VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JNANA SANGAMA”, BELAGAVI - 590 018

MINI PROJECT REPORT

on

“Brain Tumor Classification Using Deep Learning"

Submitted by

Anvitha NC	**4SF22CS030**
Kushi KC	**4SF22CS098**
Apeksha I	**4SF22CS031**
Ganesh	**4SF22CS066**

In partial fulfillment of the requirements for the V semester

BACHELOR OF ENGINEERING

In

COMPUTER SCIENCE & ENGINEERING

Under the Guidance of

Mrs Chaithrashree M

Assistant Professor,

Department of CSE

at

SAHYADRI

College of Engineering & Management

An Autonomous Institution

MANGALURU

2024 - 25

SAHYADRI
COLLEGE OF ENGINEERING & MANAGEMENT
An Autonomous Institution
MANGALURU

Department of Computer Science & Engineering

CERTIFICATE

This is to certify that the mini project work entitled **“Brain Tumor Classification Using Deep Learning”** has been carried out by **Anvitha N C (4SF22CS030), Kushi K C (4SF22CS098), Apeksha I (4SF22CS031) and Ganesh (4SF22CS066)**, the bonafide students of Sahyadri College of Engineering & Management in partial fulfillment of the requirements for the V semester of Bachelor of Engineering in Computer Science and Engineering of Visvesvaraya Technological University, Belagavi during the year 2024 - 25. It is certified that all suggestions indicated for Internal Assessment have been incorporated in the report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the said degree.

Project Guide	**Project Coordinator**	**Project Coordinator**	**HOD**
Mrs.Chaithrashree M	**Dr Adarsh Rag S**	**Ms. Poornima B V**	**Dr. Mustafa Basthikodi**
Assistant Professor	Assistant Professor	Assistant Professor	Professor & Head
Dept. of CSE	Dept. of CSE	Dept. of CSE	Dept. of CSE

SAHYADRI
COLLEGE OF ENGINEERING & MANAGEMENT
An Autonomous Institution
MANGALURU

Department of Computer Science & Engineering

DECLARATION

We hereby declare that the entire work embodied in this Mini Project Report titled **"Brain Tumor Classification Using Deep Learning"** has been carried out by us at Sahyadri College of Engineering & Management, Mangaluru under the supervision of **Mrs.Chaithrashree M,** in partial fulfillment of the requirements for the V semester of **Bachelor of Engineering** in **Computer Science and Engineering**. This report has not been submitted to this or any other University for the award of any other degree.

Anvitha N C (4SF22CS030)
Kushi K C (4SF22CS098)
Apeksha I (4SF22CS031)
Ganesh (4SF22CS066)
Dept. of CSE, SCEM, Mangaluru

Abstract

Accurate classification of brain tumors from MRI scans is essential for effective diagnosis, treatment planning, and patient management. Timely and precise identification of tumor types such as glioma, meningioma, and pituitary tumors plays a crucial role in clinical decision-making, ensuring that patients receive the most appropriate and personalized treatment strategies. This study proposes a deep learning-based methodology for brain tumor classification, focusing on distinguishing between glioma, meningioma, pituitary tumors, and normal (no tumor) cases. The methodology leverages the power of three pre-trained models—VGG16, ResNet10, and Convolutional Neural Networks (CNNs)—using transfer learning techniques. These models, known for their effectiveness in image classification tasks, have been adapted to handle the complexities of MRI brain scans, addressing challenges such as varying tumor shapes, sizes, and locations. Transfer learning allows the use of pre-trained models on large-scale datasets, which are then fine-tuned to the specific task of tumor classification, improving performance and reducing the need for large amounts of labeled data.

Table of Contents

CHAPTER 1
INTRODUCTION

Brain tumors pose a significant challenge in clinical medicine, as their early and accurate diagnosis is crucial for effective treatment and patient management. Timely detection and correct classification of brain tumors can directly impact a patient's prognosis and treatment outcomes. Among the various imaging techniques available, Magnetic Resonance Imaging (MRI) has emerged as the gold standard for visualizing brain structures and detecting abnormalities, including tumors. MRI offers superior contrast resolution, allowing for detailed imaging of soft tissues, and is particularly valuable for non- invasive assessment of the brain. This makes it an essential tool in both diagnosing brain tumors and monitoring their progression or response to treatment. However, despite its advantages, the manual interpretation of MRI scans remains a complex, time-consuming, and highly specialized task. It requires experienced radiologists to analyze a vast amount of data, making it susceptible to human error, fatigue, and variability in interpretation.

