Brain Tumour Detection Using Resnet 50 and Mobilenet

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Abstract— The scientific community defines a brain tumour as a mass or growth of abnormal cells in the brain. A brain tumour is a development of abnormal cells, some of which may develop into cancer. MRI scans are the most common way to find brain tumours and are used to detect brain cancer. There are different types of tumours exist. They are cancerous(malignant)and non-cancerous(benign) in the brain identification of unchecked tissue growth in MRI may help us diagnose brain cancer. Machine Learning and Deep Learning algorithms are used to identify this tissue growth. When these algorithms are applied to MRI scans, a faster prediction of brain tumours is made, and a better degree of accuracy aids in treating patients. MRI scans allow us to perform rapid analysis and identify the exact location of unwanted tissue growth. Various uses include image recognition and identifying objects, image classification, segmentation, neural network and data processing. The proposed model successfully classified the MRI image into four classes: glioma, meningioma, and pituitary tumour and no tumour, indicating that the given brain MRI has no tumour. In this paper the proposed models are MobileNet and Resnet50 and gives accuracy of 0.98. These models classifies the type of tumour very accurately.

Keywords- Brain Tumour, Convolution Neural Network, Segmentation, Magnetic Resonance Imaging, Malignant, Benign

I. INTRODUCTION

The brain is one of the most complex designed organs in the human body and has many cells. When cells divide uncontrollably and irregularly, the risk of developing brain tumours rises. The function of a cell in a group will interfere with brain activity's normal behaviour and harm healthy cells. Abnormal cell aggregations that develop inside the tissues of the brain are called brain tumours. There are two types of brain tumours they are malignant(cancerous) and benign(non-cancerous)[1]. Surgery can treat benign brain tumours, but malignant brain tumours, one of the deadliest forms of cancer, can be fatal. Brain tumours can also be separated into primary tumours originating in the brain or from brain nerves and metastatic tumours that have spread to the brain from other body areas. For brain cancers to be effectively treated, early detection is crucial. With the advancement of medical imaging, imaging tools may now give doctors a clear picture of the human brain's anatomy and play a significant part in diagnosing and evaluating brain tumour treatments. These imaging methods can help doctors to create a treatment strategy by providing details on the

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type of brain tumours like glioma, meningioma, and pituitary and no tumour is shown in Figure 1[2]. In neurology, MRI is the most frequently utilized scanning technique. In order to create an image of the interior of the target tissue, radio frequency signals are used to stimulate the tissue under the influence of a strong magnetic field.

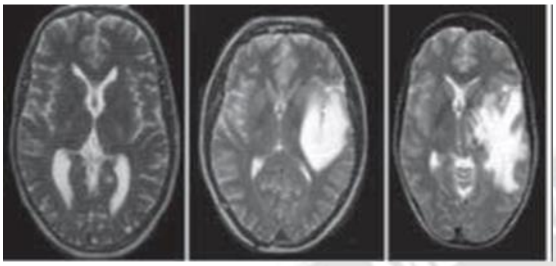

Figure 1. Normal, Benign, Malignant

II. LITERATURE SURVEY

Automatic defect detection in MRI images is essential in many applications for treating symptoms and curing diseases. However, tumour segmentation and classification are exceedingly tricky because of the extensive data in MRI images and the fuzzy borders. The accuracy and yield of the automatic brain tumour detection system introduced in this work have increased, while the time required for diagnosis has decreased. The tissues will be divided into two categories: normal and pathological. The shape of the tumour and its geometrical dimensions can be successfully determined using the proposed method. Additionally, based on that image and data analysis's discovery of vector quantization, a manipulation technique is intended to categorize brain tumours using MRI scans automatically.

Over the past few years, interest in the emerging machine learning discipline of "Deep Learning" has grown significantly. It was widely used in numerous applications and proved an effective machine-learning technique for many challenging issues[3]. It classifies a dataset into 4 categories— glioma, meningioma, pituitary and no tumour. In this study, a deep neural network classifier is one of the DL designs. The classifier was paired with principal components analysis (PCA), a practical feature extraction technique, and the discrete wavelet transform (DWT), and the performance was assessed favourably across all performance criteria.

