

Brain Tumors Detection by using Fine-tuned Deep Learning Model

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Abstract— The second reason for deaths in the world other than Cardiovascular diseases is cancer. In the world, the sixth death happens due to this reason. A mass of tissues is formed when a group of abnormal cells combine together, which is commonly known as a tumor. The tumors can be categorized into three types that are Cancerous, Non-cancerous, and Pre-cancerous. The most effective and painless technique used is MRI scans which are Magnetic Resonance Imaging. Just looking at the images and then trying to predict the type of tumor is a tough job and if done manually can have chances of human error. Recent advancements in technologies have enabled the utilization of these methods for detecting tumors present in the brain. In this study, we propose fine-tuning a MobileNet base model with Machine Learning, CNN, Deep-Learning, Image processing, Brain tumor, MRI imaging additional The precision and accuracy of the model were enhanced by restructuring its layers. The quality of MRI images was improved using pre-processing techniques, while data augmentation increased the size of the dataset and improved the model's training. The study shows that the proposed model outperforms other models, demonstrating the potential of deep learning in detecting brain tumors. Our model outperforms other CNN models, including VGG16, Xception, ResNet50, and others, as indicated by the results.

Keywords— Machine Learning, CNN, Deep-Learning, Image processing, Brain tumor, MRI imaging, etc.

I. INTRODUCTION

The deadliest disease present in the world is Cancer. People of all age groups are liable for cancer. Cancer is a disease that can affect our whole body hence disturbing the natural cycle of cell growth in the body. The prime part of our body is our Brain which weighs approximately 1.2-1.5kg. The command center of our body is the brain and any dysfunctionality which happens to the brain results in life-threatening problems for an individual. Tumor present in the brain is one of the most serious diseases when compared to other illnesses is considered to be the focus. The rate of survival is inversely related to the detection of the tumor. The likelihood of a person's survival increases when analyzed early, while a delayed diagnosis may decrease the chances of survival and even lead to death. There are several methods to detect cancer, which include but are not limited to taking tissue samples, blood tests, and X-rays, CT scans, and MRI scans are various types of imaging scans.

Tumors can be classified into three types, namely Cancerous, Non-cancerous, and Pre-cancerous. Cancerous tumors, also referred to as Malignant tumors, can be life-threatening if they grow continuously and spread to other parts of the body. Non-cancerous tumors are also called Benign tumors these are restricted to a part of an organ and don't spread to other parts of bodies and it is less harmful to the life of a person. The pre-cancerous tumor is the starting phase of the tumor and if treated on time can save the life of the person. The prominent indications of this disease are strong headaches, loss of vision, and loss of balance but in some cases, there can be no indications. The International Association of Cancer Registries (IARC) reports that over 24,000 individuals die from brain tumors each year, while 30,000 to 40,000 are diagnosed with this condition annually. The survival rate for brain tumor patients is only thirty six percent. The expected annual growth rate of brain tumor compounded is 1.11 percent till 2030.

Many ways can be used to cure brain tumors. The approach selected for treating brain tumors is based on several factors, including the tumor's size and shape. Detecting the tumor present in the brain in its early stages can be difficult, making it challenging to diagnose. Sophisticated medical imaging techniques have been effective in the healthcare industry and are frequently employed to identify tumors present in the brain. Various techniques, such as CT scans, MRI scans, X-rays, etc., are widely used for this purpose. But the above-mentioned techniques are very lengthy and time-consuming as there is a lot of human work put into them. Therefore, the utilization of Computer-aided diagnosis (CAD) can provide significant advantages in the early detection of tumors, ultimately enhancing the likelihood of the patient's survival.

At present, there are several supervised and unsupervised techniques present which are automated systems. Deep learning and machine learning technologies have proved to be a boon to the medical industry to detect the early tumor at very efficient cost and time. CNN is prominently used in these CAD systems. Convolutional Neural Networks are bundles of three different layers that are convolution layer, the pooling layer, and the fully connected layer. The characteristics are obtained by the

convolutional layer, but a large amount of training data is necessary for precise training of the system and accurate identification of test data. But getting medical data is a tedious task as the information is critical about the patients and cannot be shared openly with everyone. So there is a need of developing a precise model so that the tumor can be detected earlier resulting in saving the lives of many patients. The key contributions of our proposed study are:

To detect brain tumors and improve the system's accuracy, a new approach was employed, which involves fine-tuning the MobileNet base model. The dataset undergoes pre-processing to enhance image quality, resulting in improved precision. To address the over-fitting issue, the subsequent step involves data augmentation to increase the dataset. The outcomes of this model were evaluated on a collection of 3000 images. The proposed system is evaluated by comparing it with various existing models based on multiple metrics, including accuracy, precision, and more.

