International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Detection of Brain Tumor using Fine-Tuned Pre-Trained MobileNet Deep Learning Model

Archana J. Jadhav[1], Dipali. H. Patil[2], G. S. Mate[3], R. A. Deshmukh[4], Anjali S. More[5], Chandan Prasad[6]

Submitted: 25/01/2024 **Revised**: 03/03/2024 **Accepted**: 11/03/2024

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 distinguished into three different types as 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 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*

1. Introduction

The deadliest disease present in the world is Cancer. All people across age groups are susceptible to cancer. Cancer is a disease that can affect our whole body hence disturbing the natural growth of the body cells. The most essential organ of our body is our brain. It 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, as well as CT, MRI, and X-ray scans are various types of imaging scans.

1.1. Tumor Types

Cancerous, non-cancerous, and pre-cancerous tumours are the three categories for Cancer. 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

1.2 Tumor Detection Techniques

The prominent indications of this disease are severe headaches, blurred vision, and unsteadiness but in some cases, there can be no indications. The International Association of Cancer Registries (IARC) reports more than 24,000 persons 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. Brain tumors are expected to increase at a compound yearly growth rate of 1.11 percent till 2030.

Many ways can be used to cure brain tumors. The

[1]*IT Dept, Rajarshi Shahu College of Engineering, Pune , India*
ORCID ID : 0000-0002-0479-7462
[2] *IT Dept, Rajarshi Shahu College of Engineering, Pune , India*
ORCID ID : 0000-0001-5072-7919
[3] *IT Dept, Rajarshi Shahu College of Engineering, Pune , India*
ORCID ID : 0000-0001-8623-696X
[4] *Comp Dept, Rajarshi Shahu College of Engineering, Pune , India*
ORCID ID : 0000-0001-5319-6711
[5] *Comp Dept, Suman Ramesh Tulsiani Technical Campus Faculty of Engineering , Pune , India*
ORCID ID : 0009-0009-7268-8346
[6] *IT Dept, Rajarshi Shahu College of Engineering, Pune , India*
ORCID ID : 0009-0001-0185-4564
* *Corresponding Author Email: ajjadhav_it@jspmrscoe.edu.in*

approach selected for treating brain tumors is based on several factors, including the tumor's shape and size. 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.

1.3 Use of ML and DL

At present, there are numerous supervised as well as unsupervised techniques present which are automated systems. Technologies like Machine learning and Deep learning techniques have proved to be a beneficial in the health care industry to detect the early tumor at very efficient cost and time. CNN is prominently used in these CAD systems. CAD systems make extensive use of CNN

Convolutional neural networks are composed of three distinct layers that are fully connected layer, the pooling layer, and the convolution 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 increase the accuracy of the system for detecting brain tumours, a new approach was employed, which involves fine-tuning the MobileNet base model.
- Pre-processing techniques are applied on the dataset to to improve image quality, resulting in improved accuracy.
- To address the over-fitting issue, the subsequent step involves data augmentation to increase the dataset.
- Three thousand images were used to evaluate the model's outcomes
- The proposed model is assessed by comparing it with a various recent models based on variety of performance measures, such as precision, accuracy, F1 score etc.

2. 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 compositions are not The author has compared the results with other models that are VGG16, Inceptionv3, ResNet50, etc[7]. The manuscript authored by M.A. Ansari et al. have fine-tuned several machine learning models including AlexNet, GoogLeNet, SqueezeNet, ResNet50, and ResNet101, and found that AlexNet achieved the highest accuracy[8]. 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 first two convolution layers have5x5 filters with 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 binary cross-entropy as the loss function and the Adam optimizer. The achieved perfection in this study was 97%[22].

3. 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 explained below.

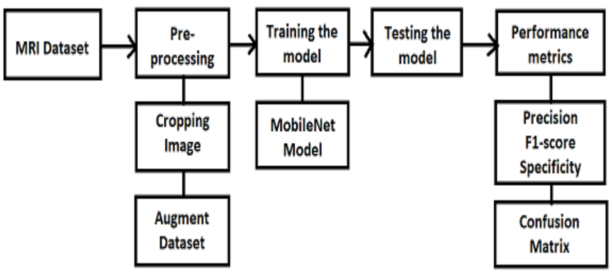

Fig.1 Proposed Methodology

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.

