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BRAIN TUMOR DETECTION AND CLASSIFICATION USING DEEP LEARNING

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Brain Tumor Detection, MRI Image Analysis, Deep Learning, Convolutional Neural Network (CNN), VGG-16, ResNet-101, Transfer Learning, Medical Image Classification, Automated Diagnosis, Feature Extraction, Image Processing, Clinical Decision Support Systems.

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Abstract

Brain tumor detection from magnetic resonance imaging (MRI) scans is a critical and challenging task in medical image analysis, where early and accurate diagnosis plays a vital role in improving patient survival rates and treatment planning. This study proposes an automated brain tumor detection and classification framework based on deep learning techniques, incorporating a basic Convolutional Neural Network (CNN), VGG-16, and ResNet-101 architectures.

The proposed models are trained and evaluated on benchmark MRI brain tumor datasets using transfer learning and optimized training strategies to address challenges associated with limited data availability. Each model is trained for 20 epochs in a GPU-accelerated environment. Performance evaluation is conducted using standard classification metrics, including accuracy, loss, precision, recall, and F1-score. The experimental results demonstrate that all three models achieve strong classification performance. Among them, ResNet-101 achieves the highest performance, with a training accuracy of 99.94% and a testing accuracy of 98.31%. VGG-16 follows closely, achieving 99.21% training accuracy and 97.85% testing accuracy, while the basic CNN model obtains 98.74% training accuracy and 94.31% testing accuracy. The corresponding loss values remain consistently low across all models, indicating effective learning behavior and strong generalization capability. Furthermore, the training and validation curves illustrate stable convergence across epochs, with minimal evidence of overfitting. These results highlight the effectiveness of transfer learning in enhancing feature extraction from MRI scans and improving classification performance. To further improve model robustness, data augmentation techniques and pretrained architectures are employed, particularly to mitigate the limitations posed by small dataset sizes. Overall, the proposed system demonstrates significant potential for assisting medical professionals in the early detection of brain tumors by providing fast, accurate, and reliable predictions. The findings suggest that deep learning architectures, particularly ResNet-101 and VGG-

16, serve as effective tools for automated brain tumor classification and can be extended for deployment in real-world clinical decision-support systems.

INTRODUCTION

Artificial Intelligence (AI) is influencing health policy. In the healthcare sector, the accessibility of various medical data sources, the advancement of contemporary deep learning methods, and the applications of these methods are all growing substantially. Numerous Deep Learning technologies (DL) are being utilized to investigate numerous computer-assisted systems and deep learning frameworks to support physicians by carrying out various tasks in healthcare. The most crucial and efficient of these beneficial AI applications is automated disease diagnosis (Humayun et al., 2024). The use of systems based on AI in healthcare enhances the identification of medication issues and elevates the standard of care through prompt and suitable treatment (which aids in reducing the survival risk of deadly diseases), supports healthcare professionals, saves substantial time and money on costly medications, and provides readily accessible medical care to individuals residing in developing nations, among other benefits. As reported by the World Health Organization, cerebrovascular conditions like stroke rank as the fifth leading cause of death in adults, representing 11% of all deaths, and are the leading cause of lasting disability. Every two seconds, a stroke occurs in individuals, leading to approximately 6.24 million fatalities globally (World Health Organization, 2020). Unhealthy ways of living are common these days. Stroke results from various factors such as hypertension, atherosclerosis, diabetes, hyperlipoproteinemia, tobacco use, smoking, and obesity (Esteva et al., 2022). There are two primary categories of Strokes:

- Hemorrhagic stroke
- Ischemic stroke.

A blood vessel breaks and results in bleeding during a hemorrhagic stroke. It compresses, destroys, and damages blood tissues (Sheth et al., 2023). An ischemic stroke occurs due to a blockage in a blood vessel that delivers blood to the brain. It got obstructed because of a decrease in blood circulation and oxygen to the brain. The reduction leads to damage and destruction of brain cells. This condition is called ischemia, and the loss of brain cells is referred to as infarction or ischemic stroke. Identifying functional disability in stroke patients requires examining the size and location of brain lesions. Identifying and classifying the infarct lesion is essential for the patient's therapy. Computer Tomography, MR spectroscopy, MR angiography, and diffusion MRI are employed for the detection, segmentation, classification, and diagnosis of strokes. Prompt identification of infarct lesions is crucial for determining their type, effects, and creating a treatment plan (Topol, 2023).

Regardless of the location and growth pattern, brain tumors are a big health problem, whether benign or malignant. Although benign tumors are non-invasive, they may present complications at vital sites, whereas malignant ones are potentially harmful as they may invade and proliferate. The timely treatment of brain tumors depends on their early diagnosis, and it is hard to diagnose brain tumors, especially at an early stage, because of factors such as the size, shape, and low-resolution imaging (Wang, W, 2020). Magnetic Resonance Imaging (MRI) is one of the medical imaging methods that produces high-contrast images. Machine learning, and in particular transfer learning, has become popular in the analysis of MRI with high accuracy. Transfer learning employs already trained DCNN, including VGG16, VGG19, ResNet50, InceptionResNetV2, InceptionV3, Exception, and DenseNet201 to identify features in MR images. The features are subsequently categorized using conventional algorithms such as Support Vector Machines (SVM), Random Forest, Decision Tree, AdaBoost, and Gradient Boosting, and the performance of each is evaluated using 10-fold cross-validation. The study (Esteva et al., 2022) examines the capabilities of these transfer learning

models and classifiers to identify the most promising for brain tumor detection and classification, even when dealing with smaller datasets. This approach reduces computational and training time for predictions and improves accuracy and generalization by reusing pre-trained model weights. As shown in Figure 1, the tumor identification process images with different model techniques are used to identify the type of tumor.