II. RELATED WORK

The use of convolution neural network has gained prominence in the field of medical image processing for detection of tumor present in the brain and has yielded positive outcomes. The author in [1] has used fine-tuned GoogleNet and has learned the features through it. In their proposed work the characteristics obtained are used in two dissimilar classifiers that are SVM and KNN. The approach utilized involves a fully connected neural network model established on CNN [2]. The paper employed a fully connected convolutional neural network (CNN) model. The base model used for transfer learning was ResNet50, from which the last five layers were removed and replaced with an additional ten layers. Through this approach, the model achieved an accuracy of 97.01% [3]. Different transfer learning models including VGG16, ResNet50, and GoogleNet were utilized to enhance the perfection of the models within a reduced number of epochs [4]. A.Rehman[5] with fellow authors has proposed a fine-tuned VGG16 model with various pre-processing techniques. They have studied three transfer learning models that are GoogleNet, VGGNet, and AlexNet. One of the findings of the study was that the VGG16 model, after being fine-tuned, achieved the highest accuracy of 98.69%. S.Tafwida and their co-authors have utilized various CNN architectures in their proposed system, which were then compared with five architectures established on CNN. The CNN model obtained perfection of 98.51%. In this paper, the author has fine-tuned EfficientNet-B0 which gives better performance than other CNN networks and pre-trained models. The author has compared the results with other models that are VGG16, Inceptionv3, ResNet50, etc[7].

The paper by M.A.Ansari[8] and his colleagues have fine-tuned several machine learning models including AlexNet, GoogLeNet, SqueezeNet, ResNet50, and ResNet101, and found that AlexNet achieved the highest accuracy. The paper by Zahid Ullah [9] shows that the model was made by using ensemble learning. The study employed three transfer learning models: DenseNet-169, Inception V3, and ResNeXt-50. The maximum accuracy that was obtained with DenseNet-169 with SVM(RGB) is 93.72%. The proposed system utilizes a seventeen-layer convolutional neural network for feature extraction, producing a count of 4096 extracted features. These features are then fed through four different classifiers. Among these classifiers, the greatest perfection was achieved with SVM, which reached 95.46% [10]. In this research, VGG19 was used and then additional layers are added to increase the accuracy. The accuracy obtained here is 98.32% [11]. The pre-processing techniques are applied to the dataset as it is cropped before training the model. The models established on CNN architecture are used in this study and InceptionResNetv2, extract features from the images, which are then passed through additional layers for classification.

The highest accuracy was achieved with Xception, according to the study [12]. The model here is a CNN architecture with training parameters of about three million[14]. This research paper utilized ResNet34, which had around nine thousand four hundred parameters, and a dense layer with one thousand twenty six parameters[15]. Here in this paper, we can see that they have implemented two CNN blocks and used the k-fold method for training. The highest accuracy obtained for this method is 96.56% [17]. The CapsNet architecture was utilized in this paper, where the initial two convolution layers consisted of 5x5 filters and 64 feature maps, and were trailed by two dense layers containing eight hundred neurons. The last layer contained a softmax function for image classification, with the highest accuracy being 90.89% [18]. The proposed system tells us that it uses pre-processing techniques such as Median filtering and Contrast enhancement. Then Adaptive fuzzy network is used with CNN to classify the images[20]. The paper reports the use of an ANN with the Adam optimizer and binary cross-entropy as the loss function. The achieved perfection in this study was 97% [22].

III. PROPOSED METHODOLOGY

Diagnosis of a tumor present in brain when done at an early stage can prove useful to doctors to decide the appropriate method to treat the tumor efficiently. Detecting a brain tumor manually by just having a glance at the MRI images is a tough job and requires a bit of expertise. This paper proposes an automated model that can accurately detect brain tumors with minimal manual intervention. The proposed methodology is depicted in Fig 1.

