International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6587
***Article Received**: 18 February 2023 **Revised**: 30 March 2023 **Accepted**: 12 April 2023*

Brain Tumor Detection by using Fine-tuned MobileNetV2 Deep Learning Model

Archana Jadhav[1], Amit Gadekar[2]
[1]Ph. D Scholar , CSE Department
Sandip University
Nashik ,India
kadamarchana75@gmail.com
[2]Associate Professor, CSE Department
Sandip University
Nashik ,India
amit.gadekar@sandipuniversity.edu.in

Abstract—Most of the deaths in the world happen due to Cancer. It is a disease in which the cells of our body organs or tissues grow in an undisciplined way which in turn can harm our normal cells and tissues in our body. These cells very smartly trick the immune system so that the cancerous cells are kept alive and are not destroyed. In the human body, tumors can be classified into three types: cancerous, non-cancerous, and pre-cancerous. Timely identification of the cancer can be helpful in many ways. As it improves a patient's chances of survival. The most valuable, uncomplicated technique used is MRI scans for predicting tumor is a tough task and have chances of human error. So to be more accurate with our predictions we have moved on to use computerized techniques to ease the work. The focus of this research is the development of an automated brain tumor classification system using magnetic resonance imaging (MRI) scans, leveraging a deep learning model. The proposed model employs a convolutional neural network (CNN) architecture known as MobileNetV2, which is trained on a pre-processed MRI image dataset to classify brain tumors into one of two categories: tumor tissues and normal brain tissue. To mitigate overfitting and expand the dataset, data augmentation techniques are employed. The trained model achieves high accuracy, sensitivity, and specificity in classifying brain tumors. Proposed CNN model outperformed other deep learning models, including VGG16, Xception, and ResNet50, which were used for comparison.

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

I. INTRODUCTION

Cancer is one of the most lethal illnesses existing in the world. It has the capability of affecting people of all age groups. Cancer has the potential to disturb the normal cycle of cell growth and division in our body. The principal part of our body is the brain which weighs between 1.2kg-1.5kg. Any dysfunctionality happening to this part of the body is a threat to our life. At present this is a life-threatening disease. There are three classifications for tumors: cancerous (malignant), non-cancerous (benign), and precancerous. Malignant tumors have the ability to metastasize, and can infect healthy tissues in those areas.. It is a big threat to the life of a person. It is also known as malignant cancer. The second type of tumor is non-cancerous, this doesn't metastasize and is stuck to one part of the body. They are easy to treat as they are accumulated in one part of the body. The third type is Pre-cancerous, which means it is the starting phase of the development of the tumor. Strong headaches, loss of vision, loss of balance, etc are the prominent symptoms of this disease. The International Association of Cancer Registries (IARC) reported that over 24,000 individuals are fatally afflicted by this ailment. And about thirty to forty thousand are diagnosed with a brain tumor every year. The likelihood of survival for an individual with a brain tumor is a mere 36%.The annual growth rate of brain tumors compounded is 1.11 percent and is expected till 2030.

Cure this disease there are many ways and methods. To cure this disease the procedure and treatment are different because the procedure depends on the size and shape of the tumor. Identifying a tumor in its initial phases can be arduous, which consequently makes it more challenging to detect during the early stages. X-rays, CT scans, and MRI images are the latest techniques available in the market majorly used for the detection of tumors present in brain. Nonetheless, the identification of tumors demands substantial human labor, which in turn prolongs the process. Therefore Computer-aided diagnosis is the new system that is been put into work for this use. It is the use of the latest technology which makes it easier to detect abnormal cells and tissues. Several supervised and unsupervised techniques are in use in the market which is fully automated. These technologies have proven to be a boon to the medical field and doctors. The prominent architecture used in such systems is the Convolution Neural network.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6587
***Article Received**: 18 February 2023 **Revised**: 30 March 2023 **Accepted**: 12 April 2023*

There is a need of making a model which would learn on small datasets and work efficiently on the test dataset and classify the images correctly. Developing such a model can help us to save the lives of people and provide them with treatment on time. Our proposed study introduces significant contributions, including the utilization of MobileNetV2 as the core model, which is fine-tuned to enhance the system's accuracy in detecting brain tumors.