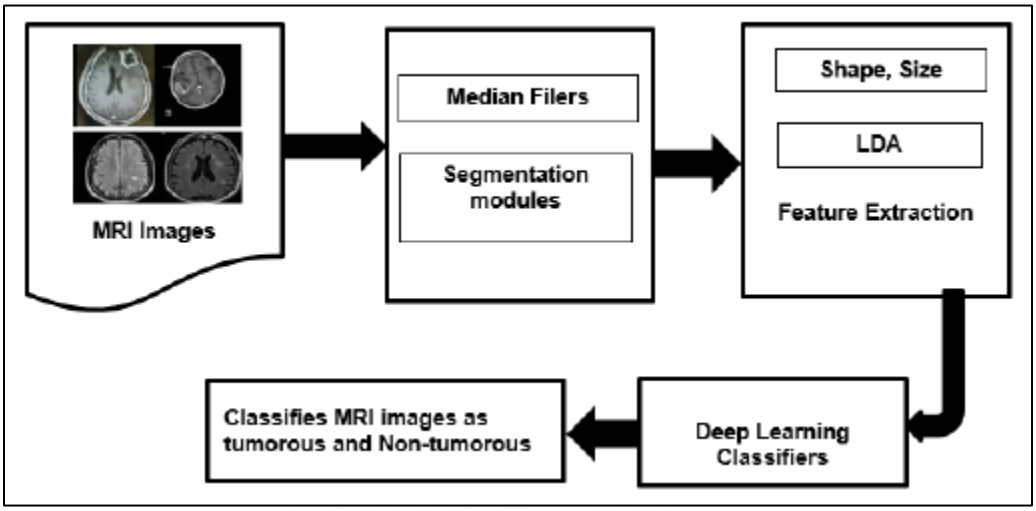


Figure 1 Generic Overview of Brain Tumor Classification

The experimental results demonstrate that all three models achieve strong classification performance. Among them, ResNet-101 achieves the highest performance, with a training accuracy of 99.94% and a testing accuracy of 98.31%. VGG-16 follows closely, achieving 99.21% training accuracy and 97.85% testing accuracy, while the basic CNN model obtains 98.74% training accuracy and 94.31% testing accuracy. The corresponding loss values remain consistently low across all models, indicating effective learning behavior and strong generalization capability. Furthermore, the training and validation curves illustrate stable convergence across epochs, with minimal evidence of overfitting. These results highlight the effectiveness of transfer learning in enhancing feature extraction from MRI scans and improving classification performance. To further improve model robustness, data augmentation techniques and pretrained architectures are employed, particularly to mitigate the limitations posed by small dataset sizes. Overall, the proposed system demonstrates significant potential for assisting medical professionals in the early detection of brain tumors by providing fast, accurate, and reliable predictions. The findings suggest that deep learning architectures, particularly ResNet-101 and VGG-16, serve as effective tools for automated brain tumor classification and can be extended for deployment in real-world clinical decision-support systems.

Literature Review

Various crucial functions like cognition, verbal communication, and physical movement can be impaired because of mental illnesses. The World Health Organization states that cancer is a condition responsible for 9 million deaths annually, representing 22% of all chronic illnesses. It is the second primary cause of mortality from cardiovascular disease, resulting in 17.9 million deaths annually (Saeedi et al., 2023). Based on the WHO standards from 2019, 86,000 of 700,000 patients were identified as having brain tumors. Cancer occurs when tumors form as a result of uncontrolled cell division, leading to a significant presence of abnormal cells in the body. Tumors, non-cancerous (benign) or cancerous (malignant). Benign tumors develop gradually and seldom spread to different areas of the body. Sufficiently

large to pinch tissue or nerves, leading to issues. Cancerous tumors grow at various speeds and infiltrate surrounding healthy tissue. Primary cancers represent 1.4% of all newly diagnosed cancer cases annually in the United States. Conversely, brain tumors represent 2.7% of all cancer fatalities in the United States (Berghout, 2024). Primary malignant brain tumors refer to cancerous brain tumors that originate in the brain and metastasize to other areas of the body. Glioma is the most prevalent malignant tumor found in the brain. The World Health Organization divides gliomas into two types: low-grade gliomas and high-grade gliomas. Patients diagnosed with glioblastoma multiforme typically survive for about 12-14 months, indicating a grim prognosis for advanced gliomas. Identify, create a treatment strategy, and handle gliomas using medical imaging techniques like MRI (Talukder et al., 2023). Secondary brain tumors originate in other areas of the body, metastasize to the brain, and commonly affect additional organs like the lungs, skin, chest, and kidneys. Besides the WHO classification, several factors influence patient survival time, including the degree of surgical resection, age of the patient, tumor site, and vice versa.