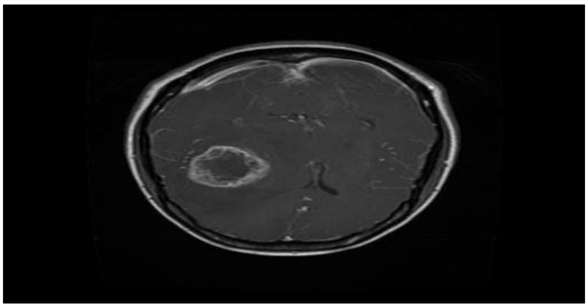


Fig 1: Glioma Tumor

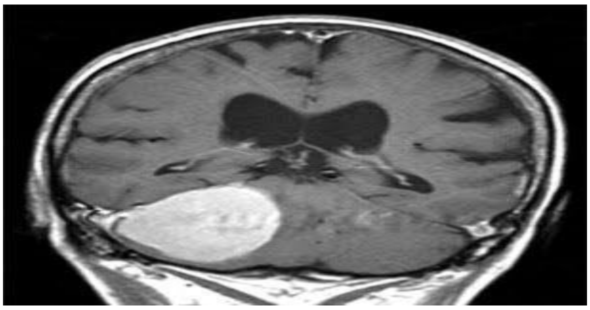


Fig 2 : Meningioma Tumor

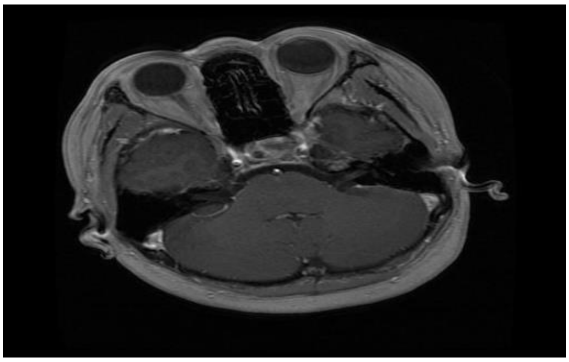


Fig 3: Pituitary Tumor

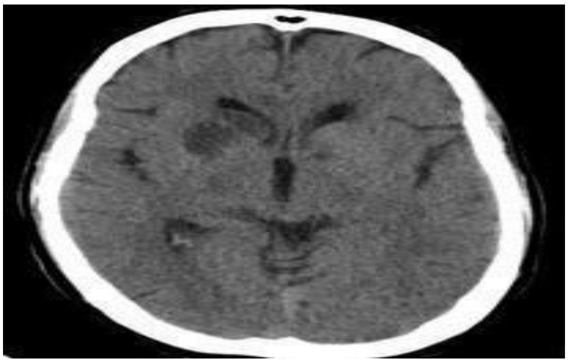


Fig 4 : No Tumor

Fig 1 illustrates a glioma, a type of tumor that originates from glial cells in the brain, which support and protect neurons. Gliomas can range from low-grade, less aggressive forms to high-grade, highly malignant ones such as glioblastomas. These tumors may cause a variety of neurological symptoms, depending on their location and size, and are typically treated with surgery, radiation, and chemotherapy.

Fig 2 illustrates a meningioma, a tumor that develops from the meninges, the protective layers surrounding the brain and spinal cord. Although most meningiomas are benign and grow slowly, they can still cause significant neurological issues if they press on brain structures or nerves. Treatment typically involves surgical removal of the tumor, with radiation used for inoperable or recurrent cases.

Fig 3 illustrates a pituitary tumor, which forms in the pituitary gland located at the base of the brain. These tumors can affect hormone production, leading to a variety of symptoms such as headaches, vision problems, and hormonal imbalances. While most pituitary tumors are benign, they can grow large enough to press on nearby structures. Treatment often involves surgery, radiation, or medication to manage hormone levels.

Fig 4 illustrates an MRI image with no tumor present, showing a healthy brain with no visible abnormalities. In the absence of a tumor, the brain structure appears normal, and there are no signs of growth or compression. This is often the baseline condition for comparison in clinical evaluations and imaging tests, providing a clear reference for detecting potential pathologies.

Diagnosing and managing brain tumors remain challenging in the present world due to the complexity of the condition, the diversity of tumor types, and limitations in current medical practices. One of the primary challenges lies in the accurate and early detection of brain tumors, as symptoms such as headaches, dizziness, and cognitive impairments often overlap with other neurological disorders, leading to potential misdiagnosis or delays in seeking advanced imaging like MRI. While MRI is the gold standard for brain tumor detection, its reliance on manual interpretation by radiologists introduces variability, as it requires specialized expertise to analyze the subtle differences in imaging patterns. This process is not only time-consuming but also prone to human error and fatigue, particularly given the increasing volume of diagnostic imaging worldwide.

Additionally, differentiating between tumor types such as gliomas, meningiomas, pituitary tumors, and the absence of tumors ("no tumor") can be particularly challenging due to overlapping imaging features and similarities in early symptoms. For instance, gliomas and meningiomas may initially appear similar on MRI scans, yet they require vastly different treatment approaches. Resource constraints in low- and middle-income countries further exacerbate the issue, where access to advanced imaging technologies and trained specialists is limited. Furthermore, brain tumors often require personalized treatment plans based on their type, grade, and location, making accurate diagnosis critical. In the present era, the complexity of these challenges calls for the integration of advanced technologies, such as artificial intelligence and deep learning models, to assist in the rapid and precise classification of brain tumors, thereby improving patient outcomes and reducing diagnostic delays.

Deep learning plays a pivotal role in the early detection of brain tumors by leveraging advanced algorithms to analyze medical imaging data with remarkable speed and precision. Early-stage brain tumors often present subtle abnormalities in MRI scans that may be difficult to identify through manual interpretation alone, especially in cases where symptoms are nonspecific or overlap with other conditions. Deep learning models, such as Convolutional Neural Networks (CNNs), can automatically learn and detect these subtle patterns from large datasets, identifying potential tumor regions with high accuracy. These models can process complex imaging data, including different MRI modalities, to highlight early signs of tumors that might otherwise be overlooked.

