

Brain Tumor Detection based on Multiple Deep Learning Models for MRI Images

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Abstract

INTRODUCTION: Medical imaging techniques are used to analyze the inner workings of the human body. In today's scientific world, medical image analysis is the most demanding and rising discipline, with brain tumor being the most deadly and destructive kind of malignancy. A brain tumor is an abnormal growth of cells within the skull that disrupts normal brain function by damaging neighboring cells. Brain tumors are regarded as one of the most dangerous, visible, and potentially fatal illnesses in the world. Because of the fast proliferation of tumor cells, brain tumors kill thousands of people each year all over the world. To save the lives of thousands of individuals worldwide, prompt analysis and automated identification of brain tumors are essential.

OBJECTIVES: To design an enhanced deep learning model for brain tumor detection and classification from MRI analysis.

METHODS: The proposed models Densenet-121, Resnet-101, Mobilenet-V2 is used to perform the task of Brain tumor detection for multi-class classification.

RESULTS: The proposed models achieved an accuracy of up to 99% in our evaluations, and when compared to competing models, they yield superior results.

CONCLUSION: The MRI image collection has been used to train deep learning models. The experimental findings show that the Densenet-121 model delivers the highest accuracy (99%) compared to other models. The system will have significant applications in the medical field. The presence or absence of a tumour can be ascertained using the proposed method.

Keywords: Brain Tumor, MRI, Mobilenet-V2, Resnet-101, Densenet-121

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1. Introduction

Image processing is a method that uses picture editing operations to improve an image to the point where relevant characteristics may be retrieved from it. Its popularity is rapidly increasing in recent years, and it has become as one of the primary study fields in science and engineering. Since the start of image processing, medical images have surely been one of the most important sectors that researchers have chosen to investigate [1]. A person's health is a primary issue in today's competitive environment. In terms of health discourse, cancer is the most dangerous and life-threatening problem. Brain, Bladder, Leukemia, Kidney, Lung, Prostate, and other cancers are extremely lethal and concerning for both children as well as adults, although leukaemia, brain tumors, as well as lymphomas are the three most prevalent juvenile cancers.

Medical technology advancements enable clinical specialists to provide more efficient e-health care solutions to patients. Brain cancer diagnosis requires the use of medical imaging [2]. Medical image analysis can help medical workers better comprehend illnesses and clinical issues in order to enhance health care quality. E-health care systems are advantageous in a variety of medical disciplines. X-ray, MRI, PET, US, and CT, among other medical imaging modalities, have profound effects on both patient diagnosis and care. By combining a stronger magnetic field and radio waves, magnetic resonance imaging (MRI) can see into the human body and create visual depictions of the brain. MRI is particularly beneficial for brain imaging which may be done without the use of radioisotopes. Multiparameter imaging is the foundation of MRI, which may produce various pictures by modifying various parameters and includes a vast quantity of information.

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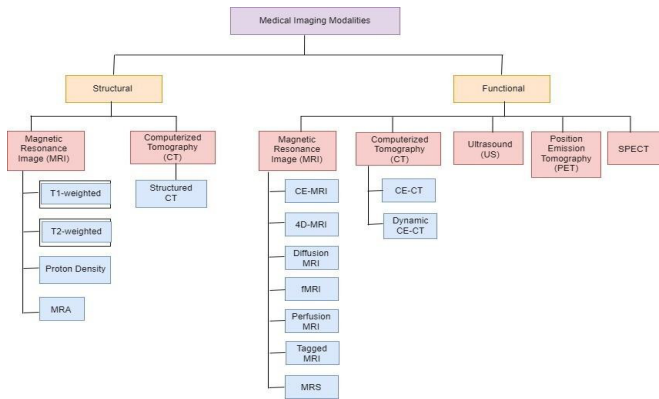