The World Health Organization states that stroke ranks as the second leading cause of mortality globally. In Pakistan, 218 individuals per 100,000 experience strokes, despite the absence of studies on strokes within the population. Research indicates that the primary socio-economic effect on society is that 30% of individuals will require assistance with mobility, while 70% of stroke survivors will be unable to resume employment. The intensity of the illness is linked to a diminished quality of life in individuals who have had a stroke (Talukder et al., 2023). Stroke is categorized into ischemic and hemorrhagic types. Ischemia refers to a state where blood circulation is decreased, leading to a temporary or permanent halt in organ function. Cerebral ischemia is defined by a reduction in blood supply to all regions of the brain. Ischemic strokes happen when the blood vessels delivering blood to the brain get blocked or obstructed, representing over 80% of all occurrences. Delayed doctor visits or diagnoses tied to low education levels, widespread poverty, and insufficient information are primary factors contributing to the rise in mortality from mental illness and cancer. Early diagnosis significantly enhances survival rates for various diseases and enables alternative care options (Mohammed et al., 2023). Although a definitive method to prevent brain tumors and strokes does not exist, various manual and imaging techniques assist in their diagnosis and detection. The primary and most prevalent form of introspection for identifying brain abnormalities is to offer individuals techniques for the early detection of diseases. Radiologists employ various imaging techniques, such as magnetic resonance angiography, computed tomography, diffusion magnetic resonance imaging, ultrasonic magnetic resonance imaging, and magnetic resonance spectroscopy, to enhance the detection and diagnosis of brain tumors and ischemic strokes. These imaging techniques help identify different brain abnormalities in individuals. Consequently, MRI is frequently utilized to diagnose, describe, and measure the progress of diseases. For instance, T2 lesions are more prevalent in WM (white matter) but also occur in MS (multiple sclerosis) in the GM (gray matter). Lesions in the periventricular or subcortical areas of the brain are more prevalent in individuals with multiple sclerosis and vary in size, shape, and dimensions, though they frequently enlarge due to blood vessel narrowing. The processes that cause these lesions vary greatly and encompass blood-brain barrier localization, inflammation, demyelination, partial axonal viability, astrocytic protrusions, and notable yet restricted. Radiologists frequently face controversy in diagnosing medical brain imaging, such as BRATS and ISLES.

Table 1 Comparative Analysis of Brain Tumor Detection Studies

Author(s) & Year	Methodology	Dataset	Task	Evaluation Metrics
Saeedi et al. (2023)	CNN-based deep learning model	MRI brain tumor dataset	Tumor classification	Accuracy, Precision, Recall
Talukder et al. (2023)	Transfer learning (pretrained CNN models)	BraTS dataset	Tumor segmentation and classification	Dice Score, Accuracy
Berghout (2024)	Deep CNN architecture	MRI scans	Brain tumor detection	Accuracy, F1-score
Mathivanan et al. (2024)	Hybrid deep learning model	Medical MRI datasets	Brain tumor and stroke detection	Accuracy, Sensitivity, Specificity
Muscogiuri et al. (2022)	Deep learning-based image analysis framework	Brain imaging datasets (MRI/CT)	Multi-class brain disease detection	Accuracy, Loss
Ismael et al. (2021)	CNN with data augmentation	BraTS dataset	Glioma classification	Accuracy, Recall
Deepak & Ameer (2019)	Pretrained VGG16 (Transfer Learning)	MRI brain tumor dataset	Tumor classification	Accuracy, Confusion Matrix
Cheng et al. (2018)	Deep CNN with feature fusion	BraTS MRI dataset	Tumor segmentation	Dice coefficient, Accuracy
Proposed Work (Your Study)	CNN, VGG-16, ResNet-101 (Transfer Learning)	MRI Brain Tumor Dataset	Tumor classification	Accuracy, Precision, Recall, F1-score

The American College of Radiology (ACR) has created guidelines for individuals with mental health disorders regarding the diagnosis and analysis of brain, ultrasound, and MRI datasets to avoid these disputes and maintain radiologist impartiality (Mathivanan et al., 2024). Manual analysis of images is a labor-intensive task that demands skilled and knowledgeable healthcare experts. Visual observation of the brain carries risks of subjectivity, time consumption, and ambiguity. Misinterpretation by humans during processing results in false positive (FP) or false negative (FN) diagnoses. Practitioners employ manual analysis to enhance predictions. Conversely, technical challenges like noise and low image quality may raise the prevalence of false positives, leading to unwarranted biopsies. Deep learning frameworks serve as the optimal solution to address these constraints and forecast the early detection of brain tumors and ischemic stroke. These technologies assist doctors and other radiologists in identifying issues and anomalies in medical images. Deep learning frameworks utilize image processing and computer vision methods to derive extensive information from medical images. Doctors utilize the Deep learning framework to identify tumors, differentiate between benign and malignant tumors, and classify tumors into various types, like primary (glioma, LGG, HGG, etc.) and metastatic. Furthermore, these frameworks assist in reducing unnecessary biopsies and conserve considerable time that would otherwise be lost on manual analysis of medical images. Figure 2.1 illustrates the overall structure of a Deep learning framework designed for identifying brain tumors and ischemic stroke while creating a multi-class disease detection system, several challenges emerge, including selecting suitable segmentation

techniques to differentiate tumor areas from the background, limited resources, choosing an imaging approach for clearly defined datasets like brain medical images, selecting features derived from the image, and recognizing the right classifier for precise classification (Muscogiuri et al., 2022). The Deep learning framework assists in powering several tasks linked to brain tumor and ischemic stroke analysis, such as automatic risk prediction, diagnosis, detection, feature learning, the identification of tumor and stroke recurrences, image registration, survival forecast, etc. Several machine learning frameworks have been established to accomplish these objectives.