Most patients didn't need help completing the questionnaire, which took about 11 minutes. Although, unlike the other multi-item scales, role functioning (job and household activities) failed to fulfil the minimal requirements for reliability (Cronbach's alpha coefficient > or =.70) before or during treatment, the data supported the questionnaire's hypothesized scale structure. Three findings demonstrated validity. Second, although all interscale correlations were statistically significant, the link was relatively mild, indicating that the scales evaluated diverse facets of the quality-of-life construct. Second, most functional and symptom measurements distinguished patients based on their treatment, weight loss, and the state as measured by the Eastern Cooperative Oncology Group performance status scale. Third, physical and role functioning, the general quality of life, exhaustion, nausea and vomiting all underwent statistically significant changes in the predicted direction for patients whose performance status had either improved or worsened throughout therapy[4]. Finally, the three language- cultural groups under research were patients from English- speaking countries, Northern Europe, and Southern Europe, and the questionnaire's reliability and validity were highly consistent across all three.

III. DATA SET

The Brain Tumor Classification dataset from Kaggle is used to evaluate the suggested model's performance and accuracy. There are 2870 MRIs in the entire dataset[5]. Training and testing datasets are two separate sections of the dataset. The training dataset shows 826, 822, 395, and 827 brain MRI scans of gliomas, meningiomas, no tumours, and pituitary tumours, respectively. Likewise, the testing dataset contains 100, 115, 105, and 74 brain MRI scans for glioma, meningioma, no tumour, and pituitary tumour. Figure 2 displays a sample of datasets, and Figures 3 and 4 display the distribution of the datasets used for training and testing within each of the four classes.

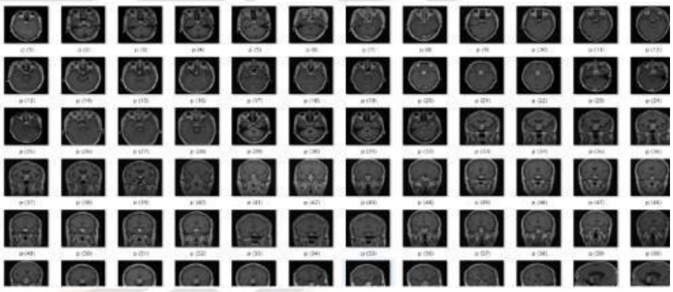

Figure 2. Sample dataset

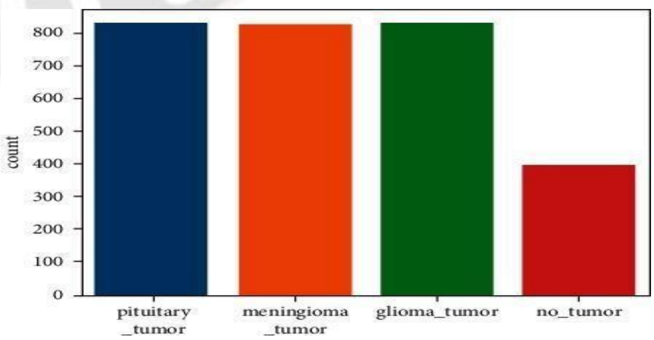

Figure 3. Distribution of training datasets across 4 classes

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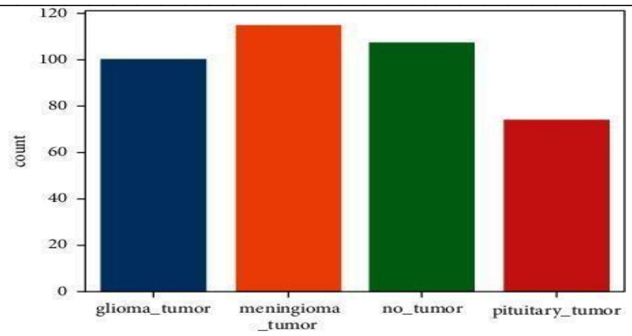

Figure 4. Distribution of testing datasets across 4 classes

IV. EXISTING SYSTEM

In deep learning, convolutional neural networks are one of the techniques employed. A subset of machine learning and artificial intelligence is called "deep learning". CNN can analyze an input image in Figure 5 and rank each component's relevance[6]. Component, and explain how they differ. CNNs are widely used in various tasks and activities, such as voice recognition in natural language processing, video analysis, and video encoding, to overcome issues with image processing, computer vision, and self-driving car obstacle detection. CNNs are widely employed in deep learning because of their significant contributions to these domains, which are rapidly growing and changing. AConvNet needs much less setup time than conventional classification techniques. The visual cortex inspired CNN's architecture, which is precisely like the neural connection network in the human brain. ConvNets is another name for convolutional neural networks, a subset of artificial neural networks[7]. There are several hidden layers in a convolutional neural network in addition to the input and output layers.