3.1. 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.

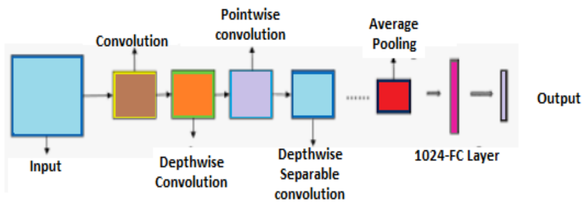

Fig.2 MobileNet Architecture

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

3.2. Proposed Layers

MobileNet architecture implemented 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.

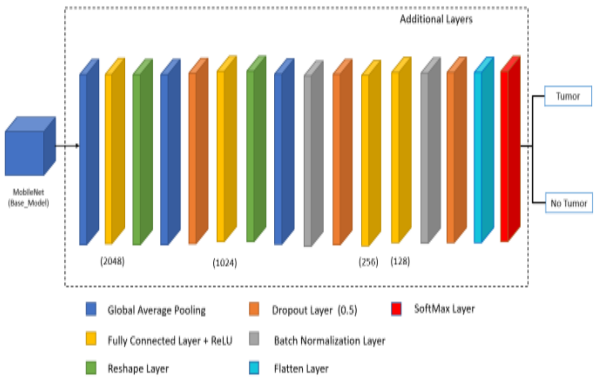

Fig. 3. Layers in Proposed System

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

$$\mathrm{S}(y)\mathrm{i} = \frac{\exp(yi)}{\sum_{j=1}^{n}(\exp(yj))} \qquad (1)$$

Here,

y is representing input Vector

yi is the ith element of vector

n is representing number of classes

Here the the softmax function's denominator is a normalization term.

3.3. Fine-tuning of Pre-trained MobileNet Model

In this section, the training process of our model is described. Here utilized the Keras framework to import a pre-trained model named MobileNet in which Imagenet dataset is used for training the model. Weights used in the pre-trained model are helpful to train out the training dataset in proposed system. This helps suggested model in learning our dataset efficiently and thus improves our accuracy of the model. Here to train our dataset we have frozen the layers of our model prior to application of fine-tuning process on 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.

3.4. Loss Function and Hyper-parameters

While training the model hyper-parameters and loss functions are used so that our perfection of the model is amplified. Any architecture's performance is based upon both the losses incurred during the model's training and the accuracy it achieves after training. Here the information that is lost between the layers is called as losses. These losses could not be carry forward for learning process. If we decrease this information loss by applying the appropriate loss function this would hence improve the performance thus resulting in performance improvement of the model. This model uses binary-cross entropy loss function, which is frequently used for binary classification problem. 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

$$\log \text{loss} = \frac{1}{N}\sum_{j=1}^{N} -(\mathrm{yi} * \log(\mathrm{Pi}) + (1-\mathrm{yi}) * \log(1-\mathrm{Pi})) \qquad (2)$$

Here, pi and (1-pi) representing probability of class 1 and class 0 respectively.

In our model Adam is used as the optimizer. It is an optimizer algorithm used for gradient-based optimization. A combination of the other two optimizers makes the Adam optimizer. These two optimizers are RMSProp and AdaGrad. The acronym for adaptive moment estimation is "The Adam.". 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

$$\omega_{t+1} = \omega_t - \alpha m_t \qquad (3)$$

Where, wt is a weight, αt is a learning rate mt is gradient’s aggregate at any given time t.

mt is calculated as follows

$$mt = \beta_{mt-1} + (1-\beta)\left[\ \frac{\delta L}{\delta \rho}\ \right] \qquad (4)$$

4. Details of Implementation

4.1. 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. For training, testing and validation the dataset is split up into three distinct subsets. For training 80% of portion and for testing 20% of portion from the dataset is used. Additionally, the training dataset portion is further split into two parts 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.