1 Methodology

The methodology of brain tumor classification using deep learning begins with collecting a labeled MRI dataset from sources such as Kaggle or the Cancer Imaging Archive, containing tumor and non-tumor images and multiple tumor types. The images are preprocessed by resizing them (typically to 224×224 for pretrained models), normalizing pixel values, reducing noise if necessary, and applying data augmentation techniques like rotation and flipping to improve generalization. The dataset is then divided into training and testing sets (commonly 80% training and 20% testing) to ensure unbiased performance evaluation. A custom CNN is built using convolutional, pooling, and fully connected layers to extract and classify features, while transfer learning approaches are applied with VGG16 and ResNet-101 by replacing their final classification layers and fine-tuning them for tumor detection; VGG16 uses deep stacked convolution layers for strong feature extraction, whereas ResNet-101 employs residual (skip) connections to overcome vanishing gradient issues and achieve higher accuracy. During training, images pass through forward propagation, loss is computed using cross-entropy, weights are updated via backpropagation with optimizers like Adam or SGD, and the models are evaluated using metrics such as accuracy, precision, recall, F1-score, and confusion matrix, with ResNet-101 generally providing the best performance, followed by VGG16 and then a basic CNN, depending on dataset quality and size.

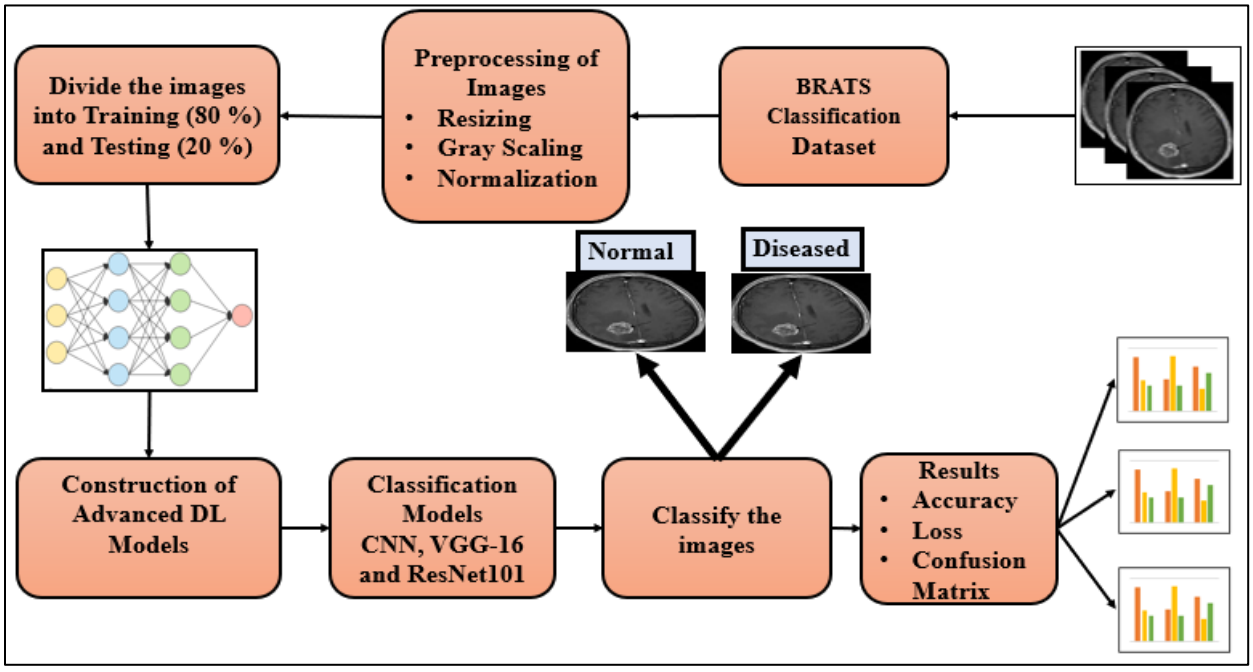


Figure 2 Research Methodology Flow

- Input Dataset for Classification
- Preprocessing steps
- Dividing images into training and testing
- Construction of deep learning models
- Classification
- Results

1.1.1 Dataset Description

The dataset of 7,200 brain MRI images is divided into four classes: Glioma, Meningioma, Pituitary tumor, and No tumor, with each class containing an equal number of images to maintain balance. To prepare the data for model training and evaluation, an 80–20 split is applied, resulting in 5,600 images for training and 1,600 images for testing. Specifically, each class contributes 1,400 images to the training set and 400 images to the testing set, ensuring that all classes are equally represented in both sets. This balanced division allows the deep learning models to learn features effectively from the training data while providing a fair and unbiased evaluation on the testing data, which is critical for achieving accurate brain tumor classification.

Table 2 Class Distribution of Downloaded Dataset

Class	Training	Testing
Glioma	1400	400
Meningioma	1400	400
Pituitary tumor	1400	400
No tumor	1400	400
Total	5600	1600

RESULTS

Table 3 Architecture of Used ResNet101

Parameter	Detail
No of Epochs	20
Batch Size	256
Optimizer	Adam
Learning Rate	0.001
Loss	Binary loss
Activation Functions	Pretrained
System	Google GPU

Table 5 displays the loss values for the ResNet101 model for the duration of training and testing. The training loss is distinctly low at 0.002, reflecting the model's excessive accuracy and effective getting to know on the training dataset. In evaluation, the test loss is barely better at 0.015, which is expected and shows that the model's overall performance on unseen information is also quite robust. The small gap between the train and test loss shows that the model generalizes nicely without overfitting, preserving a low stage of prediction errors across each dataset.