Figure 1. Types of Image Modality

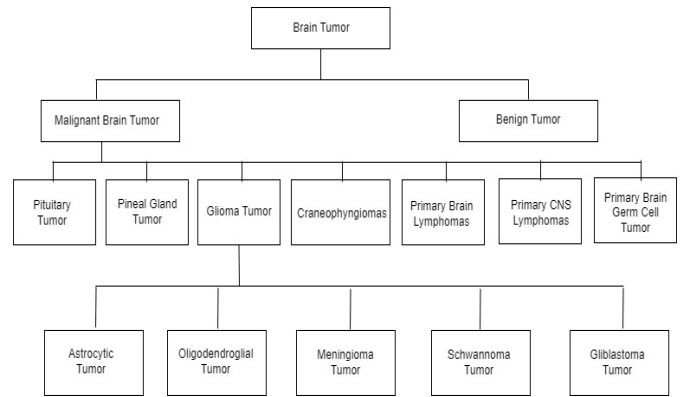


Figure 2. Types of Tumors

Brain infections, like meningitis, encephalitis, along with brain abscess, as well as brain trauma, as concussion as well as intracerebral haemorrhage, along with stroke, are examples of brain illnesses. Memory issues, loss of muscular control, convulsions, and visual impairments can all result from brain abnormalities. A fungal or bacterial infection causes a cerebral abscess, which is an accumulation of pus in the brain parenchyma. People who already have weakened immune systems are at a greater risk of contracting this illness. All bodily processes are coordinated by the brain, and it also plays a role in decision making. Inputs or impulses from the body's sensory organs are processed by the brain, which then makes decisions and delivers output information [3]-[4]. Brain tumors grow when normal brain cells divide uncontrollably, leading to the development of malignant cells. These cancerous cells can both impair normal brain function and destroy healthy cells. Researchers have spent decades attempting to figure out why brain tumor symptoms appear and how to conquer the condition. As illustrated in Fig. 1, imaging modalities may be split into six categories: structural and functional. CT (Computed Tomography) and MRI are structural modalities that primarily portray morphology (Magnetic Resonance Imaging). US (ultrasound), CT, MRI, PET (Positron Emission Tomography), and SPECT are examples of functional modalities. MRI is a cutting-edge medical imaging technique that provides a clear picture of the body with remarkable tissue contrast. Ankle, foot, and brain pathological conditions can be diagnosed with MRI. MRI is a non-invasive mode of imaging that has been found to be beneficial in the study of the human brain. The image provided by MRI helps in better understanding of normal and sick anatomy, and it is avital component in diagnosis and therapy planning. MRI, another outstanding technique, has substantially enhanced diagnostic imaging sensitivity and specificity (precision), notably in regions like the liver, brain, spinal cord, as well as joint spaces one of the main reasons why brain cancer is considered so hazardous is that it is poorly measured, recorded, and treated. The most common types of brain tumors include gliomas, pituitary tumors, and meningiomas. Meningioma develops inside the thin membranes that surround the spinal cord along with brain. Gliomas form in the brain's glial cells. Pituitary tumors occur when cells in pituitary gland divide abnormally. Therefore, saving lives requires prompt diagnosis and treatment of brain tumors.

As seen in fig.2, there are two kinds of tumors: benign (non-cancerous) as well as malignant (cancerous). Non-progressive benign tumors arise in the brain. It is classified as a slow-growing tumor that exerts potentially dangerous pressure but does not spread into brain tissue. This sort of tumor is less aggressive and does not have the ability to spread throughout the body. Malignant tumors spread throughout the body quickly. It is described as a rapidly growing tumor with the capacity to expand into the brain. Further, malignant tumors can be divided into two categories: those that originate in the brain (primary malignant tumors) and those that originate elsewhere in the body (secondary malignant tumors or metastatic tumors). The proposed clarification is to apply machine learning (ML) algorithms to detect as well as classify brain tumors in the patients. It is difficult to distinguish between meningioma, pituitary tumor, and glioma, as they vary in size, shape, and severity. Furthermore, meningioma, pituitary tumors, as well as glioma tumors have the greatest incidence rate of all brain cancers. The paper is organized in such a way as: In section 2 Related work on previous works, section 3 contains the discussion on dataset, proposed methods and pre-trained models, section 4, 5 includes results, discussion and Conclusion. We compared the results with deep learning models.