Our research introduces a fresh system that utilizes MobileNetV2 as the fundamental model, subsequently refining it to precisely detect brain tumors and enhance the system's accuracy. The dataset undergoes pre-processing techniques to heighten the image quality, ultimately enhancing the precision of the system. The subsequent stage involves augmenting the data to expand the dataset, addressing the issue of over-fitting. The results of this model are tested on a dataset containing 3000 images in total. The proposed system is subsequently evaluated against various existing models based on several metrics, including accuracy, precision, etc.

II. RELATED WORK

The majority of the researchers use a Convolution neural network for the task of detection of tumors. The performance of these neural networks has been good for a while. In this paper, we can see that the authors have used the DCNN model which is similar to the VGG16 model with modified layers. They have replaced a max polling layer with a Global Average Pooling layer which has shown a significant improvement in the accuracy of the model. The accuracy obtained here is 96% and with a high F1-score that is 0.97[1]. For this research, a total of thirteen pre-trained neural networks were employed to extract features from the images, followed by the utilization of nine distinct machine learning models to classify the images. Here they have used three different datasets[2]. Here the author M.A.Ansari and his colleagues have used five deep learning models and have compared their accuracies to each other. The Dataset used here is from The Cancer Imaging Archive. The highest performance is obtained by AlexNet with an accuracy of 99.04%[3]. The author of this paper has used CNN and VGG16 as models to perform research on. The high accuracy is obtained with VGG16 which is 92% and 85% accuracy obtained on the CNN network[4]. The model used here is a combination of 2 models that are Multimodal information fusion and Convolution neural network. Further, they have compared the results of multi-modal and single-modal neural networks. The number of epochs here is 100. And the highest accuracy obtained is 92.7% in the 3D modal and 88.1%in the 3D modal[5]. The paper by Deepak And his colleagues tells us that they have implemented GoogleNet Architecture to classify the images of brain tumors. They had a dataset of 3064 images. The best model was when they used k-NN and SVM for classification with an accuracy of 97.1%[6]. The paper by M.A. Shah and his colleagues says about the use of Efficient B0 Net as the base model for the classification of the images. They have fine-tuned it and incorporated an additional layer to enhance its performance. As a result, their model achieved a remarkable accuracy of 98.8%. They have compared this to other various deep learning models[7]. Here the author has used various deep-learning models with hyperparameter tuning for improving the accuracy and other evaluation metrics. The optimizers used in this paper are Adam, SGD, and RMSProp. The superior performance is given by Xception model as compared to other models, with an impressive accuracy of 99.67%[8]. In this paper, CNN models are employed to acquire image features, and a random forest model is utilized to categorize the images into their corresponding groups. The maximum accuracy achieved through this proposed technique is 91.43%[9]. The paper by A.Rehman and colleagues have made researched three pre-trained models that are AlexNet, GoogleNet, and VGGNet. Various data-preprocessing techniques have been applied and data augmentation is also done. The highest accuracy obtained was with fine-tuned VGG16 network which was 98.69%[10]. The suggested approach in this paper combines the ConvNet and ResNet34 models. Pre-processing and augmentation techniques are employed to improve the quality of the data. The k-fold training method is utilized to train the model, and the achieved accuracy is reported[11]. The paper by Neelum Noreen aims to tell us about the concatenation of two pre-trained models that is InceptionV3 and DenseNet201. The proposed methods in this paper produce an accuracy of 99.34% with InceptionV3[12]. It has convolutional layers with max-pooling which has a softmax layer.ResNet50 is the base model used in this research paper. The 10 layers are added at the last of the network by removing the earlier five layers present in the network. The accuracy obtained here is 97.01%[13]. The research employed the CapsNet model, with initial two convolution layers featuring 5x5 filters and 64 characteristic maps. Subsequently, two fully connected layers comprising 800 neurons were included. The ultimate layer of the model contained a softmax function to categorize the images. The peak accuracy obtained was 90.89%[14].