Table 0 Accuracy results of model-1 (Resnet-101)

Type	Accuracy
Training	99.94
Testing	98.31

The results in Tables 4 and 5 show how well the ResNet-101 model did after we trained it for 20 epochs. Table 4 shows that the model got a training accuracy of 99.94% and a testing accuracy of 98.31%. The difference between these two numbers is very small, which means the ResNet-101 model learned the patterns in the MRI brain tumor images well and did not overfit too much. The high testing accuracy means the trained model can work well with data and can correctly classify most test samples, which shows that the system we proposed is robust and reliable.

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Table 5 Loss results of model-1 (Resnet-101)

Type	Loss
Training	0.001
Testing	0.10

Table 5 shows the loss values we got during training and testing. The training loss is very low, which means the model's predictions were very close to the labels when it was learning. The testing loss is a little higher than the training loss. That is what we expect when we test the model with new data. The testing loss is still low enough to show that the model is working well. The small difference between the training and testing loss means the model trained smoothly converged within 20 epochs and did not overfit too much, which means the ResNet-101 model got useful features from the MRI images.

When we look at the accuracy graph in Figure 4.1 over the 20 epochs, we see that the training and testing accuracy values went up slowly. At first, the accuracy was lower. It got better as the model learned more from the dataset. The training accuracy curve went up to about 99.94%. The testing accuracy curve followed it closely and ended up near 98.31%. The fact that the two curves are so close together means the model learned smoothly and can work well with data. We do not see any drops or changes in the graph, which means the model learned smoothly and got better with each epoch.

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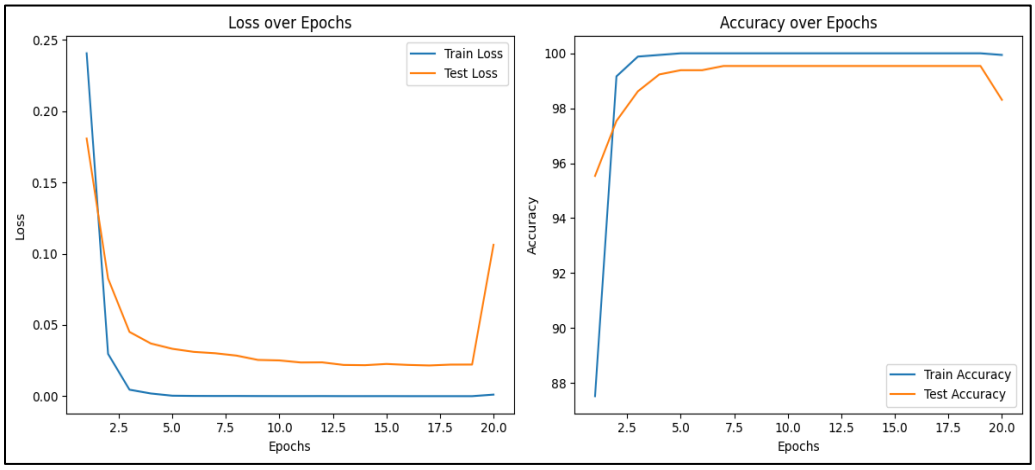


Figure 3 Accuracy and loss graph of Resnet-101

The loss graph shows that the training and testing loss went down over the 20 epochs. At first, the loss values were higher. As the model trained, the loss went down and stabilized near 0.001 for training and 0.10 for testing. This means the model's prediction errors got smaller as it learned from the data. The smooth curves in the loss graph also mean that the optimization process was stable and the model converged within 20 epochs, which shows that the ResNet-101 architecture is good for classifying brain tumors. The ResNet-101 model is really good at classifying brain tumors.

Figure 3 shows the evaluation results of the ResNet-101 model on the test dataset. The overall precision is 0.9968. This means that all samples predicted as positive were actually correct. The model makes a few wrong positive predictions. The recall is 0.9688. This shows that the model identified about 96.88% of all positive cases. So only a small number of samples were missed.

The F1-score is 0.9826. This score is a balance between identifying positive cases and minimizing wrong alarms. These values show that the ResNet-101 model works reliably on data. The classification report explains performance for each class. For Class 0, the precision is 0.97, and the recall is 1.00. This means the model correctly identified all Class 0 samples, which is 330 out of 330. A very small number of samples from the other class may have been misclassified as Class 0. For Class 1, the precision is 1.00, and the recall is 0.97. This means every predicted Class 1 sample was correct. A few actual Class 1 samples were slightly misclassified.

There were 650 test samples. The overall accuracy is 98%. This matches the results. The macro average and weighted average values are both 0.98. This indicates performance across both Class 0 and Class 1. The support values are 330 and 320. These values are nearly equal. So, the model does not show bias toward any class. The close similarity between macro and weighted averages confirms class balance and fair prediction performance for the ResNet-101 model. Overall, Figure 4.2 demonstrates that the ResNet-101 model achieves reliability and excellent classification capability on the test dataset.

