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Brain Tumors Detection by Using Fine-Tuned Transfer Deep Learning Model

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Abstract:

Cancer stands as a formidable adversary in global health, claiming a significant number of lives. This insidious disease manifests when cells within our body's organs or tissues undergo uncontrolled growth, posing a threat to normal cellular function. Cancer cells demonstrate a remarkable ability to deceive the immune system, evading destruction and persisting in their harmful proliferation. Tumors, the hallmark of cancer, can be categorized into three types: cancerous, non-cancerous, and pre-cancerous, each presenting distinct challenges in diagnosis and treatment. Early detection of cancer is crucial for enhancing a patient's chances of survival. Among the diagnostic tools, magnetic resonance imaging (MRI) scans play a pivotal role in identifying tumors. However, the reliance on manual interpretation introduces the potential for human error. In the pursuit of precision and efficiency, the scientific community has shifted towards leveraging computerized techniques to aid in tumor prediction. This research work focuses on the development of an automated system for classifying brain tumors using MRI scans, employing advanced deep learning technology. The proposed model harnesses the power of a convolutional neural network (CNN) architecture, specifically MobileNetV2. Trained on a meticulously pre-processed dataset of MRI images, the model adeptly distinguishes between brain tumors and normal brain tissue. To enhance the robustness of the model and address overfitting concerns, data augmentation techniques are integrated. The results of this study demonstrate that the CNN model, based on MobileNetV2, achieves commendable accuracy, sensitivity, and specificity in classifying brain tumors. Notably, it outperforms other deep learning models, including VGG16, Xception, and ResNet50, which were included in the comparison. This advancement in automated tumor classification not only streamlines diagnostic processes but also marks a significant stride towards improving patient outcomes in the realm of cancer care.

I.INTRODUCTION:

Cancer, a pervasive and life-threatening illness affecting all age groups, disrupts the normal cell growth cycle, particularly in vital organs like the brain. Tumors can be cancerous (malignant), non-cancerous (benign), or precancerous. Malignant tumors, capable of metastasis, pose a significant threat, while non-cancerous tumors remain localized. Pre-cancerous tumors signify the initial phase, manifesting symptoms like headaches and vision loss.

Brain tumors claim over 24,000 lives annually, with 30-40,000 new diagnoses. Survival rates are challenging, with only a 36% likelihood of survival. Detection methods include X-rays, CT scans, and MRI imaging, but early identification remains elusive. Computer-aided diagnosis, employing technologies like convolutional neural networks, streamlines detection, offering a promising avenue for timely treatment.

The proposed study introduces MobileNetV2, a fine-tuned core model, enhancing accuracy in detecting brain tumors. This model, adept at learning on small datasets, holds potential to revolutionize early diagnosis and improve treatment outcomes, ultimately saving lives. 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.

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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 suggested system is subsequently evaluated against various existing models based on several metrics, including accuracy, precision, etc.

a) MAGNETIC RESONANCE IMAGING (MRI):

MRI is a useful tool for detecting and treating brain tumours. Its ability to produce comprehensive anatomical images assists healthcare practitioners in accurately diagnosing brain tumours, planning therapies, and tracking disease development[7].

Here's an overview of how MRI used for BTD:

MRI is a non-invasive medical imaging technique that is widely used for detecting and visualizing brain tumours. It produces precise, high-resolution images of the brain, helping doctors to spot and characterise suspected tumours. Here are the key steps involved in MRI for brain tumour detection:

Image Acquisition: The individual is reclined on a table that may be slid inside the MRI scanner. The brain may be seen in great detail using magnetic fields and radio waves. Different MRI sequences are employed, such as T1-weighted, T2-weighted, and contrast-enhanced sequences, to capture various aspects of the brain tissue and enhance tumours visibility.

Image Interpretation: The acquired MRI images are then interpreted by radiologists or specialized computer algorithms. They analyse the images to identify any abnormal regions that may indicate the presence of a brain tumours. Tumours can appear as areas of abnormal signal intensity or mass-like structures within the brain tissue[9].