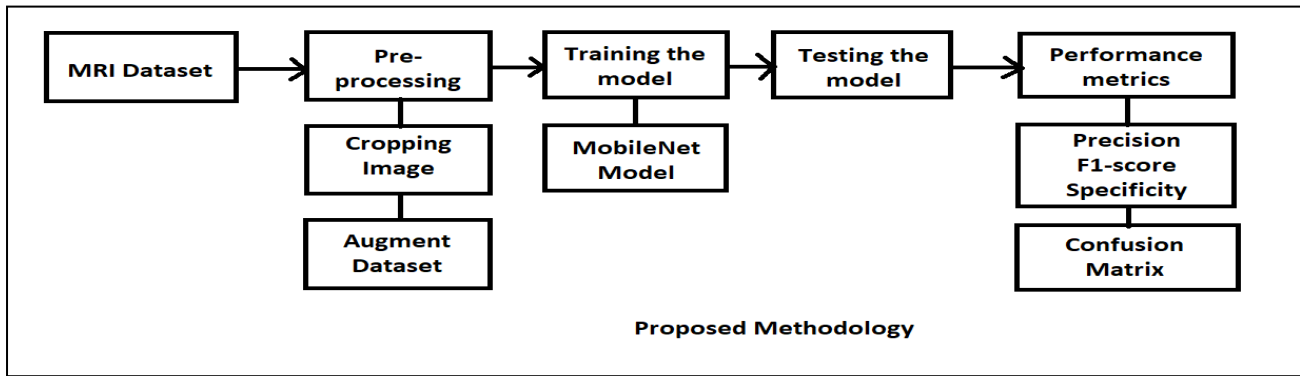


Fig. 1 Proposed Methodology

The images in the dataset are pre-processing by using some filters which are applied to the image and then the dataset is augmented. The fine-tuned MobileNet is used and the model is instructed. Then the trails are carried out on the model. The model is then evaluated on the basis of Precision, F1-score, etc.

A. MobileNet Model

MobileNet is a Convolutional Neural Network developed by Google Engineers in 2017. It is a streamline architecture. Depth-wise separable convolutions are used to construct lightweight deep CNN. The basic unit of this architecture is a dense block. It has reduced parameters and computation. Each dense block in this network contains four densely connected layers and it has growth rate of 4. The MobileNet architecture has 27 layers with total parameters of 4.2 million. 224x224x3 is the size of the input layer. It has softmax as the classifier. There are thirteen convolution layers , an individual average pooling layer and a single softmax layer.

The composition of depthwise separable layers includes two layers: depthwise convolution and pointwise convolution. When each input that is mapped separately then it is a depthwise operation. The output and input channels are same. The purpose of the pointwise convolution, which has a kernel size of 1x1, is to merge the features obtained from the depthwise convolution. In depthwise convolution uses a kernel of size KxKx1 where k depends on the input image. If X defines channel in input image then output size will be KxKxX. In pointwise operation 1x1 filter is applied to the X channels which we have got in depthwise convolution.

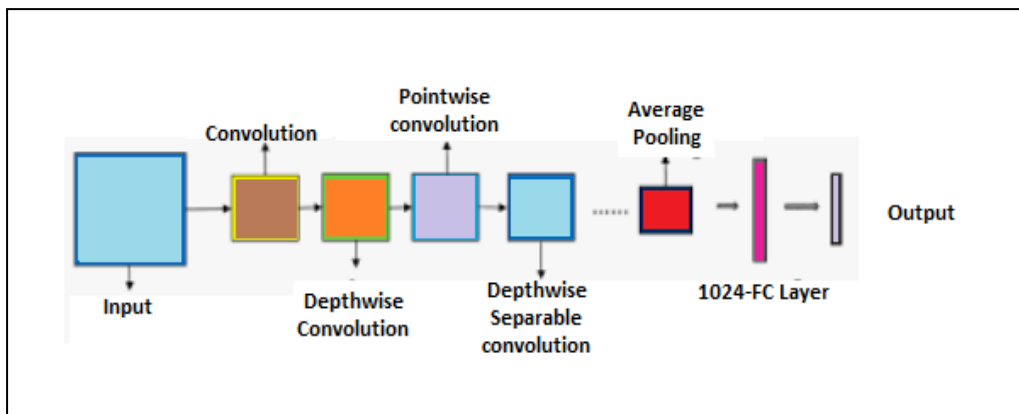


Fig. 2 Layered architecture of MobileNet

The accuracy of imagenet accuracy on this model is 70.6%. MobileNet outperforms other models in number of parameters, accuracy, etc.