III. PROPOSED METHODOLOGY

The presence of tumors when detected at an early stage is proven useful to doctors and patients in many ways. Manual detection of brain tumors is a tedious job with may have some human error. In this paper, we present a model which is an effective and efficient way of detecting brain tumors. The proposed methodology is shown in Fig. 1

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6587
***Article Received**: 18 February 2023 **Revised**: 30 March 2023 **Accepted**: 12 April 2023*

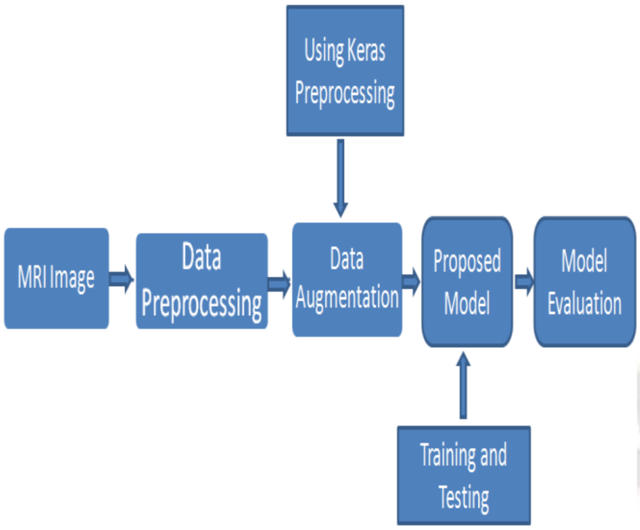


Fig 1 Proposed Methodology

A. MobileNetV2 Model

MobileNetV2 is a popular neural network architecture that is designed for mobile and embedded devices. It is a 53-layer deep architecture. It is a lightweight architecture with a small number of parameters, making it suitable for devices with limited computing resources. The model's structure is founded on depth wise separable convolutions, which drastically decrease the number of parameters needed while preserving the accuracy of the model. The design includes a sequence of convolutional layers, followed by batch normalization and ReLU activation. It is based on a residual network architecture that uses skip connections to improve the flow of information through the network. It also includes several novel features, such as linear bottlenecks and inverted residuals, that further improve its performance. The architecture also includes residual connections between the convolutional layers, which help to mitigate the vanishing gradient problem and the flow of gradients is enhanced during training. The last layer of the model is a global average pooling layer, which computes the average of the values in the feature maps, and a fully connected layer that produces the final output.

B. Proposed System Layers

Our base model is MobileNetV2. Here we add Global Average Pooling to the output of the MobileNetV2 base model. Then it is passed through batch normalization. The output of the previous layer is fed into a fully connected layer consisting of 2048 neurons with a ReLU activation function. It is then followed by another fully connected layer consisting of 1024 neurons, which is further passed through batch normalization. After that, it is processed through a fully connected layer with 512 neurons and finally, it undergoes a dropout of 0.5 and a flattened layer. Fig2 is showing the layered architecture of Proposed system.

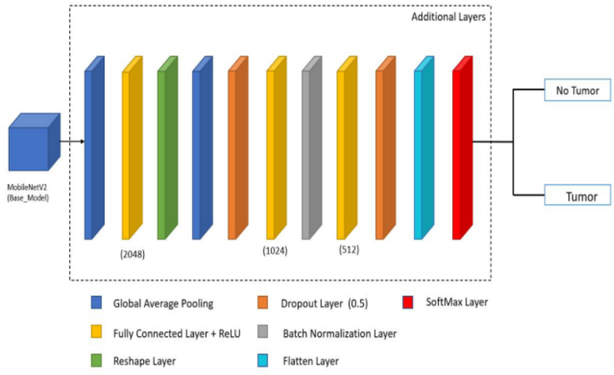


Fig 2: Layered architecture of Proposed System

The classification layer is comprised of a softmax.function for accurate classification. The softmax function is defined as shown in Eq.(1)

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

Here y is the input vector, yi the ith element of input vector. N is the number of classes. Normalization term is the denominator of the softmax function.

C. Transfer learning and Fine-tuning

Here we can see the training of the model MobileNetV2. We import our model from the Keras library. This is a pre-existing model that has been trained on the ImageNet dataset. The parameters acquired during the training of the ImageNet dataset are utilized to extract the features of the brain tumor dataset. The utilization of these parameters during training has optimized the training of the model. Here we freeze the layers before fine-tuning the model. In this step, we keep the weights obtained by the model during its training on the ImageNet dataset. The capability of the model to capture characteristics is enhanced due to these weights. In the end, we add additional layers to our model so that the model gives increased performance and enhanced accuracy. After this, the model is ready to be trained and can be tested further.