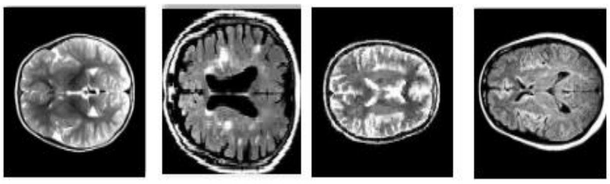

Fig. 4. MRI Images indicating Absence of tumor

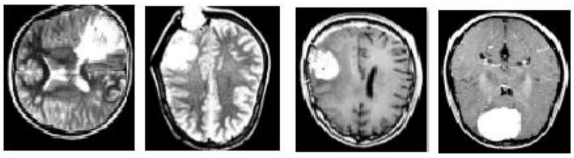

Fig. 5. MRI Images infected with brain tumor

4.2. Preprocessing and augmentation of data

Techniques for pre-processing 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.

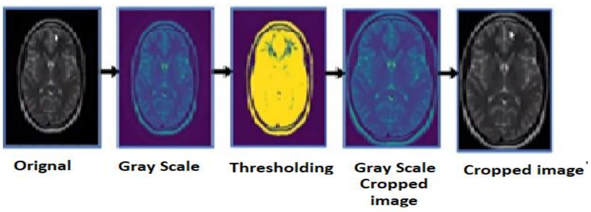

Fig.6 Pre-processing of MRI Image

Augmentation of data is a technique employed to expand the brain tumor dataset, which is often inadequate due to the restricted availability of medical record of patients. In order to efficiently train the model and improve its performance, we must carry out this crucial data augmentation phase. The techniques that we have employed for augmentation of data are angle rotation range, change in height and width, 0.2-degree zoom range and shear range with horizontal and vertical flip to the image thus having copies of the images image that increases the size of dataset. The image augmentation was performed byimporting the image data generator from the Keras pre-processing package. Then these images are given to the model for training purpose.

4.3. Configuration of Experiment

On the dataset suggested MobileNet model is deployed. The fine-tuned MobileNet model was implemented in GoogleColab with the help packages like Tensorflow and Keras. The system running the proposed model is equipped with an AMD Ryzen 5 3550H CPU, an Nvidia GEFORCE GTX 1650 GPU, and eight gigabytes of RAM. Its operating system is Windows 11 64-bit.

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 following parameters belong to the matrix:

Table1: Performance Evaluation Metric

		Predicted Class	
		Class 0	Class 1
Real Class	Class 0	tp	fp
	Class 1	fn	tn

True Positive(tp): According to the model, it is true and it matches to the real class.

False Positive(fp): According to the model, it is falseand it matches to the real class.

False Negative(fn): According to the model, it is false but it does not matches to the real class.

True Negative(tn): According to the model, it is true but it does not matches to the real class.

The various performance metrics are calculated for this model like F1-score, Precision, Sensitivity, Specificity and Accuracy etc.

5. Experimental Results

In this discussion, we will go over the outcomes obtained from training, testing and validating the dataset with the improved Pre-trained MobileNet. To enhance the image quality and increase the dataset, we employed preprocessing techniques and augmentation methods on dataset, incorporating a range of filters. Additionally, we optimized hyper-parameters to train and validate the dataset more effectively. The loss function in this model is binary cross-entropy and optimized used is the Adam optimizer. During the training 0.0001 was set as the learning rate The batch size and epcohes used were 32 and 50 respectively.

The training and validation processes' accuracy and loss are depicted in the graph given in Fig. 8. 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.