B. MobileNet Model

We implement a MobileNet architecture with additional layers that are added at the last by freezing the layers and by fine-tuning them. This model is trained to solve the problem of detecting tumors present in the brain through MRI images. The dataset of images undergoes pre-processing procedures and techniques for data augmentation, and is resized to 224x224x3 before being used to train the model and obtain its characteristics. For the task of classification, the first layer that we have added is an

average pooling followed by batch normalization. The output from this is then passed through a dense layer containing 2048 neurons trailed by an average pooling layer and batch normalization.

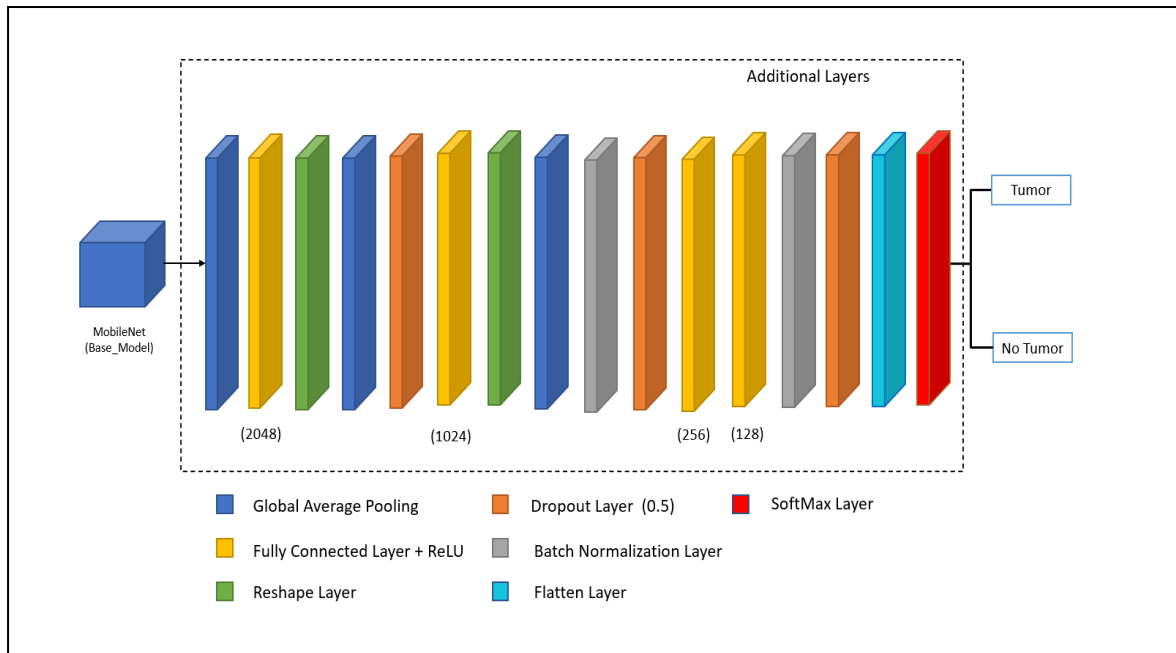


Fig. 3 Layered architecture of Proposed System

Again this output is passed through a dense layer of 1024 neurons and it is trailed by an average pooling layer. Then the result of this is passed through Batch normalization followed by a dropout of 0.5. Then we use two dense connected layers of 256 and 128 neurons respectively. Then we use a dropout of 0.5 to flatten the output and then is passed through the softmax layer. The Softmax function is computed as Here the denominator of the softmax function is a normalization term.

C. Transfer Learning and Fine-tuning

In this section, we describe the training process of our model. We utilized the Keras framework to import a pre-trained model named MobileNet that has been previously trained on the Imagenet dataset. These weights are used by the model to train out the training dataset. This helps our model to learn our dataset efficiently and thus improves our accuracy of the model. Here to train our dataset we have frozen the layers of our model before fine-tuning the model. By doing this we have kept the weights that the model has learned from the ImageNet dataset. This keeps The model's feature extraction capability more efficiently. After this step, we add the proposed layers to the model. At last, we train the model on the dataset and test it after the training.

$$S(y)_i = \frac{\exp(y_i)}{\sum_{j=1}^n \exp(y_j)}$$

Where y - Input Vector

y_i - It is the ith element of input vector

n - total number of classes

D. Hyperparameters and Loss Function

While training the model we use hyperparameters and loss functions so that our perfection of the model is amplified. The perfection of any architecture does not only depend on the accuracy that it gets after training but is also dependent on the losses that occur during the training of the model. Here the losses are defined as the information that is lost between the layers which could not be carried forward by the layer for learning. If we decrease this loss by applying the appropriate loss function this would hence improve the performance thus leading to amplified perfection of the model on the testing dataset.