2. Related Work

H. Mohsen et al [5] This study employed the Fuzzy segmentation method (FCM) to identify brain cancers from normal brain tissue. In addition, we extracted wavelet features using a multilayer discrete wavelet transform (DWT). Finally, DNNs were deployed for precise brain cancer classification. Linear Discriminant Analysis (LDA), Sequential Minimum Optimization (SMO), and the K-Nearest Neighbor (KNN) classifier were all evaluated and compared to this approach. The analysis of brain tumors using DNNs was 96.97% accurate. However, the execution was horrible, and the complexity was high.

Islam et al [6] brain tumor detection and segmentation using the AdaBoost classification system's new multi-feature feature (Multi FD). The Multi FD feature extraction method was used to recover the underlying architecture of brain cancer tissue. AdaBoost classification, a state-of-the-art method, was used to examine donated brain tissue for signs of cancer origin. Voxels

in the brain were classified using a Local Independent Projection (LIPC) based classifier, as detailed in study [4]. Likewise, the path function was derived in the same way.

Jin Liu et al [7] Segmentation of brain tumors was the subject of a presentation. Different segmentation techniques such as area-based, threshold-based, C-means fuzzy, map-based, and Margo random field (MRF) were discussed, along with their corresponding model formats, deformable geometries, accuracy, robustness, and validity. Hybrid feature selection by ensemble classification was used to the challenge of identifying brain tumors Using C-based bagging and wrapper techniques, as well as GANNIGMAC, the decision rules were constructed. The use of a hybrid feature selection method (GANNIGMAC + MRMR C + Bagging C + Decision Tree) also aided in simplifying the principles of decision making.

Y. Chen et al [8] This research relied on data collected from the Kennedy Space Centre, Indian Pives, and the University of Pavia. The CNN algorithm was able to achieve an accuracy of 88.75%. [14] cites TCIA (The Cancer Imaging Archive) as the source of the dataset. Multiple classifiers, including SVM, RF, LOG, MLP, and PCA, were used in addition to KNN. The proposed method achieved an accuracy of 83%. Cheng's Fig share data was used for analysis in [15]. An algorithm based on a CNN (Convolutional neural network) achieved an accuracy of 84.19 percent.

Musallam et al [9] Modelled using a deep convolutional neural network that was trained with data from MRI scans of brain tumors Their plan made use of lightweight techniques including convolution, max pooling, and iteration. CNN-SVM, together with VGG16 and VGG19, was examined by the team. We classified the 3394 MR scans as either showing a glioma (934), meningioma (945), no tumor (606), or the pituitary gland (909). The suggested model achieved an overall accuracy of 97.72 percent, with a detection rate of 99 percent for glioma, 98.26 percent for meningioma, 95.95 percent for pituitary, and 97.1 percent for normal images.

Nayak et al [10] It was proposed to use a CNN-based network to spot malignancies in MRIs of the brain. In tests, their dense Efficient Net performed better than ResNet-50, Mobile Net, and MobileNetV2. A 98.78% accuracy and a 98.0% F1-score were attained after training the dense Efficient Net model. They utilized four different MRI methods for cancer detection in the brain. The MR image dataset included 3,260 images in total.

Khalil et al [11] A two-step technique, based on a modified version of the dragonfly algorithm, was proposed for segmenting brain tumors in 3D MR images. The most difficult aspects of early-stage brain tumor identification and segmentation are the wide range of tumor sizes and shapes. To get over these problems and obtain the primary contour point precisely, researchers employed a two-stage dragonfly algorithm. To obtain these results, the proposed model was applied to the BRATS 2017 3D MR brain tumor dataset.

3. Proposed Methodology

In this research, we aim to make use of a previously compiled MRI dataset of brain tumors. The main purpose of this research is to create a deep learning model that can detect brain tumors with high precision and speed. We evaluate deep learning models using a number of different criteria. Densenet121 was recommended after testing and training on the same dataset as two other models yielded subpar results. Ten training iterations were used for each model. As can be seen in Figure-1, the repository dataset undergoes preprocessing based on the model's input size. The training data set is used to feed data into the models. Next, the data is trained and evaluated to guarantee the necessary precision in the evaluation process. Once the accuracy has been compared, the diseased image is removed from the dataset i.e Four Classes 1.Normal 2.Glioma 3. Meningioma 4. Pituitary.