By enabling rapid and consistent analysis, deep learning reduces the time required for diagnosis and minimizes the risk of human error. Additionally, it can assist in triaging cases, prioritizing patients with potential abnormalities for further review by radiologists, and ensuring timely intervention. Early detection is critical for improving treatment outcomes, as tumors diagnosed at an early stage are often easier to manage and treat. Deep learning systems integrated into clinical workflows can thus act as a powerful decision-support tool, enhancing the accuracy and efficiency of early diagnosis while alleviating the burden on healthcare professionals.

Deep learning has emerged as a powerful tool for the early detection of brain tumors, addressing many challenges in traditional diagnostic methods. Brain tumors often develop silently, with subtle changes in MRI scans that can be difficult for radiologists to identify, especially in the early stages. Deep learning algorithms excel at processing and analyzing vast amounts of imaging data, automatically detecting abnormalities with precision and speed.

By providing consistent and objective analysis, deep learning reduces the variability and potential errors associated with manual interpretation. This not only accelerates the diagnostic process but also ensures that critical cases are flagged for timely medical intervention. Early detection enabled by deep learning can lead to better treatment outcomes, as tumors identified at an initial stage are often easier to treat and manage. Integrating deep learning into medical workflows enhances diagnostic accuracy and empowers clinicians to make informed decisions, ultimately improving patient care.

Deep learning models like CNNs, VGG16, and ResNet10 are highly effective in the early detection of brain tumors due to their ability to analyze complex medical imaging data, such as MRI scans, and automatically identify subtle patterns indicative of early-stage tumors. Convolutional Neural Networks (CNNs) serve as the foundation for this process, as they excel in extracting meaningful features from raw image data. CNNs work by processing images through layers of convolutional filters that detect edges, textures, and shapes, progressively identifying tumor-specific characteristics. Their ability to analyze multi-dimensional imaging data makes them particularly suited for the intricate task of brain tumor detection, where early signs can be difficult to discern.

Advanced models like VGG16 and ResNet10 build on the capabilities of basic CNNs and are tailored for greater accuracy and efficiency. VGG16 employs a deep architecture with small convolutional filters, allowing it to learn intricate and hierarchical features from MRI scans. This makes it particularly adept at detecting minute changes in brain tissue, which can be crucial for identifying tumors at an early stage. ResNet10, on the other hand, introduces residual connections, which help mitigate the vanishing gradient problem and improve the model's ability to train effectively even with fewer layers. This design enables ResNet10 to capture fine-grained details and detect subtle abnormalities, making it ideal for distinguishing between normal and pathological brain tissue in the early stages of tumor development.
These models, when trained on diverse and annotated datasets, can classify brain tumors into specific types, such as gliomas, meningiomas, or pituitary tumors, or identify the absence of tumors. They also enable faster and more consistent analysis, reducing the workload on radiologists and minimizing diagnostic delays. By leveraging the strengths of CNNs, VGG16, and ResNet10, healthcare providers can enhance the accuracy of early detection, ensuring timely diagnosis and improving the chances of successful treatment and patient recovery.

CHAPTER 2
LITERATURE SURVEY

Technolgy/Method	Purpose/Focus	Key Features
Convolutional Neural Networks (CNNs), Data Augmentation [1]	Detecting glioma, meningioma, and pituitary tumors.	Utilized convolutional neural networks (CNNs) with various augmentation techniques, including rotation, scaling, and flipping. Proposed automated pipelines to streamline data preparation and improve classification efficiency.
InceptionV3, ResNet50, CNNs [2]	Comparative analysis of different CNN architectures for brain tumor detection.	Emphasized the use of hybrid models that integrate the strengths of InceptionV3 and ResNet50. Demonstrated improved accuracy and computational efficiency, proposing ensemble methods for clinical reliability.
Lightweight CNNs [3]	Efficient deployment on resource-constrained devices	Focused on creating scalable and computationally efficient models that maintain high accuracy. Recommended adaptations for underserved regions with limited access to advanced hardware.

VGG16, CNNs, Data Augmentation [4]	Impact of data augmentation on tumor classification accuracy.	Enhanced the robustness of VGG16 by introducing synthetic image generation techniques to address dataset imbalances, leading to improved classification performance.
Federated Learning [5]	Addressing data privacy in medical imaging.	Proposed a federated learning approach that ensures patient confidentiality while maintaining high model accuracy. Suggested the integration of blockchain for enhanced security.
VGG16, ResNet50, Federated Learning [6]	Combining feature extraction with privacy-preserving techniques	Proposed a federated learning approach that ensures patient confidentiality while maintaining high model accuracy. Suggested the integration of blockchain for enhanced security.
VGG16, Data Augmentation [7]	Improving generalization on small datasets.	Developed hybrid models using VGG16 and ResNet50 for feature extraction. Applied federated learning to enable secure multi-institutional collaborations.
Data Augmentation, GANs [8]	Solving issues related to small datasets using synthetic MRI data.	Used pre-trained ResNet50 and Dense Net architectures to achieve high accuracy and reliability. Advocated for hybrid approaches for better performance.