In this model, we utilized binary-cross entropy as the loss function, which is generally employed for binary classification problems. It gauges the dissimilarity between the predicted and actual probability distributions. The loss is calculated by taking the negative mean of all the correctly predicted probabilities. The formula for binary cross entropy is

$$\text{Log loss} = \frac{1}{N} \sum_{i=1}^N -(y_i * \log(p_i) + (1-y_i) * \log(1-p_i))$$

Here,

- pi – Probability of class 1.
- (1-pi) – Probability of class 0.

We have used Adam as the optimizer in our model. It is an optimizer algorithm used for gradient-based optimization. A combination of the other two optimizers makes the Adam optimizer. The two optimizers are AdaGrad and RMSProp. The Adam is an abbreviation for Adaptive moment estimation. This approach involves computing personalized learning rates for each model parameter, and is achieved by using an exponential moving average of previous gradients, therefore, helping to make adjustments in the learning rate. It is an efficient algorithm as it uses optimal memory to compute calculations. The formula for the Adam optimizer is

$$w_{t+1} = w_t - \alpha m_t$$

Here,

w_t - weight at time t

α - learning rate at time t

m_t – gradient’s aggregate at time t

m_t is calculated as follows

$$m_t = \beta m_{t-1} + (1 - \beta) \left[\frac{\delta L}{\delta w_t} \right]$$

Here,

β – parameter of moving average

δL – loss functions derivative

δw_t - derivative of time t weights

IV. IMPLEMENTATION DETAILS

A. Dataset Details

The BR35H dataset comprises 3000 MRI images classified into two categories: Yes, indicating the presence of a brain tumor, and No, indicating the absence of a brain tumor. The dataset is divided into three separate subsets for training, validation, and testing. The training and testing subsets are divided into 80% and 20% portions, respectively. Additionally, the training subset is further split into a training set and a validation set, with ratios of 90% and 10%, respectively. The resulting number of images in each subset for both Yes and No classes are 1080 for training, 300 for validation, and 120 for testing.