D. Hyper parameters and loss functions

During the phase of training the model loss function and hyperparameters are used so that the performance is enhanced. The use of loss function and hyperparameter tuning also has a big hand in the performance enhancement of the model. The information which is retrieved during the feature extraction if not passed properly to the next following layers leads to losses. In case we find a way to optimize the losses we can enhance the functionality of the model thus, raising the accuracy.

The loss function incorporated in this research is binary cross entropy. The function is used when we have a

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6587
***Article Received**: 18 February 2023 **Revised**: 30 March 2023 **Accepted**: 12 April 2023*

classification in which only two classes are present. The change in predicted and true values of the probability distribution is calculated. The formula for calculation of binary loss is shown in Eq .(2)

$$\text{Log Loss} = \frac{1}{N}\sum_{i=1}^{n} -(y_i * \log(p_i) + (1-y_i) * \log(1-p_i)) \quad (2)$$

The likelihood of class 1 is represented by Pi in the calculation above. The probability of class 0 is (1- Pi).

In this study, we have used Adam as our optimizer function. It is an optimizer that uses gradients for optimizing. It is a mixture of two optimizers resulting in an enhancement and increased performance. The two optimizers used are AdaGrade and RMSProp. The full form for Adam is Adaptive moment estimation. It is an algorithm to compute the learning rate of an individual for every parameter present in the model. The formula to compute the Adam optimizer is depicted in Eq.(3).

$$\omega_t + 1 = \omega_t - \alpha m_t \quad (3)$$

Here, ωt is the weight at time t, α that indicates the learning rate at time t. mt is the gradient's aggregate at time t. mt is calculated using formula given in Eq.(4)

$$m_t = \beta m_{t-1} + (1-\beta)\left[\frac{\delta L}{\delta \omega t}\right] \quad (4)$$

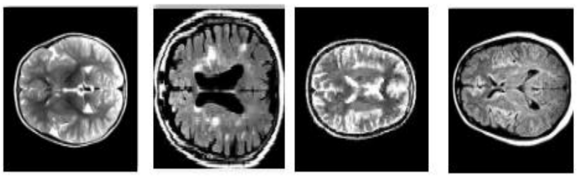
Where β indicates the parameter of moving average, δL is the loss functions derivative, and δ wt is the derivative of time t weights. The learning rate in this model is 0.0001 and the batch size is 16. The epochs here are 75.

IV. IMPLEMENTATION DETAIL

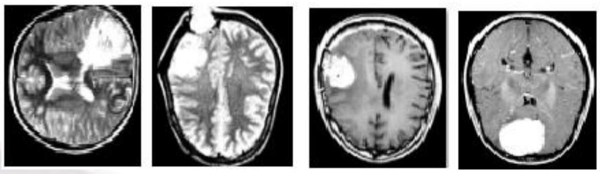
This section gives details about dataset, pre-processing techniques and experimental set used.

A. *Dataset Details*

There are 3000 images of MRI in the dataset. The name of the dataset is BR35H. Yes and No are the two classes present in the dataset. The yes class represents the images with brain tumor and No class being images with images with normal brain. Validation set, Training set and Testing set are the sets that are the dataset are divided into. A percentage of 80-20 is used to split the training and testing dataset. Moreover, the 80% training dataset is split into 90% and 10%. Each class's 1080 photos are included in the training dataset. Each class's 120 photos are included in the testing dataset. Each class's 300 photos are included in the validation dataset. Fig.3 a) depicts Normal MRI images of brain and b) depicts Tumor MRI images of brain.



