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BRAIN TUMOR DETECTION USING MOBILENET MODEL

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***Abstract*- Brain tumor detection is crucial for early diagnosis and effective treatment planning. Pre-trained deep learning models have shown promising performance in automating the detection process from MRI images. In this research work, a brain tumor detection system is developed to detect whether input brain MRI image has tumor or not. The system uses pre-trained Mobilenet model for binary classification of brain MRI images and a user interface is designed to upload the brain MRI image for tumor detection. The methodology involves acquiring a dataset of brain MRI images, preprocessing the data, training pre-trained Mobilenet model, testing and evaluation of Model. The system performance is evaluated by means of Mobilenet model performance metrics such as accuracy, precision, recall and F1-score. The results demonstrate that proposed Mobilenet- based brain tumor detection system achieves a high accuracy of 95.25 % in detecting brain tumors. This work contributes to the field of medical image analysis by providing an efficient and accurate approach for brain tumor detection, with potential applications in clinical practice and remote healthcare settings.**

***Index Terms*- Mobilenet model, MRI - Magnetic resonance imaging, Binary classification, Preprocessing.**

I. INTRODUCTION

The brain tumors are a significant health concern worldwide, often requiring timely diagnosis and intervention to improve patient outcomes. The accurate and early detection of brain tumors is crucial for effective treatment planning and prognosis. In recent years, deep learning techniques have emerged as powerful tools for automated medical image analysis, offering the potential to enhance the efficiency and accuracy of brain tumor detection. Among various deep learning architectures, MobileNet has gained prominence due to its efficiency in resource-constrained environments. Making it suitable for real-time analysis of medical images using readily available hardware, such as smartphones and tablets. Leveraging the capabilities of Mobile Net for brain tumor detection can potentially enable prompt and accessible diagnoses, particularly in remote or low-resource healthcare settings. In this paper, we present a comprehensive study on brain tumor detection using the Mobile Net model. The objective is to develop a system that combines the computational efficiency of Mobile Net with the accuracy required for effective brain tumor identification. By employing deep learning techniques, it is aimed to address the challenges associated with manual interpretation and the potential for human error in brain tumor detection. Fig 1 shows the block diagram of the system being developed.

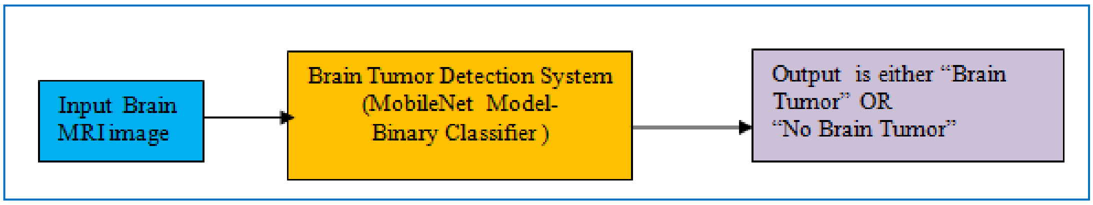

Fig 1: Block diagram of brain tumor detection system

II. LITERATURE SURVEY

Dr. Chinta Someswararao [1], paper titled "Brain Tumor Detection Model from MR Images using Convolutional Neural Network was a combination of CNN model classification problem for predicting whether the subject has brain tumor or not and Computer Vision problem for automate the process of brain cropping from MRI scans. The final accuracy achieved by the author is much higher than 50% baseline (random guess). However, it could further be increased by larger number of train images or through different models and techniques.

Masoumeh Siar and Mohammad Teshnehlab [2], paper titled "Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm" used the combination of feature extraction algorithm and the CNN for tumor detection from brain images is presented. The CNN can detect a tumor. The CNN is very useful for selecting an auto-feature in medical images. Images collected at the centers were labeled by clinicians, then, tumor screenings were categorized into two normal and patient classes.

Devkota et al. [3] established the whole segmentation process based on Mathematical Morphological Operations and spatial FCM algorithm which improves the computation time, but the proposed solution has not been tested up to the evaluation stage and outcomes as- Detects cancer with 92% and classifier has an accuracy of 86.6%.