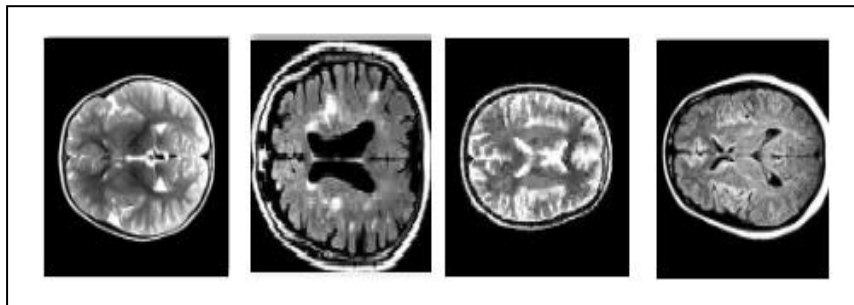


Fig. 4 Normal Brain MRI images in BR35H dataset

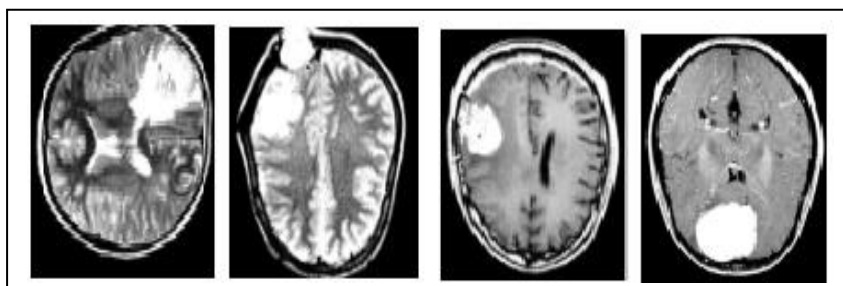


Fig. 5 Infected Brain MRI images in BR35H dataset

B. Data Pre-processing and Augmentation

Pre-processing techniques for image data enable the transformation of images into a format that can be easily comprehended by the model, enabling efficient extraction of features. This results in improved model performance and accurate classification of the images. The images comprised in the dataset have ununiform size and shape. In the first step we resize the image into 224x224. As it is the input size for the MobileNet architecture. After this many filters are applied to the dataset. The filters applied are greyscale and Gaussian filter. The color image is converted into greyscale by applying the grey filter. Then the Gaussian filter is added to the picture and the filter makes the image blurred. And after this we apply thresholding to the image so that we can find the maximum contour. The maximum contour then is detected and then it is cropped so that only the focused region can be sent to the model for training.

TABLE I
REAL AND PREDICTED CLASS MATRIX

Predicted Class		Class 0	Class 1
Real	Class 0	Tp	Fp
	Class 1	Fn	Tn

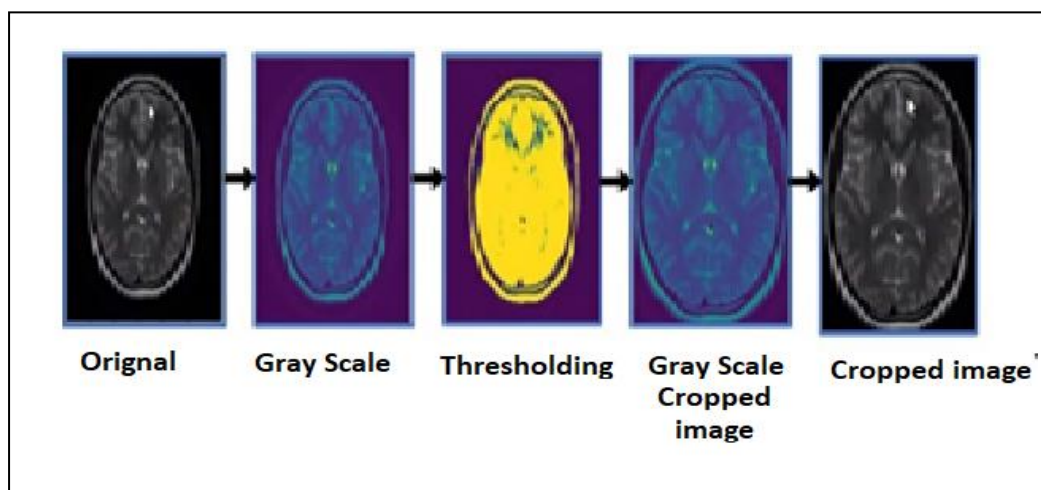


Fig. 6 Pre processed MRI images

Data augmentation is a technique used to expand the brain tumor dataset, which is often limited due to the restricted availability of medical information on patients. So to train the model efficiently and increase its performance we need to perform this crucial step of data augmentation. The techniques that we have used in data augmentation are rotation range that was 40, width and height shift, shear range and zoom range of 0.2 and at last we have used horizontal and vertical flip to the image thus having copies of the original image that expands the dataset. The image augmentation was performed by utilizing keras preprocessing library from which we had imported image data generator to generate images. Then these images are sent to the model for training purpose.

C Experimental Set-up

The model which is proposed is deployed on the dataset. The MobileNet model was executed in GoogleColab by using python frameworks such as Keras and tensorflow. The laptop on which the following model is executed has specifications as System of Windows 11 of 64 bits, CPU of AMD Ryzen 5 3550H, GPU of Nvidia GEFORCE GTX 1650, and RAM of 8GB.

D Performance evaluation metrics

Parameters that make work easier to determine the success of our model are called Performance evaluation metrics. One of the most used ways to calculate the perfection of the model is the confusion matrix. The matrix has the following parameters

- 1) tp- True Positive The model predicts it is true and it matches the real class.
- 2) fp- False Positive The model predicts it is true but it does not match the real class.
- 3) fn- False Negative The model predicts it false and it does not match to the class.

4) tn- True Negative The model predicts it false but it is true.