(a)

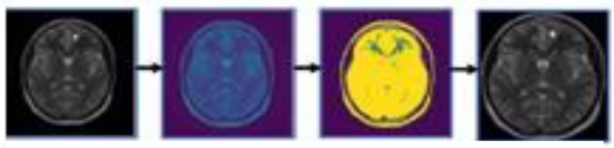


(b)

Figure 3: a)Normal MRI and b) Tumor MRI

B. *Data Pre-processing and Augmentation*

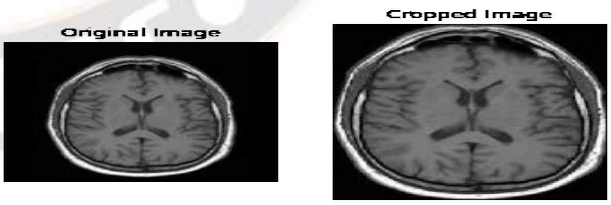
Pre-processing techniques for image data enables effective feature extraction. As a result, the model performs better and the images are correctly classified. Preprocessing stages used here are represented in Fig. 4. It is started with conversion of original image to grey scale image, grey scale image undergoes threshold calculation process and last stage used is image cropping. The sampled cropped images are represented in Fig 5.



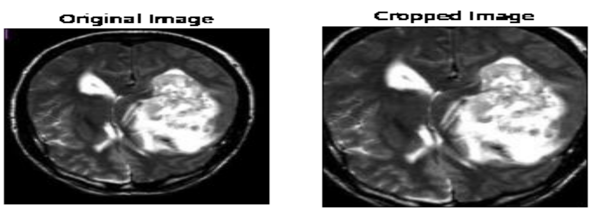
a) b)

Figure 4 Pre-processing stages of MRI images a) Original image b) Gray scale image c)Threshold image d)Cropped image

After the images are cropped it is sent to augmentation. This method is used so that the numbers of images in the dataset are increased as it prevents the model from over-fitting. This step helps the model to learn properly from all the images.



a)



b)

Figure 5 Original and cropped MRI images

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6587
***Article Received**: 18 February 2023 **Revised**: 30 March 2023 **Accepted**: 12 April 2023*

The image augmentation was performed by using the pre-processing directory of Keras. After this the images are sent to the model for training.

C. Experimental Set-up

The model is deployed on the dataset. The proposed fine tuned model as base of MobileNetV2 is executed on 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 AMDRyzen 5 3550H, GPU of Nvidia GEFORCE GTX 1650, and RAM of 8GB.

D. Performance Evaluation Metrics

The task of determination of the success of the model is done easier by use of Performance evaluation metric. These metric are parameters that help us in it. The majorly used metric is Confusion Matrix.

The performance parameters are given below.

tp- The true value is predicted and it belongs to the real true class.

fp- The true value is predicted but it doesn't belong to the real true class

fn- The false value is predicted but it belongs to the real true class.

tn- The false value id predicted but it actually is true.

E. Experimental Results

As a result of training and testing the model, we present the results in this section. Processes that were applied to the dataset are Data-preprocessing and Data- augmentation. By carrying out the above processes we make sure that the quality of the image is increased and increase the images in the dataset. Hyper parameters have been used to train the model this aims to increase the performance and accuracy. Adam has been used as the optimizer and binary cross entropy as the loss function. The learning rate kept here is 0.0001 batch size is 16 and the epochs are 75.