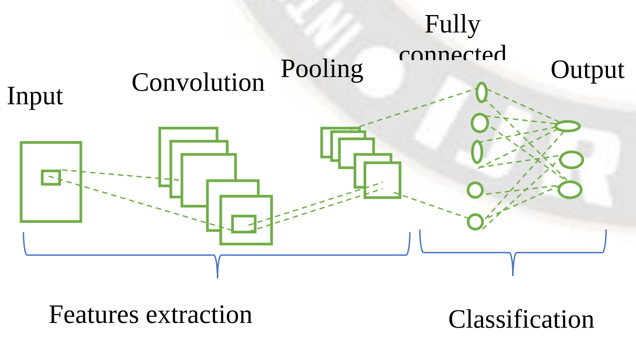

Figure 5. CNN Diagram

Convolution seeks to extract the input image's top-level features, such as its edges. Edges, colour, and gradient direction are typical low-level details that the first convolution layer frequently picks up. As layers are added, the architecture adapts to the high-level features, creating a network with a deep comprehension of the data's visuals. The pooling layer reduces the spatial size of the convolved feature. As a result, the processing resources needed to process the data are decreased with reduced dimensionality. The model training method is still flourishing as a result. Extracting crucial rotational and positional invariants is also made simpler. The two types of pooling are average and maximal pooling. The maximum number is returned by max-pooling from the kernel's region of the image. When employing average pooling, the same situation transpires, which returns the arithmetic mean of all the pixels in the image's kernel- covered region. The convolutional layer and the pooling layer are combined to create the ith layer of a convolutional neuralnetwork. Depending on how complex the photos are, the number of these layers may be raised to capture fine details. When a fully connected layer is added, the convolutional layer's output often represents the non- linear combinations ofthe trainable high-level features[8]. With this technique, the system is trained to recognize the tumour in the patient's MRIand determine if the patient has a tumour or not.

V. PROPOSED METHODOLOGY

In this proposed system, two algorithms are used to identify brain tumours: Mobilenet and Resnet. CNNs can be trained ona dataset of brain MRI scans to identify the presence or absence and detect the type of tumours in a given image. WhileResnet is a more sophisticated and intricate architecture that can achieve high accuracy on challenging image recognition tasks, Mobilenet is a lightweight CNN best suited for mobile and embedded devices. By merging these two architectures, the proposed system can balance accuracy and efficiency for identifying brain tumours[9].

The convolutional layers of the MobileNet technique are followed by depthwise and pointwise convolutions, asdisplayed in Figure 6. Due to these processes, the network needs fewer parameters and computations. To create the final output, the output from these layers is flattened and transferred through completely connected layers. Typically, a softmax function that transforms the output into a probability distribution over the output classes comes after the ultimately linked layers. Depending on the implementation and application, the architecture's specifics, such as the number oflayers and filters employed, may change. However, the MobileNet algorithm's general design, which focuses on lowering computing costs while retaining accuracy on image recognition tasks, has not changed.

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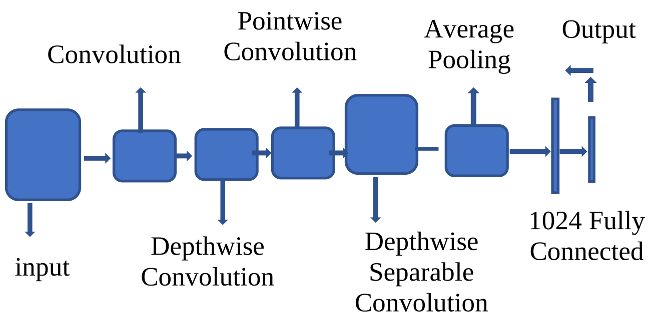

Figure 6. MobileNet Architecture

MobileNet is a lightweight, computationally efficient convolutional neural network (CNN) architecture well suited for use on embedded and mobile devices with constrained resources. To divide the conventional convolution process into two distinct layers—a depthwise convolution and a pointwise convolution—MobileNet uses depthwise separable convolutions as its core method. While thepointwise convolution applies 1x1 filters to combine the output of the depthwise convolution, the depthwise convolution applies a single filter to each input channel independently. With fewer variables and calculations needed, this method nonetheless achieves high accuracy in picture recognition tasks. Real-time image and video identification on mobile and embedded devices are one of themany use cases for MobileNet.