Various performance metrics that are calculated for this model are calculated as followed

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$$

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

$$\text{F1-score} = 2(\text{TP}) / (2(\text{TP}) + \text{FP} + \text{FN})$$

TABLE 2
EVALUATION METRICS

No	Measure	Definition
1.	Accuracy	Steadiness of the model to predict accurate output. It is quantitative relation between number of correct predictions to all predictions.
2.	Precision	The projection by the model is exact and matches the real classes.
3.	Recall	Total positive class how many were correctly categorized by our model.
4.	Specificity	Ability of the model to forecast that the observation doesn't belong to a specific class.

V EXPERIMENTAL RESULTS

In this discussion, we will go over the outcomes obtained from training, validating, and testing the dataset using the fine-tuned MobileNet model. To enhance the image quality and expand the dataset, we employed data pre-processing and augmentation methods, incorporating a range of filters. Additionally, we optimized hyper parameters to train and validate the dataset more effectively. This model uses the Adam optimizer and binary cross-entropy as the loss function. During training, the learning rate was set to 0.0001, with a batch size of 32 and 50 epochs. The graph in fig. 8 depicts the loss and accuracy of the training and validation processes. The model has been trained properly with high validation accuracy and minimal losses. The assessment of the model is done by using a confusion matrix. This matrix is useful in telling us about the mistakes done by the model in classification. Our model was able to classify 591 samples correctly for each class and 9 samples incorrectly for each class.