Hybrid CNN (VGG16 + ResNet50), Federated Learning [9]	Combining feature extraction with privacy-preserving techniques.	Leveraged Generative Adversarial Networks (GANs) to create diverse and realistic synthetic data, enhancing training outcomes and reducing overfitting.
VGG16, Data Augmentation [10]	Improving generalizationon small datasets.	Combined federated learning with InceptionV3 to balance high classification accuracy and data privacy. Demonstrated the feasibility of large-scale collaborative research.
Data Augmentation, GANs [11]	Solving issues related to small datasets using synthetic MRI data	Effectively captured spatial relationships using capsule networks, leading to improved performance on imbalanced datasets. Demonstrated superior handling of spatial hierarchies.
Capsule Networks [12]	Handling spatial hierarchies in MRI scans.	Used UNet for precise tumor segmentation combined with CNN-based classification, resulting in improved detection accuracy.
VGG16, Data Augmentation [13]	Improving generalization on small datasets.	Demonstrated ResNet50's higher accuracy (92%) compared to VGG16. Proposed the use of hybrid CNN architectures for further accuracy improvements.

UNet-based Segmentation with Classification [14]	Deeper networks like ResNet50 achieved higher accuracy, demonstrating the importance of network depth.	Incorporated attention mechanisms into VGG16, achieving 93% accuracy. Emphasized the role of attention in enhancing feature selection and proposed further studies.
VGG16 and ResNet50 [15]	Evaluating transfer learning on the BRATS 2020 dataset.	Highlighted ResNet50's ability to reduce training time without sacrificing accuracy. Advocated for model pruning techniques to optimize deployment in real-world settings.
Integration of attention mechanisms with VGG16 [16]	Enhancing classification accuracy on the BRATS dataset.	Combined UNet for segmentation with VGG16 for classification, demonstrating improved tumor detection. Proposed the use of 3D imaging for further accuracy enhancements.
ResNet50 [17]	Improving efficiency and reducing training times	Demonstrated the effectiveness of data augmentation in enhancing model robustness. Suggested automated augmentation frameworks .
UNet + VGG1[18]	Brain tumor segmentation and classification.	Integrated MRI, CT, and PET scan data for comprehensive diagnostic insights. Achieved high accuracy through fine-tuning CNN architectures

Data Augmentation [19]	To improve brain tumor classification accuracy and interpretability using ResNet layers.	Achieved 95% accuracy by combining ResNet layers with multi-scale attention mechanisms, enhancing model interpretability.
with CNNs performance on [20]	augmentation frameworks to mitigate overfitting	Reduced false positives by integrating attention mechanisms into CNN architectures. Focused on refining feature extraction for better accuracy.
ResNet with attention mechanisms [21]	Improve diagnostic reliability for tumors	Combines ResNet50 with multi-scale attention, achieving 95% accuracy.
Hybrid CNN-RNN[22]	Enhanced accuracy in brain tumor detection.	Applied federated learning across institutions, advocating for protocol improvements to enhance privacy and accuracy.
Lightweight CNNs [23]	To address challenges in classifying small tumors with limited data.	Improved feature extraction capabilities of capsule networks, offering superior performance for small datasets.
3D CNNs + attention mechanisms. [24]	Detecting complex tumor structures and enhancing volumetric tumor data analysis.	Leveraged 3D CNNs combined with attention mechanisms to improve the classification of intricate and complex tumor morphologies in MRI datasets.

Capsule Networks [25]	Improving classification of small tumors by enhancing feature extraction.	Demonstrated superior accuracy on limited datasets by employing capsule networks for better representation of spatial relationships in tumor MRI data.
Federated learning with CNNs [26]	To enable secure and scalable tumor classification across institutions.	Combined CNN architectures with federated learning for robust and secure multi-institutional research.
CNNs with attention and transfer learning [27]	To improve classification interpretability and accuracy.	Integrated attention mechanisms with transfer learning to enhance model reliability and performance.
Multi-scale CNNs with residual connections [28]	To improve performance on imbalanced datasets	Used data augmentation and residual connections to enhance feature extraction, achieving better accuracy.
DenseNet201 [29]	To reduce over fitting and improve generalization in MRI tumor classification.	Leveraged transfer learning with DenseNet201, demonstrating its effectiveness for small datasets.
CNN-LSTM [30]	To analyze spatial-temporal MRI data for tumor detection.	Combined CNNs for spatial analysis and LSTMs for temporal data, improving detection accuracy in complex datasets.

CHAPTER 3
PROBLEM FORMULATION

3.1 Problem Statement

The goal of this project was to develop an advanced brain tumor classification system using deep learning techniques to accurately classify brain MRI scans into four categories: glioma, meningioma, pituitary tumor, and no tumor. The existing solution for brain tumor classification typically relied on a binary approach, categorizing MRI scans as either "tumor present" or "no tumor." In some cases, a tertiary classification system had been used, but it proved to be challenging. As a result, we improvised by developing a multi-class classification system that could accurately differentiate between glioma, meningioma, pituitary tumor, and no tumor. Gliomas and meningiomas were the two most prevalent types of brain tumors, while pituitary tumors, although less common, required specialized classification due to their distinct features.By employing advanced optimization strategies, the system aimed to enhance the accuracy and reliability of tumor detection, reducing the chances of misclassification. This improved diagnostic capability was critical for early detection, as it aided clinicians in making more informed decisions regarding treatment plans.We used three models—CNN, VGG16, and ResNet10—to evaluate their accuracy, and the best-performing model was selected for further work to improve classification performance and its clinical application.

3.2 Objectives

- To enchance the accuracy of brain tumor diagnosis.
- To classify multiple types of brain tumors accurately.
- To enable early and precise tumor identification , which will be helpful in diagnosis.
- To develop an interface for predicting brain tumors, facilitating user-friendly and accessible tumor classification.