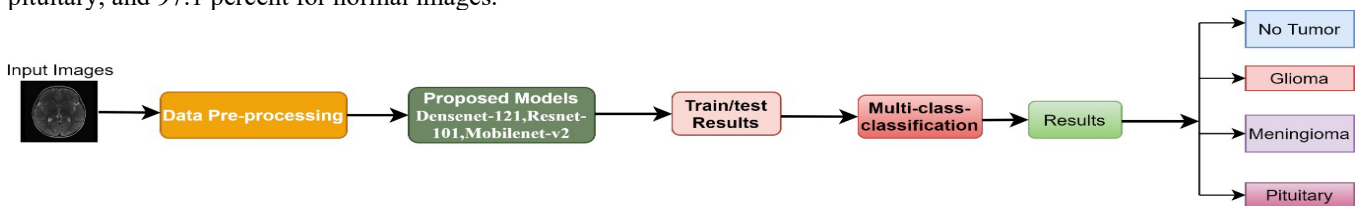


Figure 3. Flowchart for proposed Methodology

3.1 Dataset Description

The Kaggle website has been analysed for data. This data collection contains MRI images of brain cancers. The 7023 images in this set have been divided into the following four groups: Normal, Glioma, Meningioma, and Pituitary. We split the functionality in two, using 70% of it for training and 30% for testing.

Table 1. MRI dataset into four classes for use in Testing and training

S. No	Train/ Test	Classification	No.of Images	Total	Percentage
1	Training	no tumor	1595	5712	70%
		glioma	1321		
		meningioma	1339		
		pituitary	1457		
2	Testing	No Tumor	405	1311	30%
		Glioma	300		
		Meningioma	306		
		Pituitary	300		
Total				7023	

3.2 Proposed Models

Densenet-121

The state-of-the-art Convolutional Neural Network (CNN) architecture DenseNet can recognise visual objects with less parameters than earlier methods. With a few important modifications, DenseNet is very similar to ResNet. DenseNet uses a concatenates (.) attribute to mix the results of several layers, whereas ResNet uses an additive (+) attribute to do the same thing. The DenseNet Architecture suggests a straightforward solution by densely interconnecting all layers. As can be seen in fig. 4, the DenseNet-121 architecture was used in this study. Five convolution and pooling layers, three transition layers, one classification layer, and two dense blocks are required for Densenet-121.

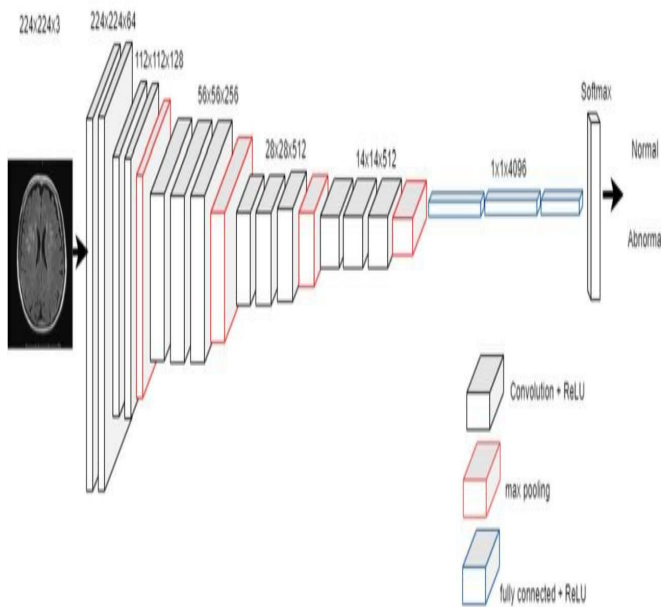


Figure 4. Proposed Densenet121model basic architecture

Instead of adding the layer output functionality maps to the inputs, DenseNet connects them. Densenet is a lightweight framework designed to improve interlayer communication. Features from all lower layer’s feed into the l th layer. An activation function (like ReLU or sigmoid) must be applied to the weight values in order to increase their nonlinearity. we can classify the output as Normal or Abnormal. If it is abnormal again, we classify to Glioma, Meningioma, and Pituitary.