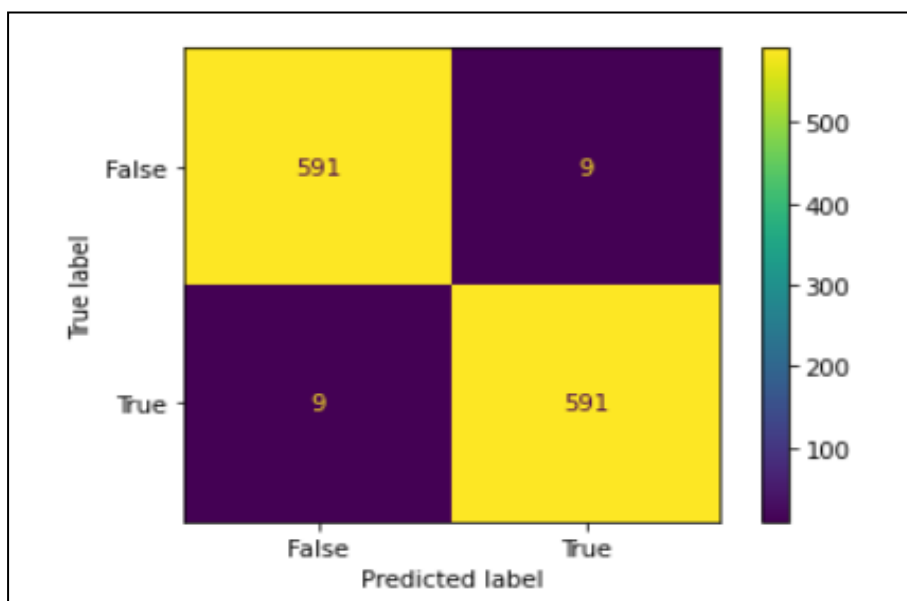


Fig. 7 Confusion Matrix for proposed system

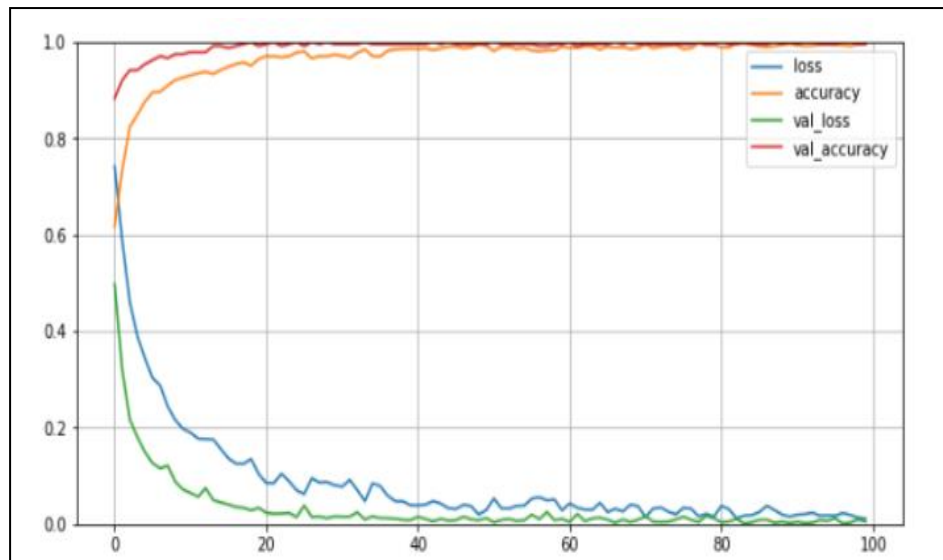


Fig. 8 Loss and accuracy of the training and validation

The bar graph shown below represents the various performance metric such as F1-score is 0.9856, Precision is 0.9826, Recall is 0.985 and recall is 0.015. The images shown in fig. 9 are examples of correctly classified and incorrectly classified samples. If the sample shows the picture of a brain tumor, then it is classified as true. And if it doesn't have an image of a brain tumor then it is shown as false.

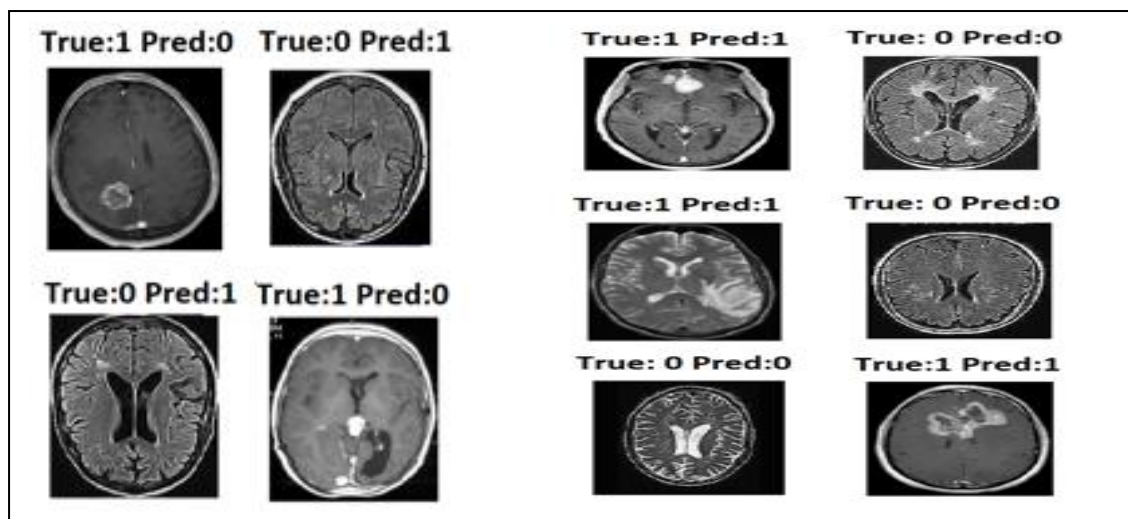


Fig. 9 Accurately and Inaccurately classified MRI Images

The table 3 given below gives us a picture of the various implemented ML and DL models with their accuracies compared to the accuracy of our proposed model. The direct comparison is not done with the other proposed models as the techniques of pre-processing and the training of the model were different as compared to our work. But we can see that our model outperforms them in terms of accuracy. As our work has got excellent accuracy of 98.50%

TABLE 3
COMPARATIVE ANALYSIS

Sr. No.	Previous work	Accuracy	Method use
1.	Bhatele [19]	95.2%	Hybrid Ensemble
2.	Murthy[20]	95%	CNN Ensemble
3.	Kang[9]	98.04%	Dense-Net
4.	Badza[17]	97.39%	Four-Layer CNN
5.	Deepak[1]	97.10%	GoogleNet

VI CONCLUSION

The objective of this research is to identify tumors present in the brain through the use of MRI scans. The implementation and algorithms successfully classify brain tumors by collecting MRI images and processing them into grayscale images. The images undergo additional processing by implementing a Gaussian filter and thresholding technique to identify the most prominent contour. Once the most significant contour is detected, the image is cropped. These images are sent for training and features are extracted to detect the tumor. A test parameter, the complexity matrix, is used to test the precision of the model. The proposed MobileNet model achieves an accuracy of 98.50%. Future research could explore other CNN architectures and hyperparameter tuning, while increasing the MRI image dataset to improve accuracy. The suggested model could also be utilized for other medical images, like CT scans, which provides potential for future exploration.

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