CHAPTER 4
METHODOLOGY

This methodology classifies brain tumors into four categories—glioma, meningioma, pituitary tumor, and no tumor—using MRI images and deep learning. Pre-processing is performed on MRI scans, including resizing, normalization, and augmentation, to improve model performance and generalization. Convolutional Neural Networks (CNNs) are used for automatic feature extraction and classification, leveraging pre-trained architectures like VGG16 and ResNet10. VGG16 captures fine-grained features with its 16-layer depth, while ResNet10 uses skip connections to extract complex patterns efficiently. The extracted features are used to categorize tumors based on their size, location, and texture. This system aids in accurate and automated brain tumor diagnosis, supporting clinical decision-making. Figure 5 depicts the project methodology, encompassing data collection, preprocessing, feature extraction, and classification**.**

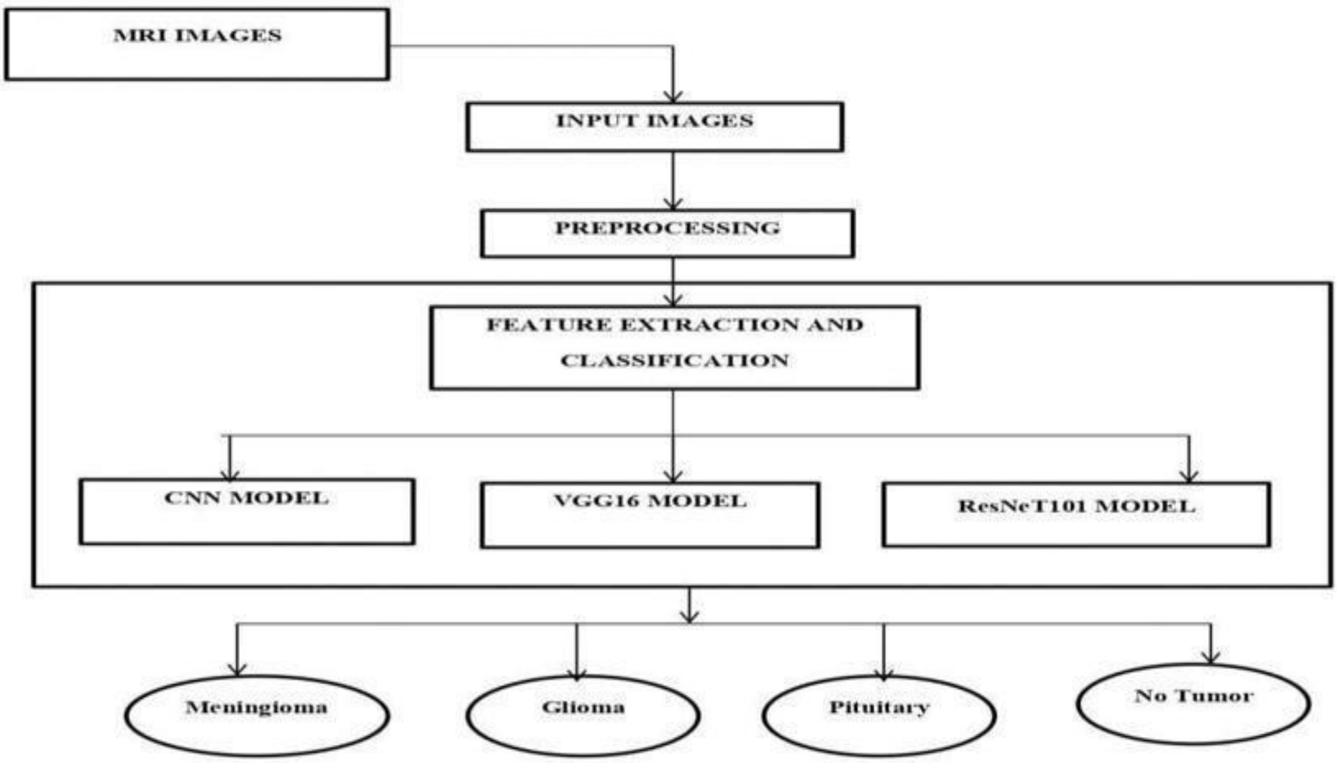


Fig 5 : Architecture Diagram

4.1 Data Collection

The dataset consisted of labeled MRI images categorized into glioma, meningioma, pituitary tumor, and no tumor. These labels formed the foundation for training and validating the models, enabling the algorithms to learn distinctive patterns and features associated with each tumor type. The dataset was crucial for developing accurate and reliable models that could automatically classify brain tumors, aiding in early detection and diagnosis. By using this labeled data, the models were fine-tuned to distinguish between various tumor types and identify healthy brain scans as well. The total dataset size was 1.4GB, with 5,712 files allocated for testing and 1,311 files for training. To enhance the model's performance, data augmentation techniques such as rotation, scaling, flipping, and cropping were applied, increasing the dataset size to approximately 2.7 GB. This augmented dataset helped create a more diverse and robust training set, improving the accuracy and generalization of the model.

