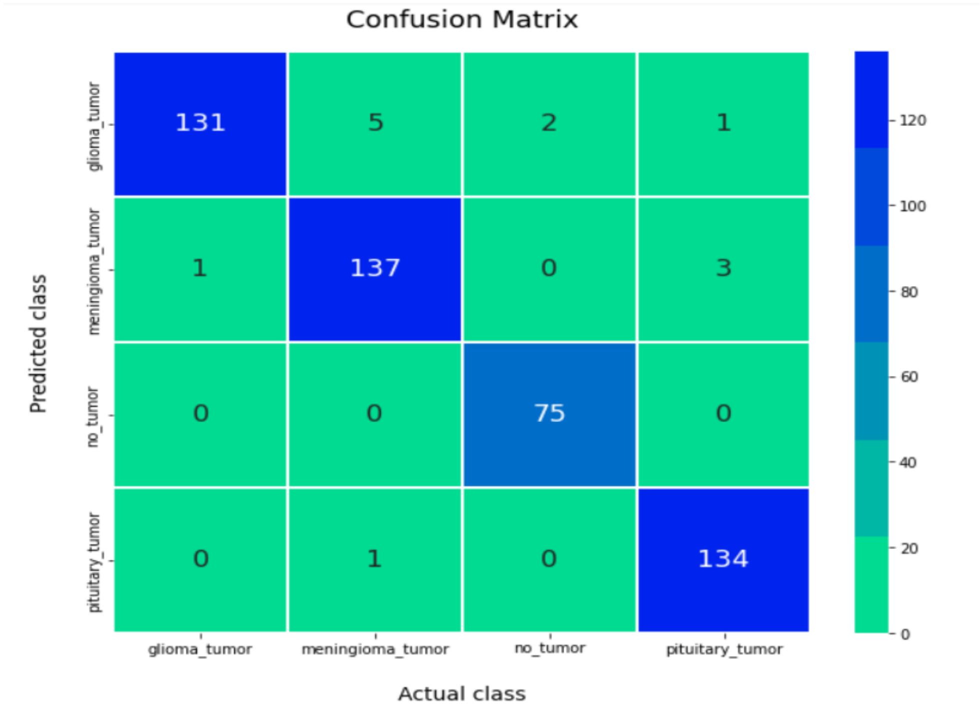


FIGURE12: Confusion matrix of the proposed EfficientNet-B3

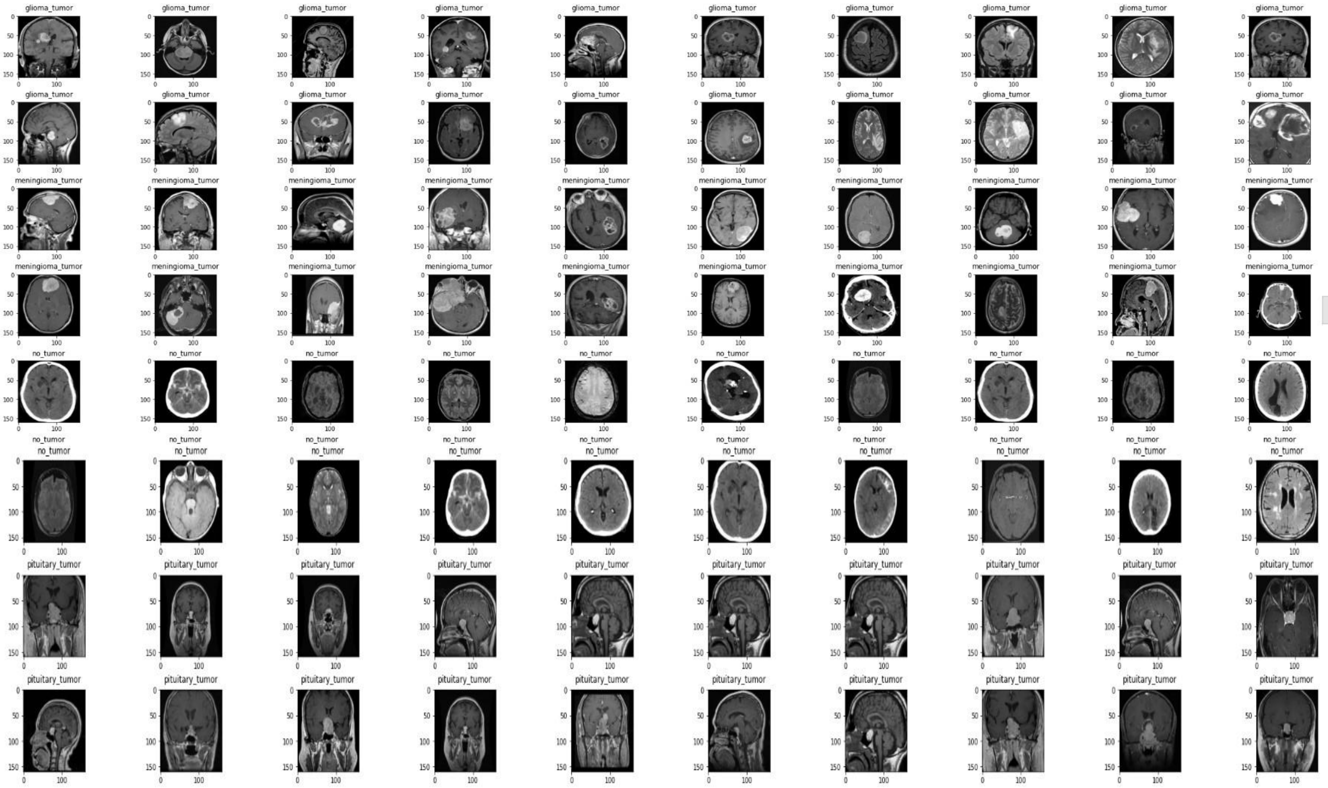
K. COMPARISON OF THE PERFORMANCES OF THE PROPOSED MODEL AND EXISTING MODEL.

Models	Glioma (%)			Meningioma (%)			Pituitary (%)			Accuracy%
	Precision%	Recall%	F1 Score%	Precision%	Recall %	F1 Score%	Precision%	Recall%	F1 Score%	
Existing Efficient Net-B3 Without Fine Tuning	96	91	93	79	84	82	88	88	88	88
Proposed EfficientNet-B3 With Fine Tuning	99	94	97	96	97	96	97	99	98	97.34