A traditional convolutional neural network with 50 layers is referredto as ResNet50, as seen in Figures 7 & 8. It serves as the foundationfor numerous computer vision tasks. A network is built by an Artificial Neural Network (ANN) by stacking leftover bricks on topof one another[10]. These blocks benefit from the concept of skipping connections to improve model precision. A fundamental link that skips some model layers is called a skip connection. These skip connections combine the results of stacked layers with those from earlier levels to address the vanishing gradient issue. This lowers the error rate and enables the training of deeper networks. TheResNet50 `model consists of 48 convolutional layers, one MaxPool layer, and one Average Pool layer[11].In MaxPool layer 3.8 x 109, floating point operations are available.

ResNet is a frequently employed model, and its framework can be used to train ultradeep neural networks. Even networks with hundreds or thousands of layers can use these networks. The initial challenge for ResNet was the picture recognition issue. However, the framework can be applied to address problems other than computer vision to improve accuracy[12].

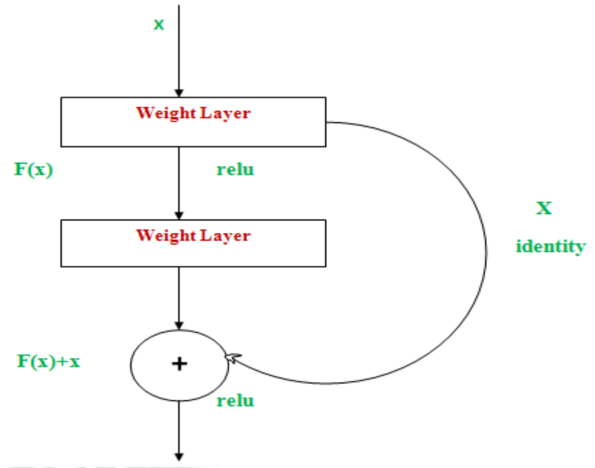

Figure 7. Skip Connection

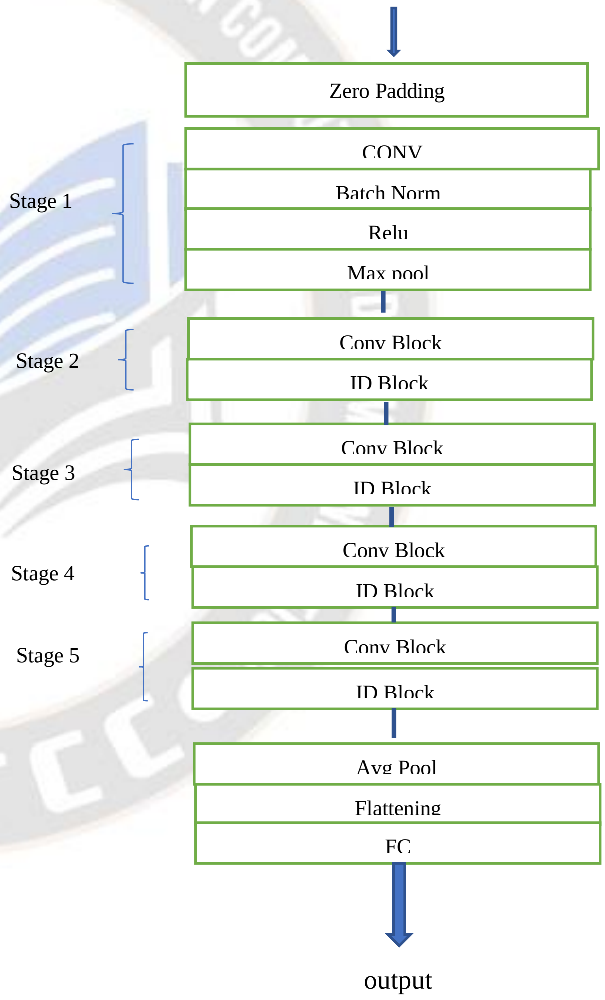

Figure 8. ResNet50 Architecture

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The user will input a brain image from an MRI scan, and the results will show four different sorts of tumours, as seen in Figure 9: gliomas, meningiomas, pituitary tumours, and no tumours. When the image is uploaded, it is categorized according to the following types of tumours.