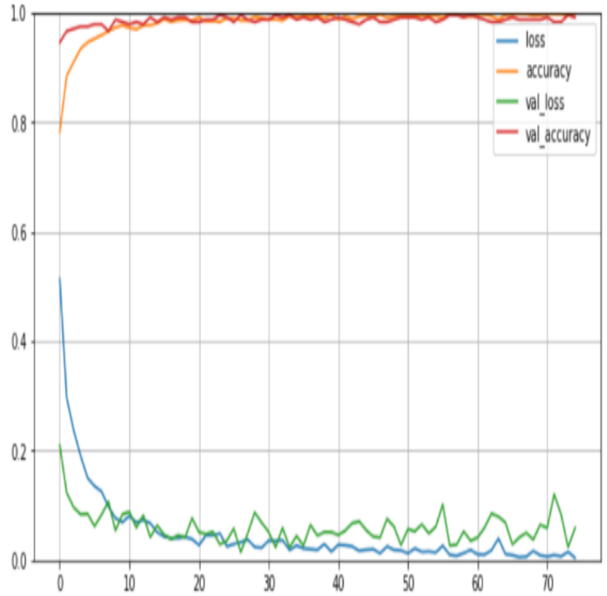


Fig. 6 Loss and accuracy of Model

A loss graph and an accuracy graph are shown in Figure 6 to illustrate the model's output during training and validation. We can see that the model has been trained well with minimal loss. So to evaluate the model we have used a confusion matrix which is shown in Fig 7. This matrix tells us about the correctly classified and incorrectly classified samples of the MRI scans. Our model was able to correctly identify 596 images and it identified 4 images incorrectly of both the first and second classes. Sample predicted model output is depicted in Fig 9. The proposed model's performance indicators are presented in Fig 8 with bar graph.

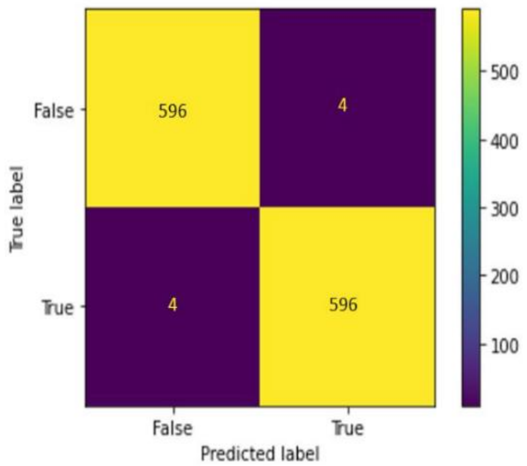


Fig. 7 Confusion Matrix of proposed Model

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6587
***Article Received**: 18 February 2023 **Revised**: 30 March 2023 **Accepted**: 12 April 2023*

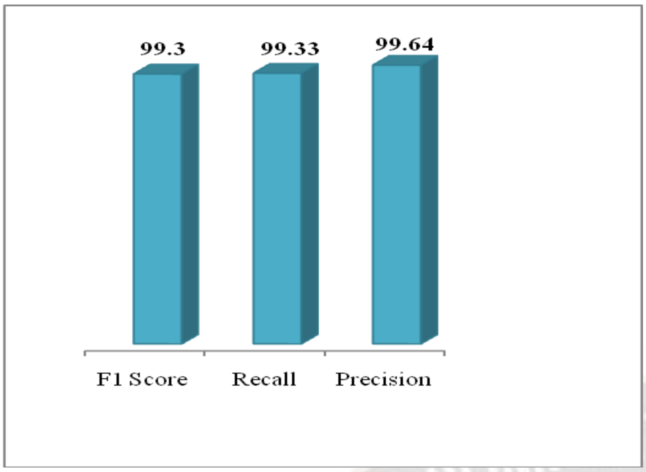


Fig. 8 Performance indicators of Model

Here we can see that the F1-score obtained is 0.9930, Precision is 0.9964, Recall is 0.99333 and specificity is 0.00666. Below are shown some of the correctly classified and incorrectly classified samples by the proposed model. If the image has a tumor, then it is classified as true and if the image doesn't have a tumor, then it is classified as false.

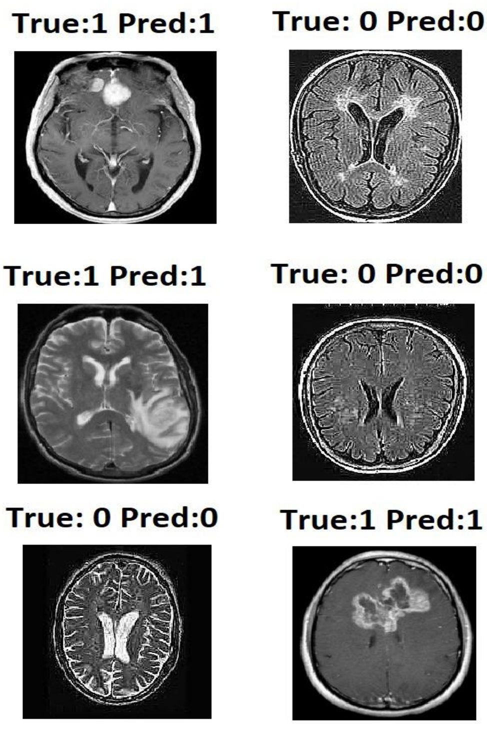


Fig. 9 Accurately and inaccurately predicted MRI images

Here we can see that the image has a tumor but it is classified as False by the model. This tells us that the model has misclassified it. Fig 9. shows correct classification and misclassification examples of MRI images.