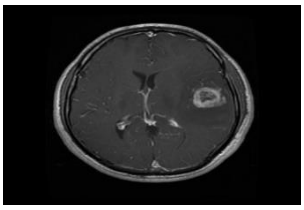


Fig 6: Glioma

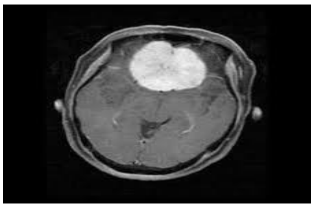


Fig 7 : Meningioma

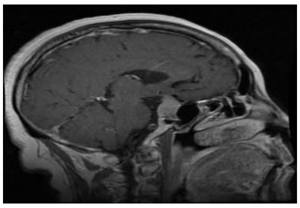


Fig 8:Pituitary

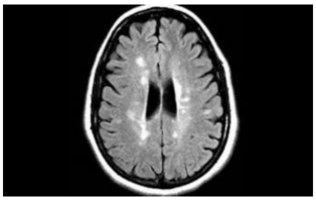


Fig 9: No Tumor

Figure	Tumor Types	Training	Testing
6	Glioma	1,321	300
7	Meningioma	1,339	306
8	Pituitary	1,457	300
9	No Tumor	1,595	405

Table : Dataset Size

4.2 Preprocessing

Image preprocessing was a critical step to ensure the dataset was optimized for model training. Techniques such as image normalization were applied to standardize image sizes and pixel values, ensuring consistency across the dataset. To improve the quality of the input data, noise and unnecessary artifacts were removed, enhancing the clarity of the images and preserving important features relevant for classification. Additionally, data augmentation methods like rotation, flipping, cropping, and brightness adjustments were used to artificially expand the dataset, increasing its diversity and improving the model's robustness. Contrast enhancement and sharpening techniques were also applied to highlight critical features in MRI images.

4.3 Feature Extraction Using Pre-trained Models and Classification

Feature extraction and classification were performed using a combination of CNN, VGG16, and ResNet10, which worked together to process MRI images and accurately identify brain tumor types. The custom CNN was designed to capture basic, fundamental patterns from the images, laying the groundwork for classification. VGG16, a 16-layer deep neural network, excelled at extracting hierarchical features, enabling it to effectively distinguish subtle differences in the MRI images. This hierarchical approach allowed VGG16 to capture increasingly complex details as the network deepened. ResNet10, which incorporated residual connections, addressed the common problem of vanishing gradients in deep networks. These connections allowed ResNet10 to efficiently learn deeper, more complex features without performance degradation, making it especially effective for capturing intricate relationships in the data.

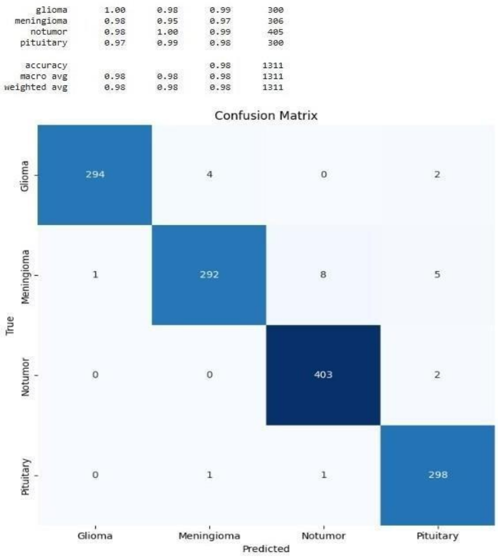
The CNN focused on basic patterns, VGG16 captured more layered and hierarchical features, and ResNet10 deepened the learning process by refining complex relationships. By using different model such as CNN, VGG16, and ResNet10, the system became a powerful ensemble capable of handling diverse MRI images and classifying them into four categories: glioma, meningioma, pituitary tumor, or no tumor. This collaboration between the models ensured that the system performed robustly in real-world diagnostic applications, making it a reliable tool for brain tumor classification.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Convolutional Neural Network(CNN):

The Convolutional Neural Network (CNN) model achieved an accuracy of 97.94% on the test dataset, demonstrating its ability to effectively classify brain tumors into four categories: Glioma, Meningioma, NoTumor, and Pituitary. The model showcased efficient training with a steady improvement in accuracy and reduction in loss during the initial epochs. However, signs of overfitting became apparent in the later stages of training, as indicated by the gap between training and validation performance. Despite these limitations, the CNN model successfully captured complex patterns in MRI scans, enabling reliable predictions across most categories.



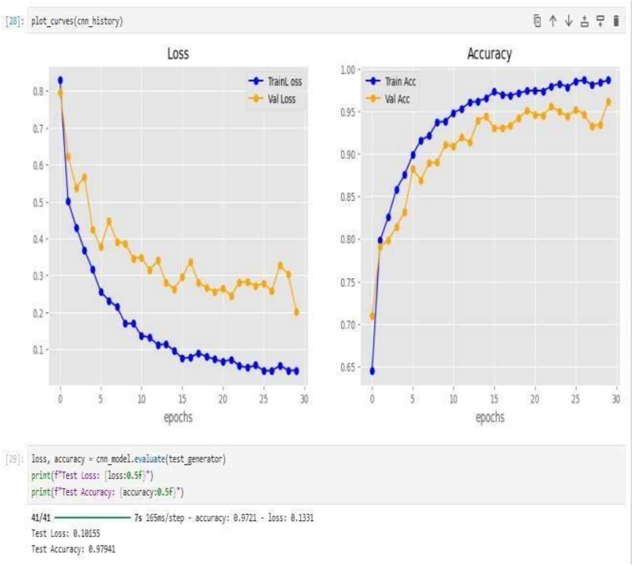


Fig 10: Confusion Matrix **Fig 11: Loss and Accuracy graph**

Figure 10 highlights that the model performed exceptionally well in predicting Glioma, NoTumor, and Pituitary tumors, with only a few misclassifications observed. The Meningioma category, however, exhibited slight overlaps with Pituitary and NoTumor classes, suggesting feature similarities that caused prediction challenges.