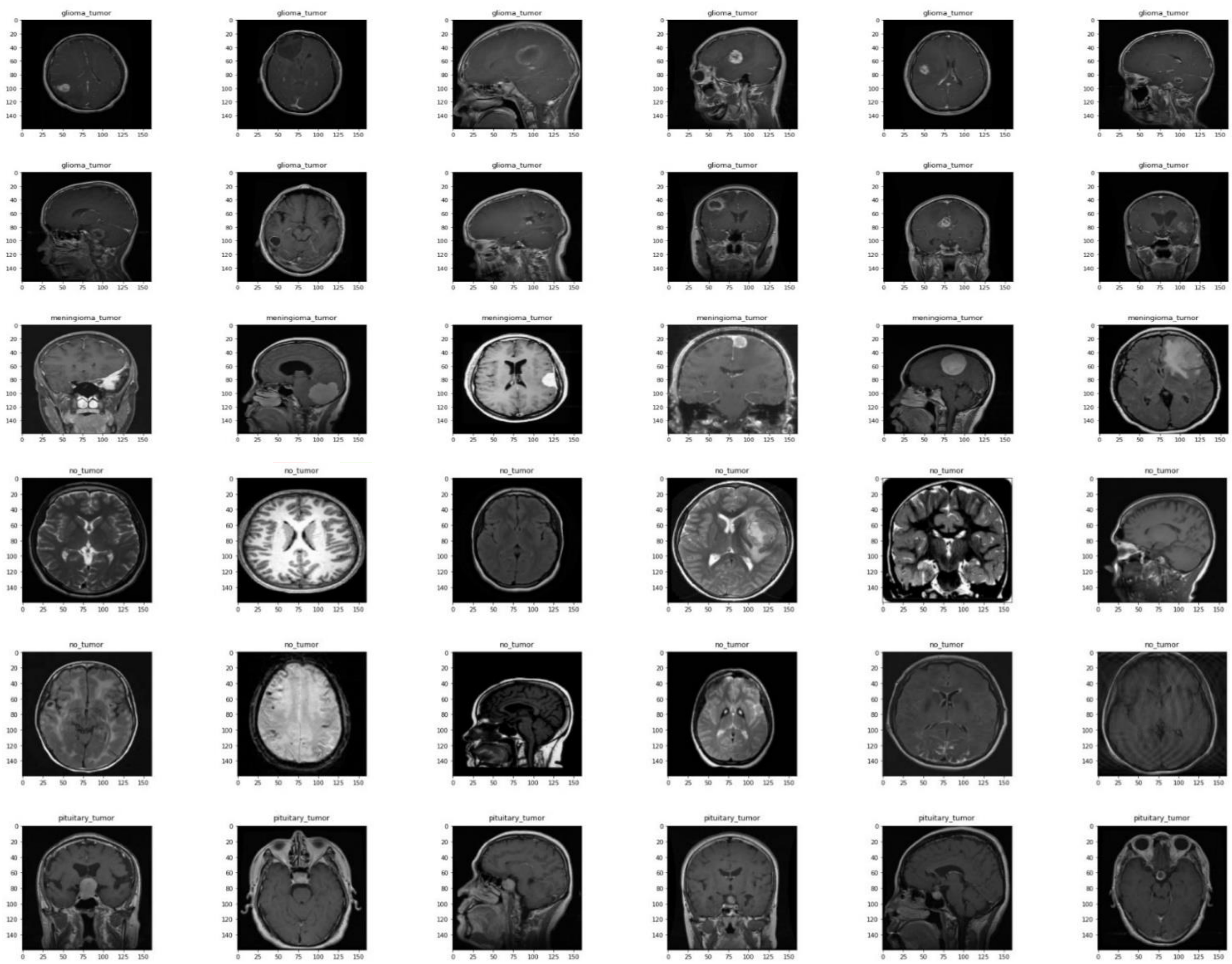
L.PRACTICAL VALUES:

```
                  precision    recall  f1-score   support

    glioma_tumor       0.99      0.94      0.97       139
meningioma_tumor       0.96      0.97      0.96       141
        no_tumor       0.97      1.00      0.99        75
 pituitary_tumor       0.97      0.99      0.98       135

        accuracy                           0.97       490
```

Plot of some MRI images in the dataset



36 TEST DATASET IMAGES AND THEIR OWN PREDICTED CLASS:



CONCLUSION AND FUTURE WORK:

MR imaging for the detection of brain tumor research has gained significant popularity because of the rising requirement for a practical and accurate evaluation of vast amounts of medical data. Brain tumors are a deadly disease, and manual detection is time-consuming and dependent on the expertise of doctors. An automatic diagnostic system will be required to detect abnormalities in MRI images. Therefore, this study developed an efficient, fine-tuned EfficientNet-B3 based transfer learning architecture to identify brain cancers from MRI scans. The proposed technique achieved the maximum performance in brain tumor detection, with 97.34% validation accuracy. Although this study focused on five other convolutional models and transfer learning designs for brain tumors in the medical imaging field, further research is needed. We will investigate more significant and influential deep CNN models for brain tumor classification and conduct segmentation with reduced time complexity in future approaches. Also, to improve the accuracy of the proposed model, we will increase the number of MRI scans in the dataset used for this study. Furthermore, we will also be applying the proposed approach to other medical images such as x-ray, computed tomography (CT), and ultrasound which may serve as a foundation for future research.

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