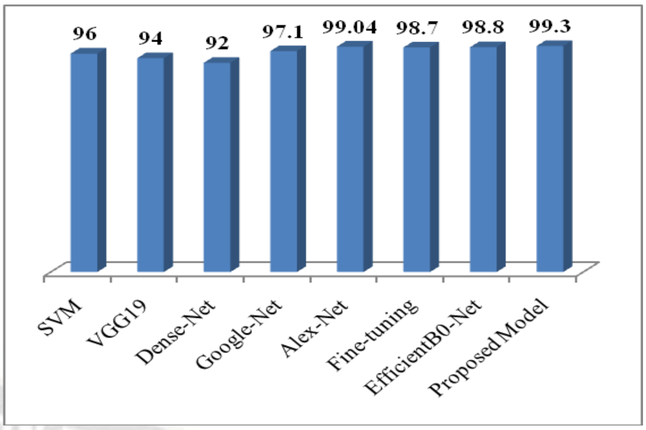


Figure 10 Comparative Analysis of Accuracies with Proposed Model

Proposed model with base as MobileNetV2 achieves more accuracies compared with other models. It takes less time for training and testing as MobileNetV2is light weight. The graph in Fig.10 depicts the comparative analysis of accuracies of other models with proposed model.

The Table 1 tells us about the comparison of the proposed model with other proposed and previous ML and DL methods. While there are differences in the pre-processing methods, training and validation procedures, and the computational power employed in their methodologies, we haven't directly compared our suggested model to these models. But we can see that our proposed model has an excellent accuracy of 99.33% overall the accuracies.

Table 1. Comparative Analysis

Sr. No	Previously done work	Model	Accuracy
1.	Latif [15]	SVM	96%
2.	Khan [16]	VGG19	94%
3.	Yahyaoui [17]	Dense-Net	92%
4.	Deepak [6]	Google-Net	97.10%
5.	R.Mehrotra[3]	Alex-Net	99.04%
6.	Chelghoum[18]	Fine-tuning	98.71%
7.	Hasnain Shah[7]	EfficientB0-Net	98.8%
8.	Proposed Model	Fine tuning MobileNetV2	99.3%

CONCLUSION

In this research work, we aim to detect the tumor through MRI scans. Above implementation and algorithm approaches to successful classification of brain tumor. Collected MRI images pre-processed converting them into greyscale images and applying a Gaussian filter and thresholding. These images are then sent to training. Then characteristics are extracted. After the extraction of the features, it is further used to detect the tumor from the images. To test the precision of the model we use a test parameter which is a complexity matrix that helps us to check the precision of the model. The proposed MobileNetV2 model gives an accuracy of 99.33%. Further research can be done on various other CNN architectures by applying various pre-processing techniques and hyper-parameter tuning. Further to increase the performance of the model and accuracy we have to increase the dataset of the MRI images so that our model can learn accurately about the features. In the future, we can also use the proposed model for other medical images such as CT scans, Computed tomography, etc. These are the base to the foundation for future research work.

ACKNOWLEDGMENT

I would like to express my deepest gratitude to my supervisor Dr. Amit Gadekar, Associate Professor, Department of Computer Science Engineering, for his thoughtful suggestion and excellent guidance. I have been enriched personally and professionally by working with him. I would like to thank my beloved husband and daughters for sacrificing their time and pleasure during my pursuit and always encouraging me. Lastly, I would like to thank GOD for giving me the strength and help me in acquiring the knowledge.

REFERENCES

[1] M. A. B. Siddique, S. Sakib, M. M. R. Khan, A. K. Tanzeem,M. Chowdhury, and N. Yasmin, ‘‘Deep convolutional neural networks model-based brain tumor detection in brain MRI images,’’ in Proc. 4th Int. Conf. I-SMAC (IoT Social, Mobile, Anal. Cloud) (I-SMAC), Oct. 2020,pp. 909–914.