Tumours Characterization: Once a potential tumour is identified, further analysis is conducted to determine its characteristics. This includes assessing the tumours' size, location, shape, and relationship to surrounding structures. Additionally, contrast-enhanced MRI can help identify areas of increased vascularity or blood-brain barrier disruption, providing additional diagnostic information.

Treatment Planning: The MRI findings play a critical role in treatment planning. The detailed information obtained from the MRI images helps determine the best course of action, such as surgical resection, radiation therapy, chemotherapy, or a combination of treatments. The MRI results guide the neurosurgeon or oncologist in devising a tailored treatment plan based on the tumours' location, size, and characteristics[8].

Follow-up and Monitoring: After treatment, MRI is used for follow-up and monitoring purposes. Sequential MRI scans are performed at regular intervals to assess treatment response, detect potential tumours recurrence, or evaluate the effectiveness of ongoing therapies. Changes in tumours size and appearance over time can be monitored through these follow-up MRI scans.

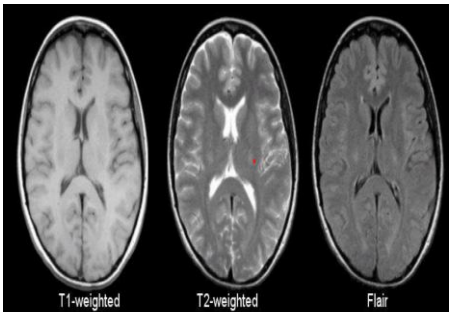

Figure.1 : T1, T2 , Flair image

T1-weighted and T2-weighted MRI sequences are the most typical. Figure.1 shows Bright FAT makes up the sole type of tissue in T1 weighted, while Bright FAT and Water make up both of the two categories of tissue in T2[5]. Repetition time (TR) is low when T1 weighting is used, whereas TE and TR are long when T2 weighting is used. The TE and TR parameters of the pulse sequence stand for the repetition time and the time to echo, respectively, and are measured in milliseconds (ms).[9] The echo time is depicted in the image as the interval between the centre of the RF pulse and the centre of the echo, and TR is the interval between the TE repeating sequence of pulse and echo. Figure.2 shows TE & TR Graph.

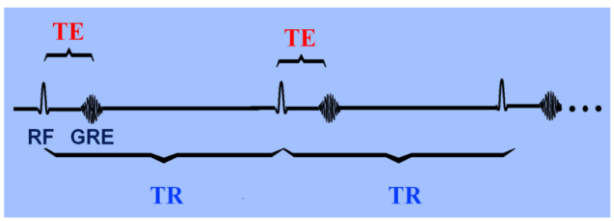

Figure. 2: Graph of TE & TR

various methodologies used in the detection and classification of brain tumours:

b) Medical Imaging Techniques:

i. MRI: It is widely used for BTD and characterization. It provides detailed anatomical information about the brain and helps visualize tumour location, size, and

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morphology.

ii. Computed Tomography (CT): X-rays are utilised in CT scans in order to obtain images of the brain in a cross-sectional format. They have the ability to provide information regarding the location, size, and density of the tumour.

iii. Positron Emission Tomography (PET): PET scans use radioactive tracers to detect metabolic activity in the brain. They help identify areas of increased glucose metabolism, which can indicate tumour presence[7].

iv. Functional MRI (fMRI): fMRI detects variations in blood flow to the brain in order to evaluate brain activity. It can be used to map tumour-related functional deficits or identify eloquent brain regions that should be preserved during surgery.

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].

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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. 3

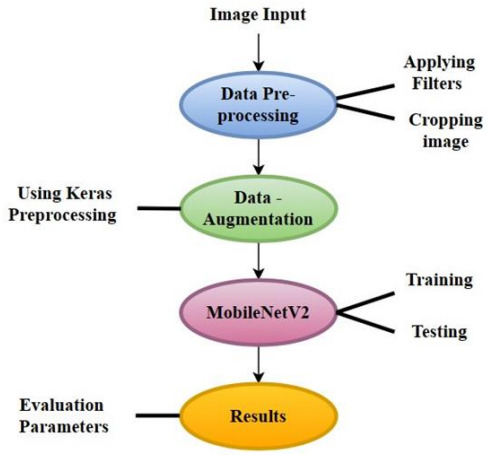

Figure 3 Proposed Methodology

The input image is sent to pre-processing. The image is convolved with filters and subsequently passed through data augmentation to expand the image set in this case. Then these images are sent to fine-tuned MobileNetV2. The model is trained by the images that are augmented. After training the model is introduced to the testing dataset. Results are obtained and are evaluated based on recall, precision, etc[10,32].