Khurram Shahzad and Imran Siddique [4], paper titled "Efficient Brain Tumor Detection Using Image Processing Techniques "focused on an easy, fully automatic and efficient algorithm for extraction of brain tumor has been introduced. Morphological operation like erosion and dilation along with morphological gradient and threshold are used. Morphological gradient is used for calculating threshold. Threshold is used to binarize the image which results an image having tumor and some noise with it. Erosion is used for thinning the image as it shrinks the image and helps to reduce noise or unwanted small objects. Dilation is being used after erosion so that to get removed tumor portion back which was being removed by erosion.

III. METHODOLOGY

a) Data acquisition

The dataset used for training and validation was collected from the Kaggle dataset. It contains brain MRI Image is in which some of them are containing tumor (with tumor) and some are normal (without tumor). The tumor images are segregated in the folder name "Brain tumor" and normal images are kept in the folder named as "healthy". In this study thus we have used 3000 Images out of these images 1500 images are with tumor and 1500 images are without tumors. For testing and evaluation model performance 253 images are used. Fig. 2 and Fig. 3 illustrate the sample brain MRI images with and without brain tumors respectively.

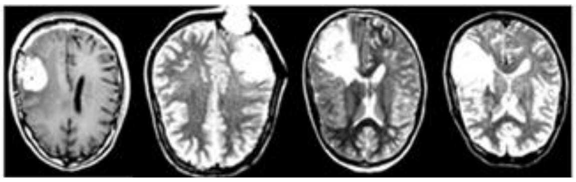

FIG 2. Brain Tumor MRI images from Kaggle Dataset

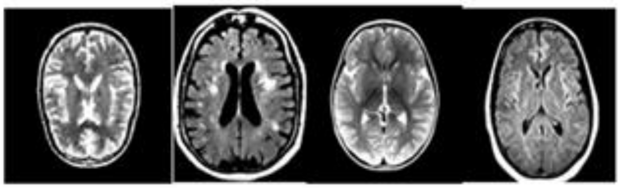

FIG 3. Healthy Brain MRI images from Kaggle Dataset

b) Data pre-processing

For any deep learning project image pre-processing is the first initial step. As mentioned, the dataset which may contain noise leading to errors while classifying between normal and tumor images. So, pre-processing will reduce this problem, pre-processing also includes cropping, shifting etc. This can be achieved by using image data generator method by keras library. All the images may be transformed into NumPy arrays (available in python) so that the model can take up less space. Before splitting the dataset, data is shuffled so that the model can train on unordered data. After shuffling the data, dataset is divided into three sections including train, validation, and test set. Image normalization converts the output pixel value between 0 and 1. The normalization is performed by dividing the image pixels by 255.

c) Model Training and Testing

Transfer learning is a machine learning method that uses previously trained model. The pre-trained MobileNet model is used in the proposed brain tumor detection system. Mobile Net is open sourced by google. Mobile Net uses depth wise separable convolutions to build a light weight deep neural networks and provides an efficient model for classification. This architecture allows the Mobile Net to detect and classify brain tumor efficiently while maintaining a high-level accuracy. The primary difference between the Mobile Net architecture and CNN architecture is the use of a convolution layer or layer with a filter thickness corresponding to the thickness of the input image. MobileNet divides convolution into depth wise convolution and pointwise convolution, as shown in Fig 4. The structure of MobileNet is divided parts into deep separable convolutions except for the first layer, which is a full convolution.