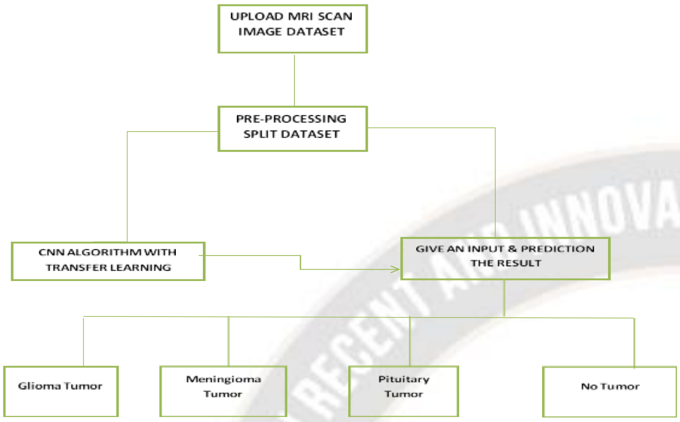

Figure 9. Block diagram to detect the type of tumour

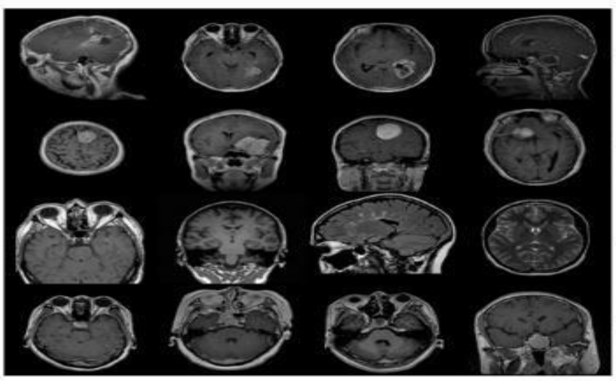

Figure 10. Types of tumours

A glioma tumour is a particular kind of brain tumour that arises in the glial cells, which are cells that nourish and shield the brain's nerve cells[13]. Gliomas can be divided into distinct categories, benign or malignant, based on their unique cell origin and characteristics. The operation, radiation therapy, and chemotherapy are frequently used to treat glioma tumours, and thedifferent types of tumours are categorized in Figure 10.

The meninges, the tissue layers that encase and safe guard the brainand spinal cord, are one type of brain tumour that can arise from the meninges.

Meningiomas are mostly benign, slow-growing tumours, though they can occasionally be cancerous. Meningioma symptomsmight vary depending on the location and size of the tumour, but they can include headaches, seizures, issues with eyesight, and limbweakness or numbness. Meningiomas can be treated with surgery, radiation therapy, and occasionally with observation.

A pituitary tumour is an abnormal growth that arises in the pituitarygland, a little gland near the base of the brain that generates hormones that regulate several biological activities. Depending onsize and form, tumours can result in various symptoms, including headaches, eyesight troubles, hormonal abnormalities, and other health concerns. Medication, surgery, and radiation therapy are available as treatments. To control the illness,regular monitoring and follow-up care are frequently required.

The body isn't experiencing any abnormal growth if there isn't a tumour. To rule out any underlying causes of any symptoms or problems you may be having, it's crucial to speak with a healthcareprofessional. However, there may still be a variety of other health ailments or concerns. For preserving general health and well-being,it's also crucial to have regular checkups and adopt appropriate lifestyle choices.

Architecture:

To know the type of tumour identified in the patient's brain, the user must register into the application using their credentials. After entering the application, the user mustupload the MRI scan given by the specialist. The registered user's data is stored in the database. When the user submits anMRI image, the model predicts the patient's tumour into fourtypes glioma, meningioma, and pituitary tumours. If the MRI image determines nothing, then no tumour is shown in Figure 11[14].