Resnet-101

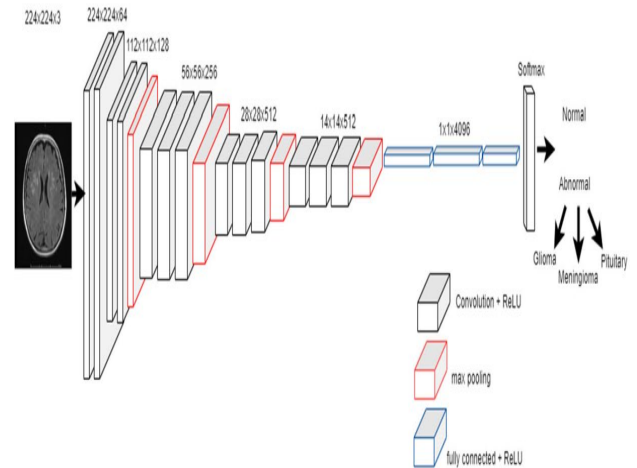


Figure 5. Proposed Resnet-101 model basic architecture

ResNet is acronym for the residual network and plays a crucial role in solving computer vision problems. The 104 convolutional layers of ResNet101 are organized into 33 blocks of layers, and 29 of these squares are recycled from earlier blocks. The ImageNet dataset, which has 1200 classes, was used to initially train this network. Fig. 3 depicts the original design's architectural layout. This diagram illustrated how the input images are divided into residual blocks, with multiple layers constituting each block. We make some adjustments to this model, getting rid of the FC layer and its thousands of object types.

As shown in fig-5 Based on the number of classes, we were required to create an additional FC layer. The dataset we have chosen has four distinct categories: Normal, Glioma, Meningioma, and Pituitary The redesigned model has a constant $224 \times 224 \times 3$ input size and a N3 output size. It consists of the following layers: convolution, max pooling (with a stride of 2), avg pooling (with a stride of 4), and a new fully connected layer and we can classify the output as Normal or Abnormal. If it is abnormal again, we classify to Glioma, Meningioma, and Pituitary.

Mobilenet-V2

MobileNet-V2 is a convolutional neural network architecture that was designed specifically with portability in mind. The foundation of this method is an inverted residual structure with residual links unique to the bottleneck layer. In order to filter features from a non-linear source, the extended middle layer makes use of lightweight depth convolutions. The convolutional layer of the MobileNetV2 architecture has 32 filters, and the bottleneck layer has 19.

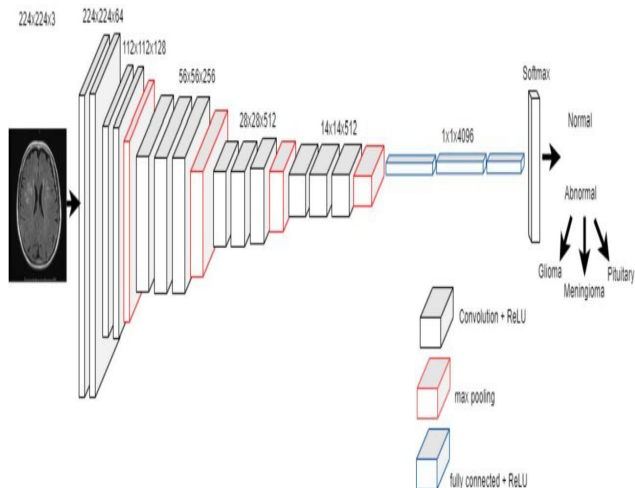


Figure 6. Proposed MobileNet-V2 model Basic architecture

As shown in fig-6 MobileNet-V2 supports two distinct types of building blocks. A residual block of only one stroke is unique. A further reduction in size would require two steps. There are three tiers for both types of blocks. This time around, the 1x1 convolution seen in ReLU6's first layer is utilized. Layer 2 is the convolution in depth. The 1x1 convolution in the third layer does not exhibit any non-linearity. In the region of the output domain where the volumes are non-zero, it is said that deep networks can only perform as well as a linear classifier. The deep network will perform no better than a linear classifier if ReLU is reapplied in the non-zero volume region of the output domain.