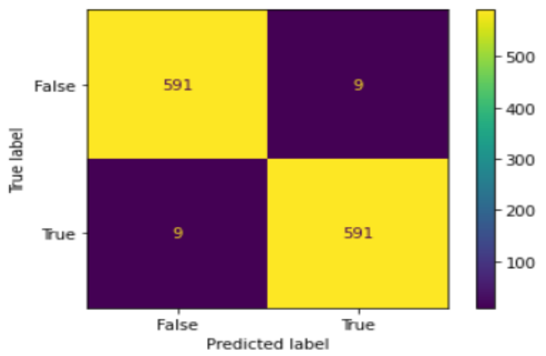

Fig. 7. Confusion Matrix for Proposed System

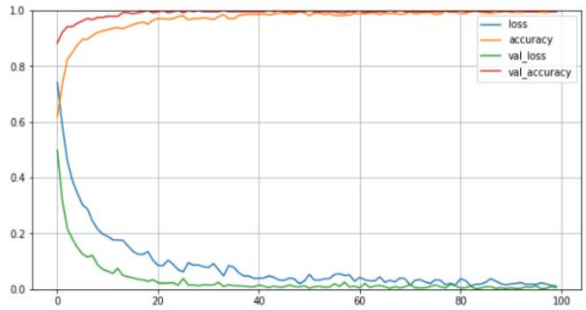

Fig. 8. Training and Testing Loss and Accuracy

Several performance metrics of MobileNet model are displayed in the bar graph given in Fig 9 such as F1-score of 0.9856, precision of 0.9826, recall of 0.985, and recall of 0.015.

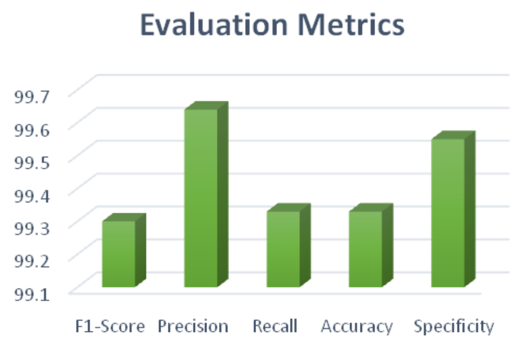

Fig. 9. Performance metric of Proposed System

The images in Fig. 11 are examples of correctly classified and incorrectly classified samples. The image is classified as true if the sample shows the picture of a brain tumor. And it classify the image as false if it doesn't have an image of a brain tumor.

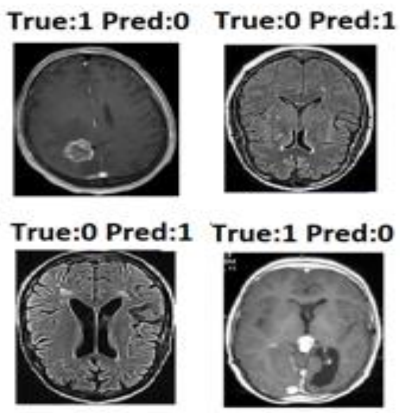

Fig. 10. Misclassified MRI images

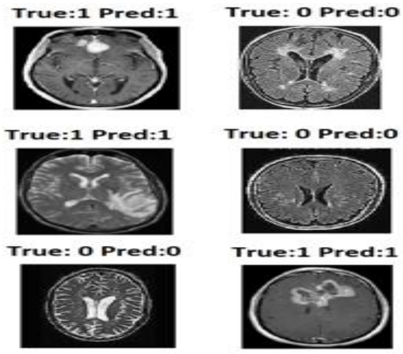

Fig. 11. Correctly Classified MRI images

The table 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 2. Comparative Analysis

Sr. No	Previous work	Accuracy	Method use
1	Bhatele [19]	95.20%	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

6. 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 supplied for training and features are extracted to detect the tumor. A test parameter, the complexity matrix, is used to test how accurate the model is predicting. The accuracy achieved by the MobileNet model is 98.50%. Future research could explore other CNN architectures and hyper-parameter tuning, while increasing the MRI image dataset to improve accuracy. The suggested model could also be utilized for other types of medical images such as computed tomography (CT) scans, which provides potential for future exploration.

Conflicts of interest

The authors declare no conflicts of interest.

References

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

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

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

[4] R. Chelghoum, A. Ikhlef, A. Hameurlaine, and S. Jacquir, ‘‘Transferlearning using convolutional neural network architectures for brain tumorclassification 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.