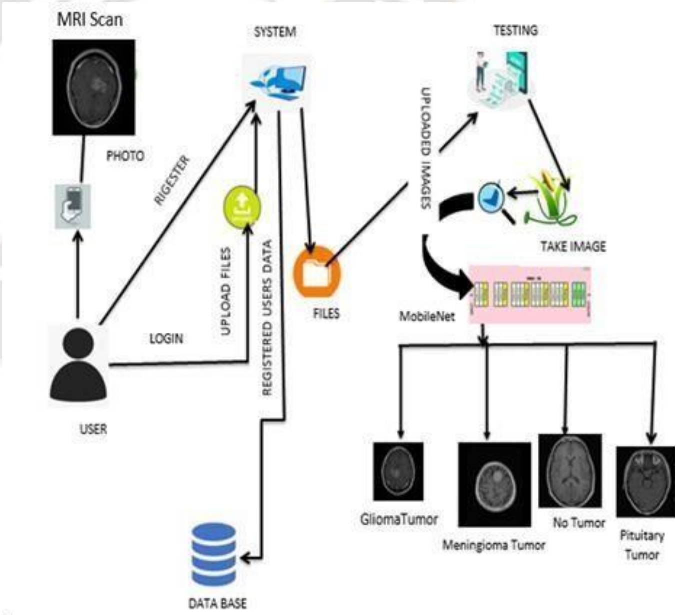

Figure 11. Architecture diagram

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VI. RESULTS

Figures 12 and 13 depict the comparison results after applying the same dataset to CNN, mobile net, and ResNet50.These layers enables the faster training of each layers. These networks are huge and gives low error rate.

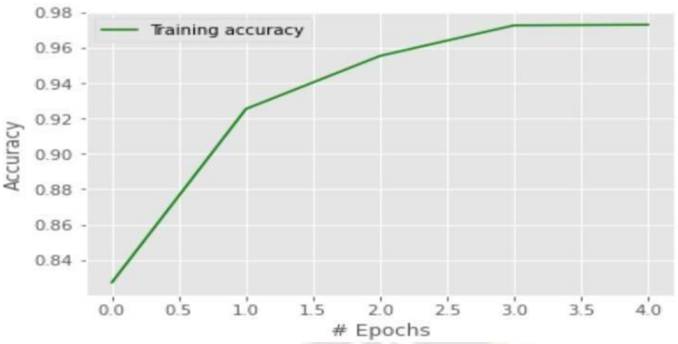

Figure 12. Accuracy graph

Figure 12 demonstrates the model's accuracy during training and validation. The keras callbacks function calculated it. Working with the various epoch counts, we noticed the training and validation accuracy. We observed that the model had the highest accuracy for both training and validation after 35 epochs.

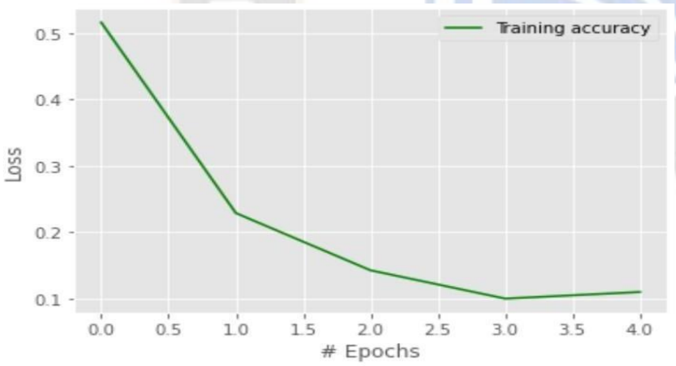

Figure 13. Loss chart

The epochs and loss graphs in Figure 13 show how the model has changed through time. The graph's horizontal axis denotes the number of training epochs, while the graph's vertical axis displays the value of the loss function. On the training set, lower loss function values indicate better model performance, and larger values indicate worse performance. These models gives accuracy of 98% and correctly classifiesthe type of tumour.

Table 1: Parameter-wise comparison

Parameter	**CNN**	**MobileNet and ResNet**
Number of images used	2870 Training-2000 Testing-500	2870 Training-2000 Testing-500
Time consumed	0:37:10 [37mins:10sec]	0:40:25 [40mins:25sec]
Epochs carried out	35	35
Accuracy	0.891	0.986

VII. CONCLUSION

In this work, existing methods address many issues, including accuracy, tumour quality, and tumour detection time. This research used various techniques, including the MobileNet and ResNet50 algorithms. The original preprocessed segment uses median filtering techniques to preprocess MRI pictures, and its accuracy is 98%. These learned traits served as feedback for three thousand—these classifier performances in terms of accuracy, validity testing and sensitive feeling. CNN approaches work well for accuracy levels with a reduced rate of error. As a result, the target area is segmented, and the technique presented here enables us to determine the presenceof a tumour. The advantages of this approach are that it improves performance compared to the alternative system by increasing the segmentation level and spatial localization of the image. Compared to networks with fewer parameters, it isfaster to train and compute. The accuracy will be improved witha lowrate of error.