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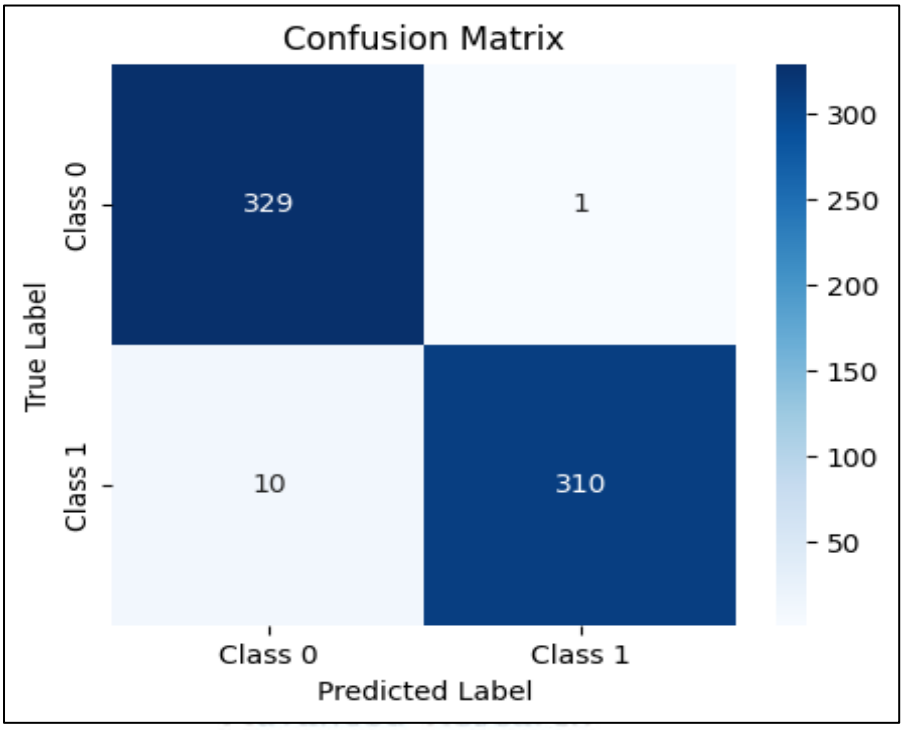


Figure 0 Resnet 101 Confusion Matrix Graph

The results in Tables 6 and 7 show how well the CNN model did after we trained it for 20 epochs. Table 6 shows that the model got a training accuracy of 98% and a testing accuracy of 94%. The difference between these two numbers is very small, which means the CNN model learned the patterns in the MRI brain tumor images well and did not overfit too much. The high testing accuracy means the trained model can work well with data and can correctly classify most test samples, which shows that the system we proposed is robust and reliable.

Table 6 Accuracy results of model-2 (CNN)

Type	Accuracy
Training	98.74
Testing	94.31

Table 7 shows the loss values we got during training and testing. The training loss is very low, which means the model's predictions were very close to the labels when it was learning. The testing loss is a little higher than the training loss. That is what we expect when we test the model with new data. The testing loss is still low enough to show that the model is working well. The small difference between the training and testing loss means the model trained smoothly converged within 20 epochs and did not overfit too much, which means the CNN model got useful features from the MRI images.

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Table 7 Loss results of model-2 (CNN)

Type	Loss
Training	0.038
Testing	0.192

When we look at the accuracy graph in Figure 4.4 over the 20 epochs, we see that the training and testing accuracy values went up slowly. At first, the accuracy was lower. It got better as the model learned more from the dataset. The training accuracy curve went up to about 98.34%. The testing accuracy curve followed it closely and ended up near 94.31%. The fact that the two curves are so close together means the model learned smoothly and can work well with data. We do not see any drops or changes in the graph, which means the model learned smoothly and got better with each epoch.

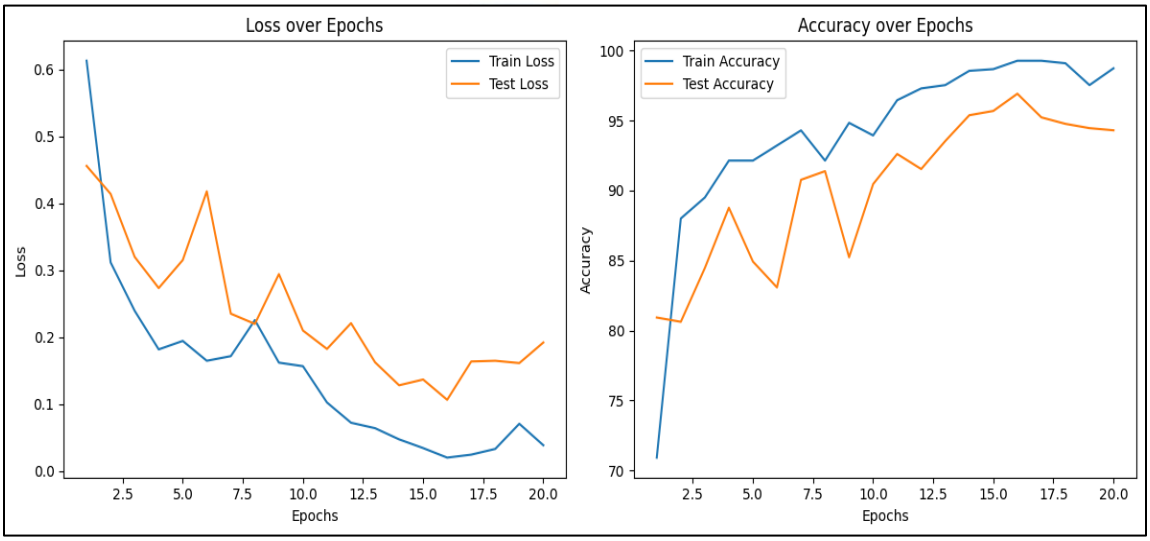


Figure 5 Accuracy and Loss Graph of CNN

The final evaluation results on the test set are given in Figure 5 and demonstrate strong and well-balanced model performance. The model achieved a precision of 0.9579, a recall of 0.9250, and an overall F1-score of 0.9412, indicating a high level of accuracy in both identifying positive instances and minimizing false predictions. The overall classification accuracy is 94% across 650 samples, reflecting consistent predictive capability.