4. Results and Discussion

In this study, we compared three distinct models using the same data. This brain tumor identification model works very well with MRI images. Starting from scratch, the network is being trained using 10 data epochs, each of which consists of 412 Batches. Training data (typically 70%) and test data (typically 30%) are always separated before an experiment is executed.

However, only 15% of the data in the train set is actually used in the validation set. Dense Net 121 obtained a training and testing accuracy of 98.43% and 99% and an overall accuracy of 99%. Overall accuracy for the Resnet-101 model is 98%, with individual training and testing accuracy of 97.82% and 98%, respectively. The Mobilenet-v2 model achieved similar results, with a 97.09% training accuracy, a 97% testing accuracy, and an overall accuracy of 97%. The performance metrics used for classification are shown in the following equation.

$$Accuracy = TP + TN / TP + TN + FP + FN$$

The correct positive prediction's proportion is referred as recall. It is also called as true positive or sensitivity.

$$Recall = TP / TP + FN$$

Accuracy, defined as the proportion of correct predictions, is

given by the equation,

$$Precision = TP + TN / TP + FP$$

The following figures 7,9,11 shows the classification metrics for, Densenet-121, Resnet-101 Mobilenet-V2 Models and figure-8,10,12 shows the confusion matrix for Densenet-121, Resnet-101 Mobilenet-V2.

	precision	recall	f1-score	support
0	1.00	0.99	0.99	356
1	0.98	0.99	0.99	353
2	1.00	0.99	1.00	419
3	0.99	1.00	0.99	387
accuracy			0.99	1515
macro avg	0.99	0.99	0.99	1515
weighted avg	0.99	0.99	0.99	1515

Figure 7. Classification metrics of Densenet-121 Model

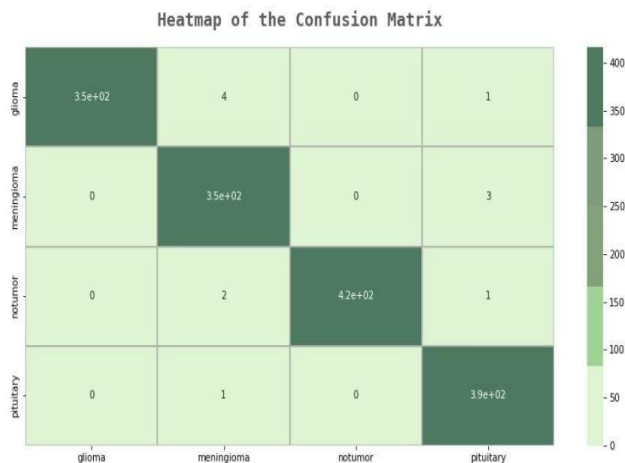


Figure 8. Confusion Matrix of Densenet-121 Model

	precision	recall	f1-score	support
0	0.97	0.98	0.97	356
1	0.97	0.95	0.96	353
2	1.00	0.99	1.00	419
3	0.97	0.99	0.98	387
accuracy			0.98	1515
macro avg	0.98	0.98	0.98	1515
weighted avg	0.98	0.98	0.98	1515