REFERENCES

[1] Hemanth, L. Sujihelen, G. Janardhan, April 2019.Machine Learning Approach for Brain Tumor Detection: Design and Implementation. The third International Conference on Electronics and Information Technology will occur in 2019 IEEE.

[2] In January 2017, A. Minz and C. Mahobiya. MR photo categorization for the type of brain tumour using Adaboost. The 7th IEEE International Advance Computing Conference (IACC) was held in 2017.2018 January, Polly, F.P., Shil, S.K., Hossain, M.A., Ayman, A., and Jang, Y.M. IEEE— machine learning for the detection and categorization of HGG and LGG brain tumours.

[3] In January 2018, Hossain, M.A., Ayman, A., Jang, Y.M.,Polly, F.P., Shil, S.K., and Ayman machine learning for detecting and categorizing HGG and LGG brain tumours. 2018 saw the ICOIN IEEE.

[4] Siddappa, M., Suresha, M., and B.B. Shankaragowda, December 2017. a brand-new method for classifying and detecting brain tumours using support vector machines. The third 2017 saw the holding of the iCATccT, an international conference on theoretical and applied computing and communication technologies. (pp. 90-93). IEEE.

[5] In May 2017. Sonavane, R., Sonar, P., and Sutar brain MRI tumour and mammography image classification utilizing a vector quantization education network of neurons. Sensing, Signal Processing, and Security: The Third International Conference (ICSSS) occurred in 2017.

[6] Kandula, Ashok Reddy, K. Tamilarasi, and Srikrishna Maan. "Deep Neural Network for Image Recognition In Medical

Diagnosis." Journal of Pharmaceutical Negative Results 13 (2022).

[7] Ragavamsi, D, Ragupathy, R 2022, 'Improved Classification Model using CNN for Detection of Alzheimer'sDisease, Journal of Computer Science, vol 18, no 5, pp. 415–425.

[8] It was published in 2020 by Noreen N., S. Palaniappan, I. Ahmad, M. Imran, and A. Qayyum, as well as M. Shoaib.IEEE Access, vol. 8, p. 55135–55144, "AConcatenation-Based Deep Learning Model for the Diagnosis of Brain Tumors."

[9] Ragavamsi, D, Ragupathy, R 2022, 'A Pre-Trained Neural network to Predict Alzheimer's Disease at an Early Stage', International Journal of Advanced Computer Science and Applications, vol 13, no 5, pp. 194–200.

[10] K. S. Sudharani, T. C. Sarma, and K. S. Rasad, December 2015.using the k-NN technique, intelligently classify and identify brain tumour lesions from MRI images.2015 saw the first-ever ICCICCT IEEE.

[11] Allada A.; Bhavani, R.; Chaduvula, K. & Priya R.(2023). Early Diagnosis of Alzheimer's Disease from Mri Using Deep Learning Models. Journal of Information Technology Management, 15 (Special Issue) 52-71. https://doi.org/10.22059/jitm.2022.89411.

[12] Ragavamsi, D, Ragupathy, R 2022, 'Neuro–Imagingbased Diagnosing System for Alzheimer's Disease using Machine Learning Algorithms, Lecture Notes in Networks and Systems, vol 385, pp. 501–509.

[13] Mamun, M. A., M. A. Hossain, and M. P. Uddin, 2018. Anisotropic Filtering, SVM Classifier, and Morphological Operation for Detecting Brain Tumors from MR Images, Rashid, M.H.O. Computer, Communication, Chemical, Material, and Electronic Engineering International Conference were held in 2018. (pp. 1-4). IEEE.

[14] Shariff, T.A., and Zulkoffli, Z., June 2019. Brain tumour detection and feature extraction from MRI images using morphological operations and K-means clustering. The I2CACIS, an IEEE conference on automatic control and intelligent systems, will take place in 2019. IEEE.