III.I 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 depthwise 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[12].

III.II Proposed Layers:

Here we use our base model as 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. The classification layer is comprised of a softmax function for accurate classification. The softmax function is defined a

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

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.

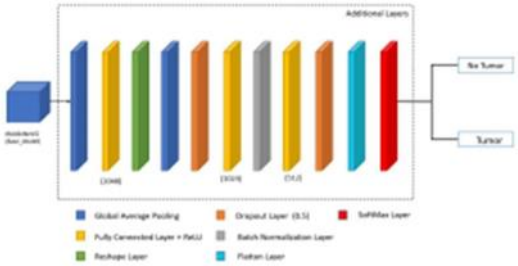

Figure 4 Layered architecture Proposed System

III.II 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

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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[21].

III.IV Hyperparameters 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 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.

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

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

Here, wt is the weight at time t, αt that indicates the learning rate at time t. mt is the gradient's aggregate at time t. mt is calculated as follows

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

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.

III.V 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.

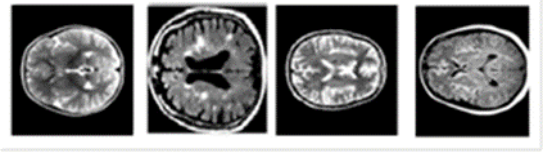

Figure (a)

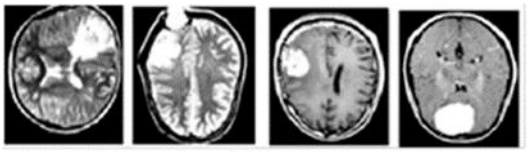

Figure (b)

Figure 5 a)Normal and b) infected MRI images

III.VI Data Pre-processing and Data-Augmentation:

The translation of pictures into a format that the model can readily understand thanks to pre- processing techniques for image data enables effective feature extraction. As a result, the model performs better and the photos are correctly classified

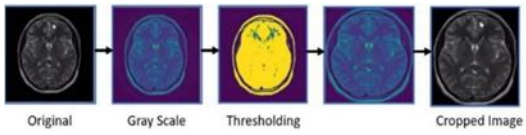

Figure 6 Pre-processing stages of MRI images

After the images are cropped it is sent to augmentation. This method is used so that the number 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.

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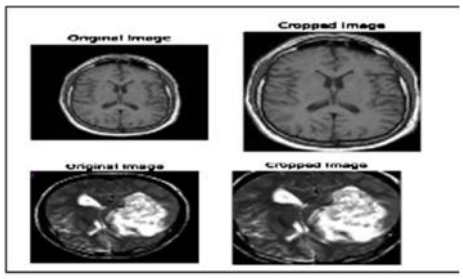

Figure 7 Original and cropped MRI images

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

IV.Experimental Set-up:

The model is deployed on the dataset. The proposed MobileNetV2 is executed on Google Colab 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 i5 processor and above, GPU of Nvidia GEFORCE GTX 1650, and RAM of 8GB.

V. Performance Evaluation Metrics:

i.Accuracy: Accuracy measures the proportion of correct predictions over the total number of predictions.

VI 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. Hyperparameters 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.

Accuracy = (TP + TN) / (TP + TN + FP + FN),

where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives. However, accuracy may not be the most reliable metric when dealing with imbalanced datasets.

ii.Precision: Precision measures the proportion of correctly predicted positive instances (true positives) out of all instances predicted as positive. It provides insights into the model's ability to minimize false positives.

Precision = TP / (TP + FP).