Figure 9. Classification metrics of Resnet-101 Model

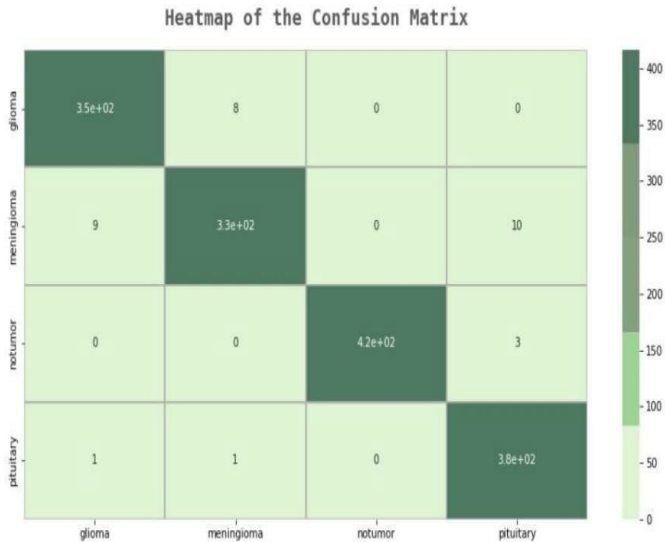


Figure 10. Confusion Matrix of Resnet-101 Model

	precision	recall	f1-score	support
0	0.93	0.99	0.96	356
1	0.97	0.92	0.94	353
2	0.99	1.00	0.99	419
3	1.00	0.97	0.99	387
accuracy			0.97	1515
macro avg	0.97	0.97	0.97	1515
weighted avg	0.97	0.97	0.97	1515

Figure 11. Classification metrics of MobileNet-V2 Model

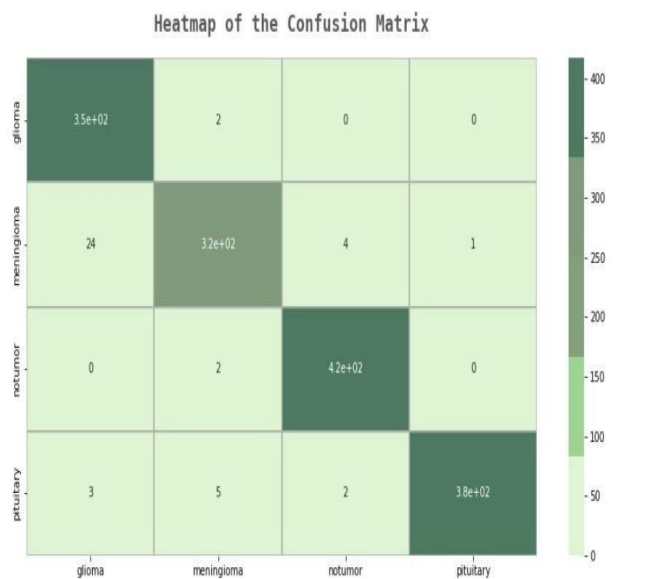


Figure 12. Confusion Matrix of MobileNet-V2 Model

The procedure of training and validating the precision/loss for the DenseNet121 network is depicted graphically in Fig-13. The test correctness and loss are nearly constant after a particular number of epochs, whereas the reliability and loss of validation vary substantially at first for several epochs, then settle to a constant value after a certain number of epochs.

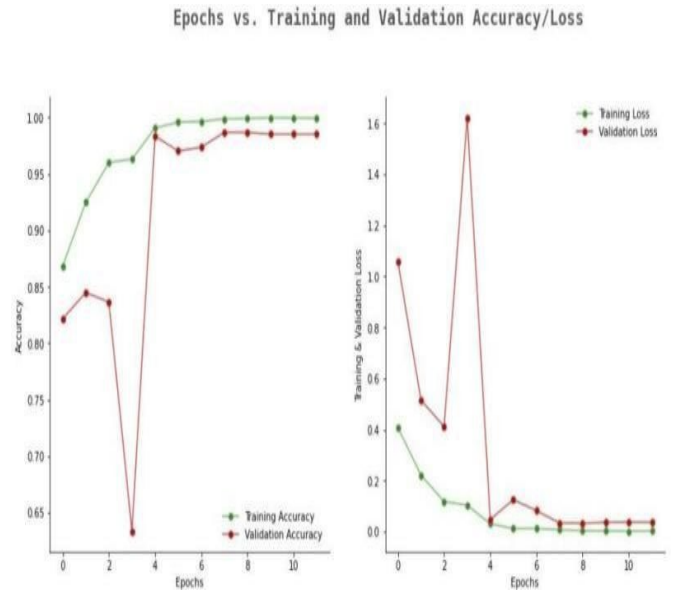


Figure 13. Densenet-121 Model Training and Validation Accuracy/Loss

The training procedure and evaluation correctness/loss for the ResNet101 model are graphically illustrated in Fig-14. The test reliability, loss are almost similar as number of epochs rises, however the precision of evaluation changes dramatically as the number of epochs rises, while the loss from validation remains constant.