[2] J. Kang, Z. Ullah, and J. Gwak, ‘‘MRI-based brain tumor classification using ensemble of deep features and machine learning classifiers,’’ Sennsors, vol. 21, no. 6, p. 2222, Mar. 2021

[3] R. Mehrotra, M. A. Ansari, R. Agrawal, and R. S. Anand, ‘‘A transfer learning approach for AI-based classification of brain tumors,’’ Machine Learn. with Appl., vol. 2, Dec. 2020, Art. no. 100003

[4] Sangeetha, A. Mohanarathinam, G. Aravindh, S. Jayachitra, and M. Bhuvaneswari, ‘‘Automatic detection of brain tumor using deep learning algorithms,’’ in Proc. 4th Int. Conf. Electron., Commun. Aerosp. Technol. (ICECA), Nov. 2020, pp. 1–4

[5] M. Li, L. Kuang, S. Xu, and Z. Sha, ‘‘Brain tumor detection based on multimodal information fusion and convolutional neural network,’’ IEEE Access, vol. 7, pp. 180134–180146, 2019.

[6] S. Deepak and P. M. Ameer, ‘‘Brain tumor classification using deep CNN features via transfer learning,’’ Comput. Biol. Med., vol. 111, Aug. 2019, Art. no. 103345.

[7] A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet Hasnain Ali Shah, Faisal Saeed, Sangseok Yun,Jun-Hyun Park, Anand Paul,And Jae-Mo Kang

[8] Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors From MR Images Sohaib Asif,Wenhui Yi ,Qurrat Ul Ain3,Jin Hou,Tao Yi5and Jinhai Si

[9] S. Paul, A. J. Plassard, B. A. Landman, and D. Fabbri, ‘‘Deep learning for brain tumor classification,’’ Proc. SPIE, vol. 10137, Mar. 2017,Art. no. 1013710.

[10] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, ‘‘A deep learning-based framework for automatic brain tumors classification using transfer learning,’’ Circuits, Syst., Signal Process., vol. 39, no. 2, pp. 757–775, Feb. 2020.

[11] M. Talo, U. B. Baloglu, Ö. Yıldırım, and U. R. Acharya, ‘‘Application of deep transfer learning for automated brain abnormality classification using MR images,’’ Cogn. Syst. Res., vol. 54, pp. 176–188, May 2019.

[12] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran, and M. Shoaib, ‘‘A deep learning model based on concatenation approach for the diagnosis of brain tumor,’’ IEEE Access, vol. 8, pp. 55135–55144, 2020.

[13] A. Çinar and M. Yildirim, ‘‘Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture,’’ Med. Hypotheses, vol. 139, Jun. 2020, Art. no. 109684.

[14] P. Afshar, K. N. Plataniotis, and A. Mohammadi, ‘‘Capsule networks for brain tumor classification based on MRI images and coarse tumor boundaries,’’ in Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP), May 2019, pp. 1368–1372

[15] G. Latif, G. B. Brahim, D. N. F. A. Iskandar, A. Bashar, and J. Alghazo, ‘‘Glioma Tumors’ classification using deep-neural-network-based features with SVM classifier,’’ Diagnostics, vol. 12, no. 4, p. 1018, Apr. 2022

[16] A. R. Khan, S. Khan, M. Harouni, R. Abbasi, S. Iqbal, and Z. Mehmood,‘‘Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification,’’ Microsc. Res. Technique, vol. 84, pp. 1389–1399, Feb. 2021.

[17] H. Yahyaoui, F. Ghazouani, and I. R. Farah, ‘‘Deep learning guided by an ontology for medical images classification using a multimodal fusion,’’ in Proc. Int. Congr. Adv. Technol. Eng. (ICOTEN), Jul. 2021, pp. 1–6

[18] R. Chelghoum, A. Ikhlef, A. Hameurlaine, and S. Jacquir, ‘‘Transfer learning using convolutional neural network architectures for brain tumor classification from MRI images,’’ in Proc. 16th IFIP WG 12.5 Int.Conf. Artif. Intell. Appl. Innov. (AIAI), Neos Marmaras, Greece, vol. 583, Jun. 2020, pp. 189–200.