Precision is especially useful when the cost of false positives is high.

iii.Recall (Sensitivity or True Positive Rate): Recall calculates the proportion of correctly predicted positive instances (true positives) out of all actual positive instances. It indicates the model's ability to identify positive instances

Recall = TP / (TP + FN). Recall is valuable when the cost of false negatives is high.

iv.Confusion Matrix: A confusion matrix compares predicted labels to actual labels to summarise model performance. It provides a detailed breakdown of true positives, true negatives, false positives, and false negatives, allowing for a comprehensive evaluation of the model's performance.

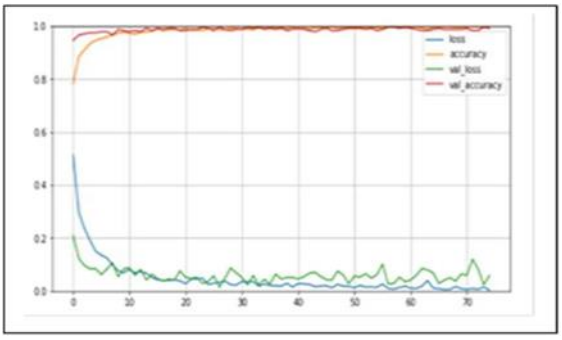

Figure 8 Loss and accuracy of Model

A loss graph and an accuracy graph are shown above 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. 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

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incorrectly of both the first and second classes.

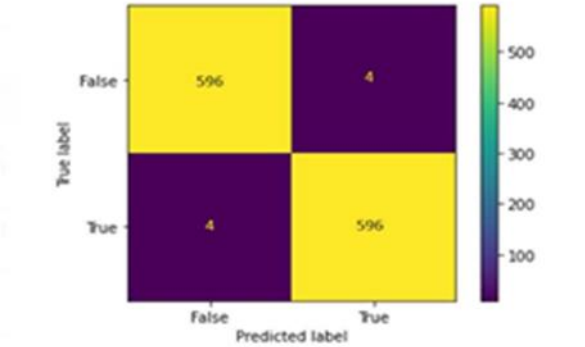

Figure 9 Confusion Matrix of proposed Model

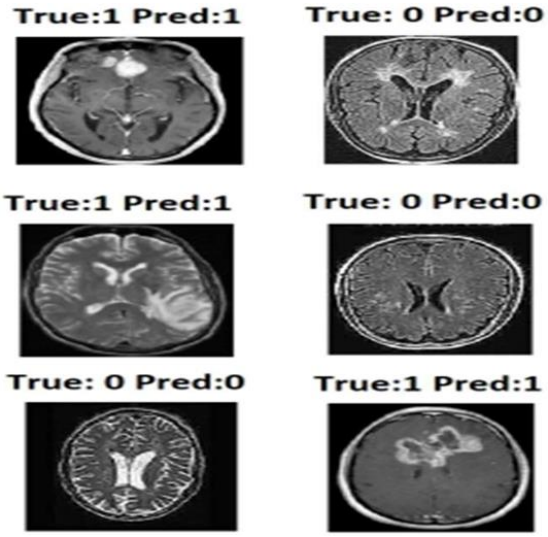

Figure 10 Accurately and inaccurately predicted MRI images

The below table 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.

The suggested model's performance indicators are presented below in a bar graph. 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. 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

able 1 Comparative Analysis

S. No	Previously done work	Model	Accuracy
1.	Latif [15]	SVM	95.6%
2.	Khan [16]	VGG19	94.7%
3.	Yahyaoui [17]	Dense-Net	94.5%
4.	Deepak [6]	Google-Net	97.10%
5.	R.Mehrotra[3]	Alex-Net	99.04%
6.	Chelghoum[8]	Fine-tuning	98.71%
7.	Hasnain Shah[7]	EfficientB0-Net	98.8%

VII. Conclusion and future work:

This paper focuses on tumor detection using MRI scans, employing a MobileNetV2 model. The approach includes preprocessing MRI images, converting them to grayscale, applying a Gaussian filter, and thresholding. Training involves feature extraction, leading to successful tumor detection. The proposed model achieves an impressive 99.33% accuracy, suggesting its efficacy. Future research could explore other CNN architectures, diverse preprocessing techniques, and hyperparameter tuning. Increasing the MRI dataset is crucial for improved learning, and extending the model's applicability to CT scans and other medical images presents avenues for future investigation.

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