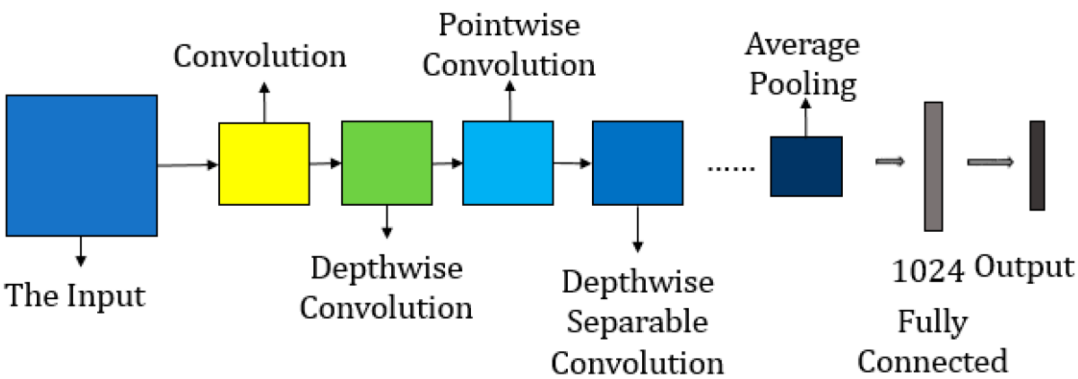

Fig 4. MobileNet Architecture

The flow diagram of proposed work is illustrated in Fig 5. Split the preprocessed dataset into training and validation sets using a predefined split ratio. In this work total of 3000 images are split into train dataset and validation dataset at 3 different split ratios viz 9:1, 8:2 and 7:3. The split ratio 8:2 means that there are 2400 images in train data set and 600 images in validation dataset.

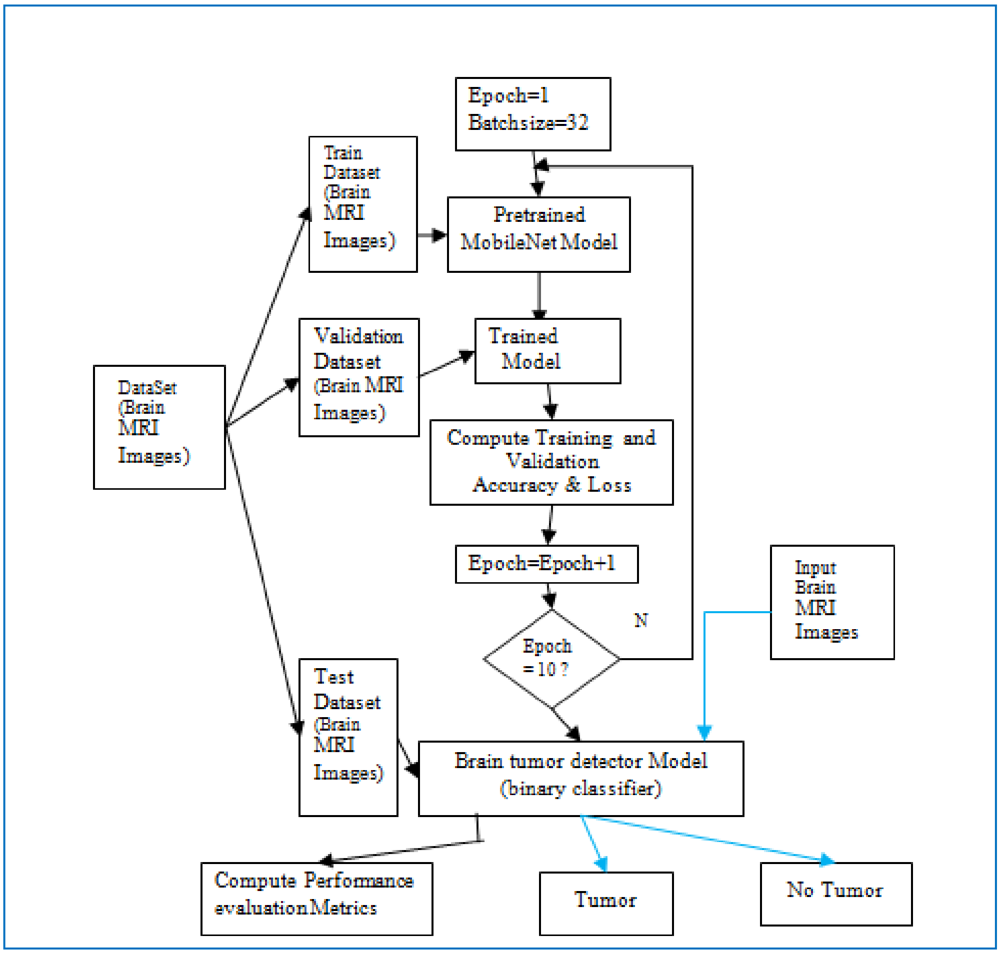

Fig 5: Flow diagram of proposed system

Set up the training parameters, such as batch size to 32, number of epochs to 10 and optimizer to "Adam" to train the MobileNet model. MobileNet model is trained using the training set. During training, feed batches of preprocessed images through the model, compute the loss using an appropriate loss function "binary cross-entropy" and back propagate the gradients to update the model's weights. The hyper parameter used for model tuning is epoch. During training phase, the base layers of pre trained model are not trained but only the dense layer is trained to get fine-tuned model for binary classification of brain MRI images. During every epoch model is trained by training data set and validated by validation data set. Both accuracy and loss metrics for model training and validation are recorded for each epoch. The trained MobileNet model is evaluated by using the test data set for predicting the input as “Tumor” or “No Tumor “. The confusion matrix is used to compute Accuracy, F1 Score, Precision, Recall of the model.