Figure 11 illustrates the loss and accuracy graphs reveal that while the training loss decreased consistently, the validation loss plateaued and fluctuated after around 15 epochs. Similarly, training accuracy continued to improve, nearing 97%, while validation accuracy stabilized between 85-90%.

This divergence indicates over fitting, suggesting a need for techniques such as dropout layers, early stopping, or data augmentation to improve the model's generalization capability.

5.2 Visual Geometry Group 16 (VGG16):

VGG16 is a convolutional neural network (CNN) architecture widely used for image classification tasks. It is characterized by its deep structure with 16 layers, primarily using 3x3 convolutional filters and max-pooling layers. This model is well-suited for feature extraction and has been pre-trained on large datasets like ImageNet. In this case, VGG16 has been fine-tuned to classify brain MRI images into four categories. The results demonstrate excellent performance, with a reported test accuracy of approximately 97.86% and a low test loss of 0.0837, indicating a well-generalized model.

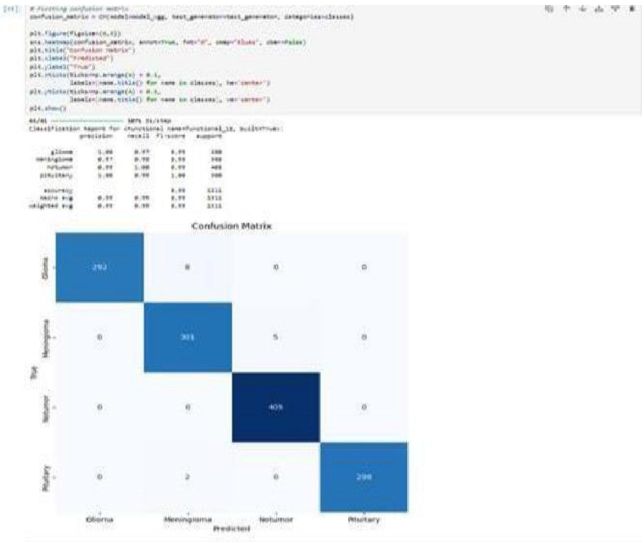


Fig 12 :Confusion Matrix

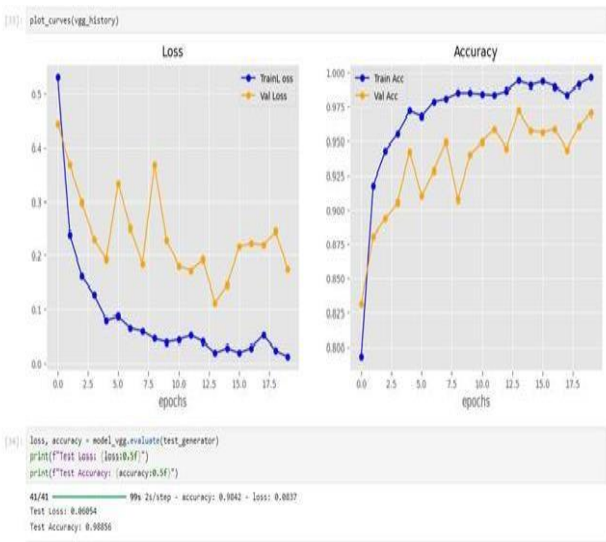


Fig 13 : Loss and Accuracy graph

Figure 12 highlights the classification performance across the four categories. The diagonal entries, representing correct predictions, dominate, showing high accuracy for all classes. Minimal misclassifications are observed, with very few instances classified incorrectly. The classification report corroborates this, showing precision, recall, and F1-scores close to 1.0 for all classes. Figure 13

illustrates the training curves depict loss and accuracy for both training and validation datasets across 20 epochs. The training loss steadily decreases, indicating effective learning, while the validation loss stabilizes without significant over fitting. Similarly, training and validation accuracy curves converge at high accuracy values ,the model's strong predictive capability and robustness. Together, these results confirm the VGG16 model's suitability for the given classification task.

5.3 Residual Network 10(ResNet10):

The ResNet10 model is a convolutional neural network architecture known for its deep structure and ability to extract hierarchical features from images, making it highly effective for image classification tasks. In this application, the model is used to classify different types of brain tumors, including glioma, meningioma, pituitary tumors, and others. The results indicate that the model performs exceptionally well, achieving an overall accuracy of 98.16% on the test dataset and high accuracy on both the training and validation datasets. This suggests that the model has effectively learned to differentiate between the various tumor types.