For class 0, the model attained a precision of 0.93 and a recall of 0.96, while for class 1, it achieved a precision of 0.96 and a recall of 0.93. These results show that the model performs comparably well across both classes, with only minor variation between precision and recall. Additionally, the macro and weighted averages (both 0.94) further confirm that the classifier maintains balanced performance without significant bias toward any single class. Overall, the evaluation indicates that the model generalizes effectively to unseen data and provides reliable classification results.

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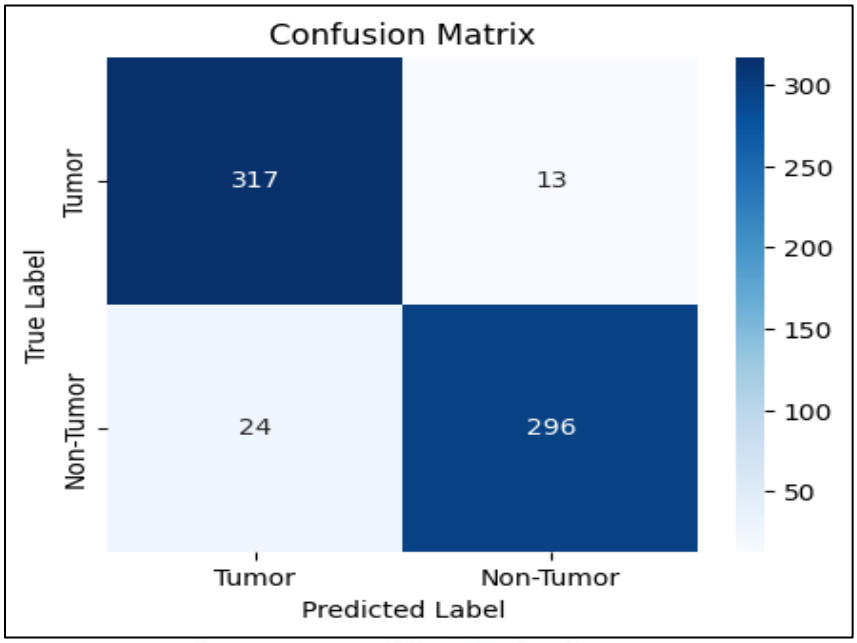


Figure 1 CNN Confusion Matrix Graph

Table 8 tells us about the training setup for the VGG-16 neural network that was used in the experiment. The VGG-16 convolutional neural network was trained for 20 epochs. This means the entire dataset was passed through the VGG-16 neural network 20 times. This helps the VGG-16 convolutional neural network learn patterns. The batch size was 32. So, 32 images were processed together before the model weights were updated. This balances memory usage and learning stability for the VGG-16 neural network

.

Table 8 Architecture of Used VGG-16

Parameter	Detail
No of Epochs	20
Batch Size	32
Optimizer	Adam
Learning Rate	0.0001
Loss	Binary loss
Activation Functions	Pretrained functions
System	Google GPU

The Adam optimizer was used to adjust the model parameters for the VGG-16 neural network. It did this efficiently. The learning rate was 0.0001. This is the learning rate. It helps the VGG-16 convolutional neural network learn gradually and stay stable. It does not overshoot the values. The task was classification for the VGG-16 convolutional neural network. So, a binary loss function was used. This could be cross-entropy. It measures the prediction errors for the VGG-16 neural network. The VGG-16 convolutional neural network used pretrained activation functions and weights from ImageNet. This allows transfer learning. Transfer learning improves accuracy. Reduces training time for the VGG-16 convolutional neural network. The training was done on a Google GPU system. This speeds up deep learning computations. It reduces the training time for the VGG-16 convolutional neural network.

Table 9 Accuracy results of model-3 (VGG-16)

Type	Accuracy
Training	99.21
Testing	97.85

The results in Tables 4.9 and 4.10 show how well the **VGG-16** model performed after 20 epochs of training, indicating that the model successfully learned patterns from the dataset and was able to make accurate predictions on new data. The model achieved 99.21% accuracy on the training set, which means it correctly classified almost all training samples and effectively captured important features during learning. It also achieved 97.85% accuracy on the testing set, which is only slightly lower than the training accuracy, showing that the model did not simply memorize the training data but learned general patterns that work well on unseen data.

Table 10 Loss results of model-1 (VGG-16)

Type	Loss
Training	0.0001
Testing	0.116

The training loss of 0.0001 is extremely low, meaning the model made almost no errors on the training dataset, while the testing loss of 0.116 is slightly higher but still acceptable, indicating good performance on new samples.