IV. RESULTS AND DISCUSSIONS

The results shown in Fig 6 and Fig 7 demonstrate that system is successful in detecting the tumor in given brain MRI image.

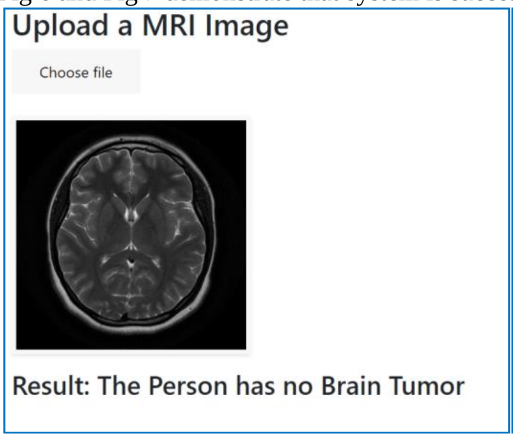

Fig 6. Prediction of Healthy Brain

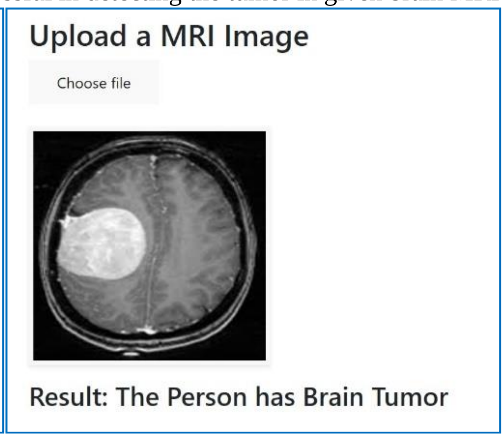

Fig 7. Prediction of Brain Tumor

With the split ratio of 8:2, sigmoid activation function in final layer and Adam optimizer the result obtained for 10 epochs is shown in Fig 8.

```
Epoch 1/10
75/75 [==============================] - 89s 1s/step - loss: 0.4725 - accuracy: 0.7912 - val_loss: 0.3631 - val_accuracy: 0.8533
Epoch 2/10
75/75 [==============================] - 90s 1s/step - loss: 0.2925 - accuracy: 0.9038 - val_loss: 0.3046 - val_accuracy: 0.8733
Epoch 3/10
75/75 [==============================] - 89s 1s/step - loss: 0.2316 - accuracy: 0.9371 - val_loss: 0.2416 - val_accuracy: 0.9117
Epoch 4/10
75/75 [==============================] - 89s 1s/step - loss: 0.1995 - accuracy: 0.9413 - val_loss: 0.2106 - val_accuracy: 0.9200
Epoch 5/10
75/75 [==============================] - 89s 1s/step - loss: 0.1748 - accuracy: 0.9508 - val_loss: 0.2036 - val_accuracy: 0.9150
Epoch 6/10
75/75 [==============================] - 89s 1s/step - loss: 0.1589 - accuracy: 0.9579 - val_loss: 0.1957 - val_accuracy: 0.9200
Epoch 7/10
75/75 [==============================] - 89s 1s/step - loss: 0.1456 - accuracy: 0.9608 - val_loss: 0.1616 - val_accuracy: 0.9483
Epoch 8/10
75/75 [==============================] - 87s 1s/step - loss: 0.1356 - accuracy: 0.9667 - val_loss: 0.1668 - val_accuracy: 0.9283
Epoch 9/10
75/75 [==============================] - 90s 1s/step - loss: 0.1260 - accuracy: 0.9712 - val_loss: 0.1498 - val_accuracy: 0.9500
Epoch 10/10
75/75 [==============================] - 101s 1s/step - loss: 0.1178 - accuracy: 0.9708 - val_loss: 0.1639 - val_accuracy: 0.9250
```

Fig 8. Final output of our proposed system with split ratio 8:2

The training and validation accuracy curves with respect to the number of epochs are shown in Fig 9. The training and validation loss curves are shown in Fig.10.The split ratio used in this case is 8:2.