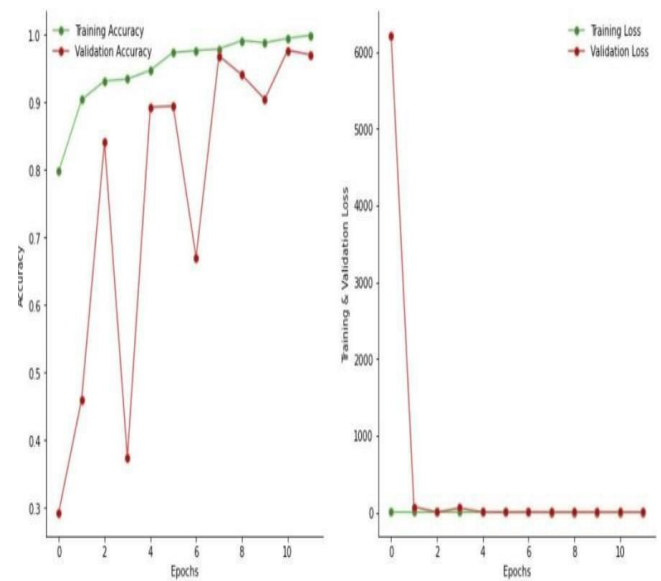


Figure 14. Resnet-101 Model Training and Validation Accuracy/Loss

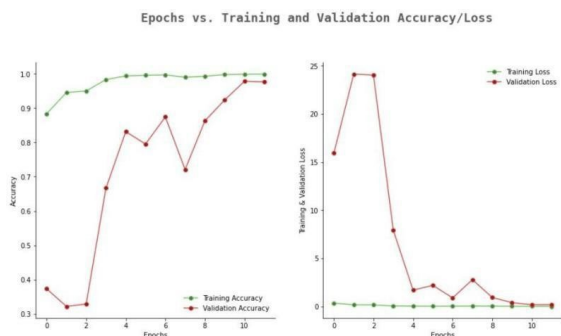


Figure 15. MobileNet-V2 Model Training and Validation Accuracy/Loss

Fig-15, we have a visual representation of the steps required to train and validate the precision/loss of the MobileNet-V2 model. While the test's precision and loss remain relatively stable as the number of epochs grows, the validation's precision and loss fluctuate widely as the epoch count rises.

Here Table-2 shows the final performance metrics comparison for deep learning models.

Table 2. Comparison of Three Deep Learning Techniques' Classification Metrics

Deep Learning Models	kinds of Tumor	Precision	Recall	f1 Score	Support
Dense Net 121	The tumor Glioma	1.00	0.99	0.99	356
	A tumor Meningioma	0.98	0.99	0.99	353
	No tumor is present	0.98	0.99	1.00	419
	A tumor Pituitary	0.99	1.00	0.99	387
ResNet 101	The tumor Glioma	0.97	0.98	0.97	356
	A tumor Meningioma	0.97	0.95	0.96	353
	No tumor is present	1.00	0.99	1.00	419
	A Pituitary tumor	0.97	0.99	0.98	387
MobileNet-V2	The tumor Glioma	0.93	0.99	0.96	356
	A tumor Meningioma	0.97	0.92	0.94	353
	No tumor is present	0.99	1.00	0.99	419
	A tumor Pituitary	1.00	0.97	0.99	387

5. Conclusion

Malignant brain tumors, which account for most of such cases, are universally regarded as terminal. Because brain tumors can present with seemingly innocuous symptoms at first, early identification is crucial. The most prevalent symptom of brain disorders is a headache, which, in the case of brain tumours, tends to develop over time. As a result, there are many reports of increased brain tumour mortality

because to delayed diagnoses. Recently, MRI has shown useful in a variety of contexts, including the diagnosis of brain tumors, and as a result has become a standard tool in clinical research. When deep learning methods are used to these MRI scans, the tumour can be located. The MRI image collection has been used to train deep learning models. The experimental findings show that the Densnet-121 model delivers the highest accuracy (99%) compared to other models. The system will have significant applications in the medical field. The presence or absence of a tumour can be ascertained using the proposed method.

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