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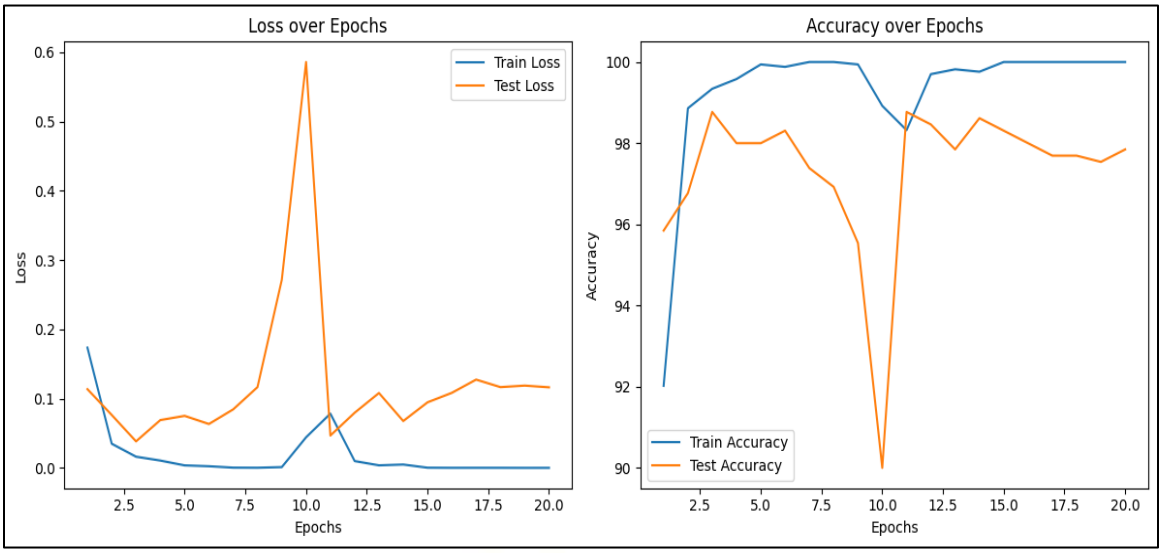


Figure 2 Accuracy and Loss of VGG-16

The graphs shown in Figure 7 visually confirm these results, where the accuracy graph shows training and testing accuracies very close to each other, proving stable learning and reliable performance, and the loss graph shows very low training loss and slightly higher testing loss, demonstrating that the model minimized prediction error effectively over the 20 training epochs. Overall, these tables and graphs confirm that the VGG-16 model learned well, achieved high accuracy, maintained low loss, generalized effectively to new data, and is dependable for accurate classification in this application

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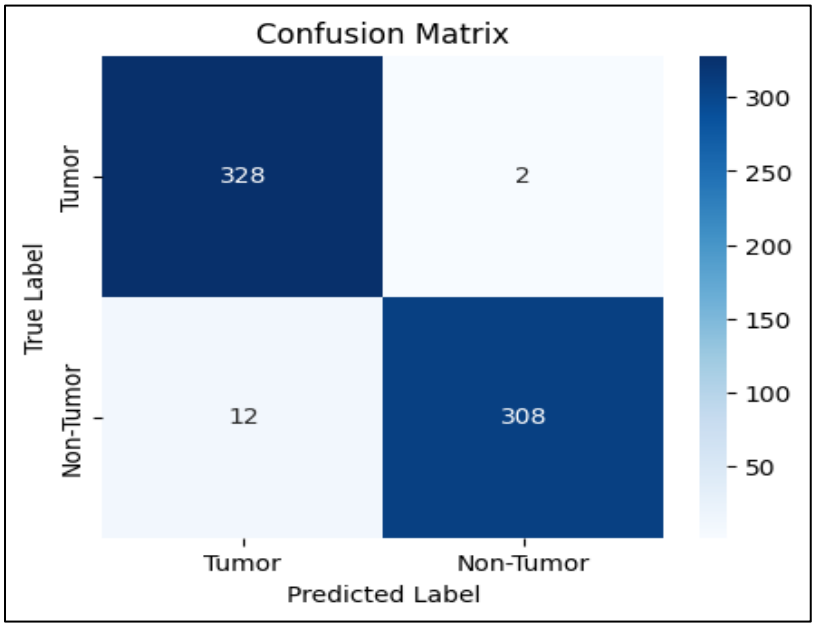


Figure 8 VGG-16 Confusion Matrix Graph

Conclusion

This study presents a comprehensive investigation into automated brain tumor detection and classification using deep learning techniques applied to MRI images. Three convolutional neural network architectures, including a basic CNN, VGG-16, and ResNet-101, are implemented, trained, and comparatively evaluated to assess their effectiveness in distinguishing tumor-affected regions. All models are trained for 20 epochs using optimized hyperparameters in a GPU-accelerated environment. Their performance is evaluated using standard metrics, including accuracy, loss, precision, recall, and F1-score. The experimental results demonstrate that deep learning models are capable of extracting highly discriminative features from MRI scans, even under conditions of limited dataset availability. Among the evaluated models, ResNet-101 achieves the highest overall performance, followed closely by VGG-16, while the basic CNN also provides stable and reliable results. The marginal difference between training and testing accuracies across all models indicates strong generalization capability and minimal overfitting. In addition, consistently low loss values and smooth convergence trends confirm the stability and effectiveness of the training process. The findings further emphasize the significance of transfer learning in medical imaging applications, as pretrained architectures enhance feature extraction capability and reduce training complexity and time requirements. The proposed system demonstrates that deep learning–based approaches can serve as effective decision-support tools for clinicians by delivering fast, consistent, and accurate predictions. Overall, this study confirms that advanced convolutional neural network architectures are robust and reliable for brain tumor detection and have strong potential to support early diagnosis and treatment planning in clinical practice.

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