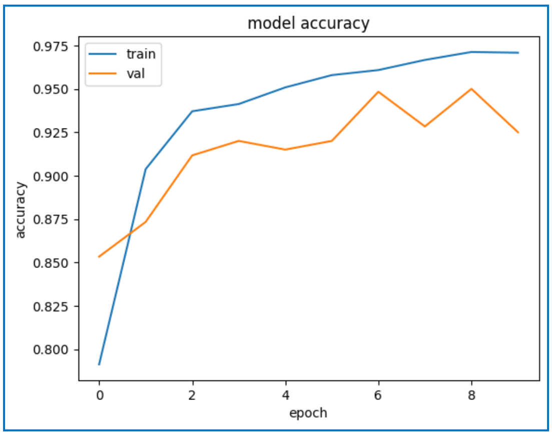

Fig 9. Training and validation Accuracy Curves.

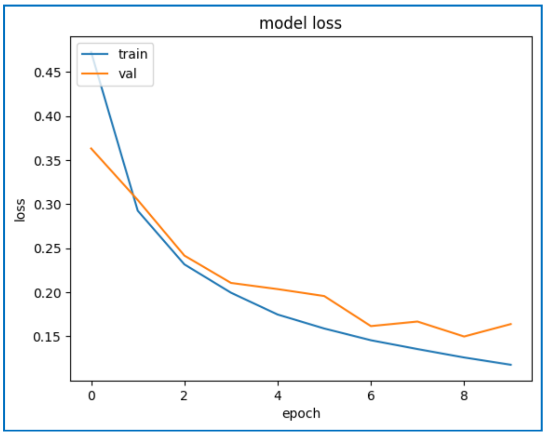

Fig 10. Training and validation loss Curves

The confusion matrix is a valuable tool for evaluating the performance of a classification model, such as the brain tumor detection system using MobileNet. It provides a detailed breakdown of the model's predictions and can help assess its accuracy, precision, recall, and F1-score metrics.

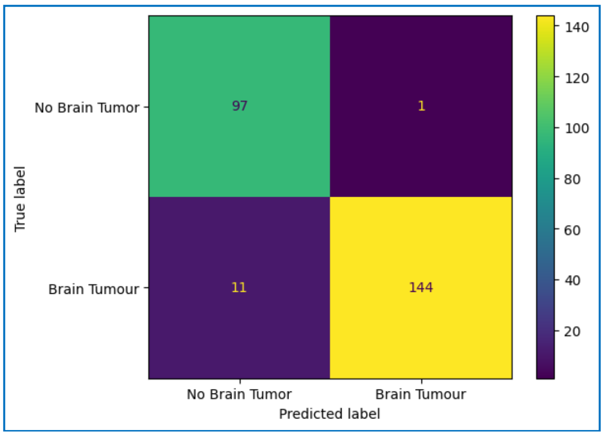

FIG 9. Confusion Matrix for split Ratio 8:2

Table 1 shows the comparison of performance metrics for various split ratios. The results show that for split ratio of 8:2 the model accuracy is highest i.e 95.25%.

Table 1: Performance Evalution Metrics

Validation Split	Precision	F1 Score	Recall	Accuracy
0.1	94.63 %	94.49 %	94.46 %	94.46 %
0.2	**95.63%**	**95.29 %**	**95.25 %**	**95.25 %**
0.3	93.94 %	93.71 %	93.94 %	93.67 %

V. CONCLUSION

In this paper, we presented a comprehensive study on brain tumor detection using the Mobile Net model. Our work is aimed to develop an efficient and accurate solution for detecting brain tumors. Through dataset acquisition, preprocessing, model training, and evaluation, it is demonstrated that MobileNet model is effective in accurately identifying brain tumors from medical images. Our research also identified opportunities for future investigations. Expanding the dataset with a larger and more diverse sample can enhance the generalizability of the MobileNet model. Additionally, exploring transfer learning techniques, incorporating clinical data, and investigating multi-modal fusion could further enhance the model's performance and contribute to personalized medicine in brain tumor diagnosis and treatment.

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