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

[6] N. Abiwinanda, M. Hanif, S. T. Hesaputra, A. Handayani, andT. R. Mengko, ‘‘Brain tumor classification using convolutional neuralnetwork,’’ in Proc. World Congr. Med. Phys. Biomed. Eng. Singapore:Springer, 2018, pp. 183–189.

[7] Hasnain Ali Shah, Faisal Saeed, Sangseok Yun,Jun-Hyun Park, Anand Paul,And Jae-Mo Kang, “A Robust Approach for Brain Tumor Detectionin Magnetic Resonance ImagesUsing Finetuned EfficientNet”

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

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

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

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

[12] Sohaib Asif, Wenhui Yi ,Qurrat Ul Ain3,Jin Hou,Tao Yi5and Jinhai Si., “Improving Effectiveness of Different DeepTransfer Learning-Based Models for DetectingBrain Tumors From MR Images”

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

[14] F. J. Díaz-Pernas, M. Martínez-Zarzuela, M. Antón-Rodríguez, andD. González-Ortega, ‘‘A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network,’’Healthcare, vol. 9, no. 2, p. 153, Feb. 2021.

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

[16] H. Yahyaoui, F. Ghazouani, and I. R. Farah, ‘‘Deep learning guided by anontology for medical images classification using a multimodal fusion,’’ inProc.

Int. Congr. Adv. Technol. Eng. (ICOTEN), Jul. 2021, pp. 1–6.

[17] M. M. Badža and M. Č. Barjaktarović, ‘‘Classification of brain tumors fromMRI images using a convolutional neural network,’’ Appl. Sci., vol. 10,no. 6, p. 1999, Mar. 2020.

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

[19] K. R. Bhatele and S. S. Bhadauria, ‘‘Machine learning application inglioma classification: Review and comparison analysis,’’ Arch. Comput.Methods Eng., vol. 29, pp. 247–274, Apr. 2021.

[20] M. Y. B. Murthy, A. Koteswararao, and M. S. Babu, ‘‘Adaptive fuzzydeformable fusion and optimized CNN with ensemble classification forautomated brain tumor diagnosis,’’ Biomed. Eng. Lett., vol. 12, no. 1, pp. 37–58, Feb. 2022.

[21] M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed,‘‘A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned,’’ Magnetic Resonance Imaging,vol. 61, pp. 300–318, Sep. 2019.

[22] S. Somasundaram and R. Gobinath, ‘‘Current trends on deep learningmodels for brain tumor segmentation and detection—A review,’’ in Proc.Int. Conf. Mach. Learn., Big Data, Cloud Parallel Comput. (COMITCon), Feb. 2019, pp. 217–221.

[23] G. Kumar, P. Kumar, and D. Kumar, ‘‘Brain tumor detection using convolutional neural network,’’ in Proc. IEEE Int. Conf. Mobile Network WirelessCommunication. (ICMNWC), Dec. 2021, pp. 1–6.

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

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

[26] S. Grampurohit, V. Shalavadi, V. R. Dhotargavi, M. Kudari, and S. Jolad,‘‘Brain tumor detection using deep learning models,’’ in Proc. IEEE IndiaCouncil Int. Subsections Conf. (INDISCON), Oct. 2020, pp. 129–134.

[27] R. Sangeetha, A. Mohanarathinam, G. Aravindh, S. Jayachitra, andM. 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

[28] M. Li, L. Kuang, S. Xu, and Z. Sha, ‘‘Brain tumor detection based onmultimodal information fusion and convolutional neural network,’’ IEEEAccess, vol. 7, pp. 180134–180146, 2019.

[29] M. S. Majib, M. M. Rahman, T. M. S. Sazzad, N. I. Khan, and S. K. Dey,‘‘VGG-SCNet: A VGG net-based deep learning framework for brain tumordetection on MRI images,’’ IEEE Access, vol. 9, pp. 116942–116952,2021.

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

[31] Dr. S. P. Predeep Kumar1, Dr. K. John Peter2 , Dr. C. Sahaya Kingsly3 “Analysis on Methods for Detecting Brain Tumor from MRI images” (aug 2022)