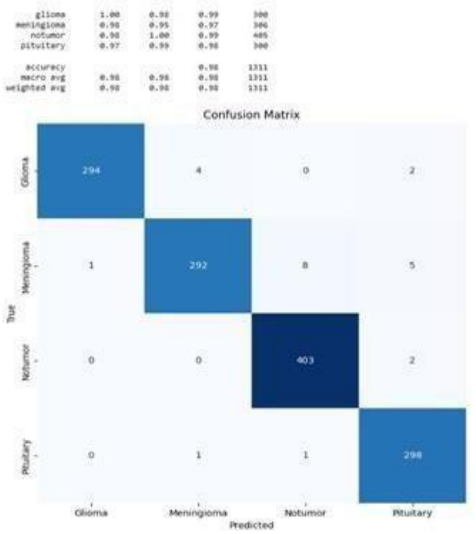


Fig 14: Confusion Matrix

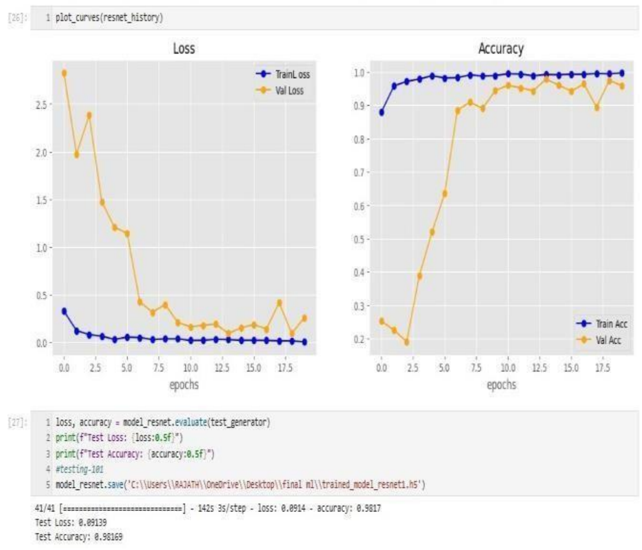


Fig 15: Loss and Accuracy graph

Figure 14 illustrates the model's precision and recall for each tumor type. Most classifications are correct, with only minor misclassifications, e.g., slight overlaps between glioma and pituitary tumors. Each class demonstrates high recall and precision, reinforcing the model's strong predictive ability.

Figure 15 illustrates the loss and accuracy graphs, revealing that the training process resulted in a steady decline in both training and validation loss, achieving convergence after approximately 10 epochs. Simultaneously, the accuracy graphs show rapid improvement during the early epochs, eventually stabilizing at nearly 100% for both training and validation accuracies. These trends indicate that the model learned effectively and maintained strong generalization performance on unseen data.

5.4 Front-End Interface for Brain Tumor Classification :

Since the ResNet10 model achieved the highest accuracy of 98.16%, we developed a simple and intuitive web interface to implement it. Figures 16 to 20 illustrate the interface, which allows users to seamlessly upload MRI images for classification into various brain tumor types, including glioma, meningioma, and pituitary tumors. The interface is designed with ease of use in mind, enabling quick, accurate predictions, and providing detailed results. This implementation ensures the model's practical applicability, making it a valuable tool for real-world medical diagnostics.

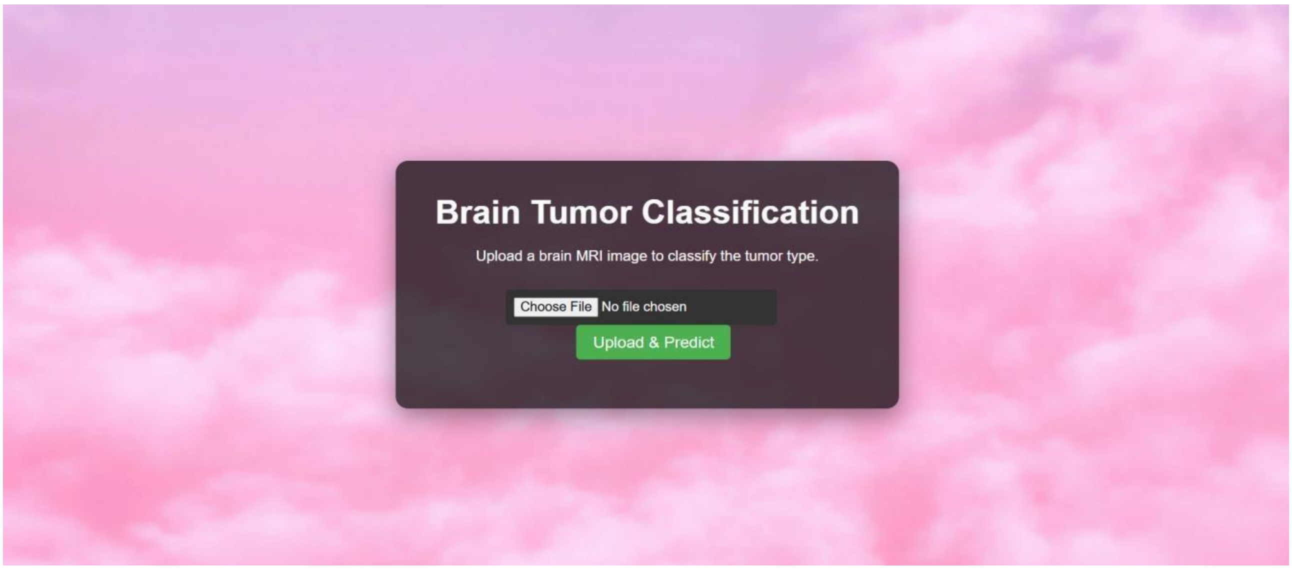


Figure 16

Figure 17

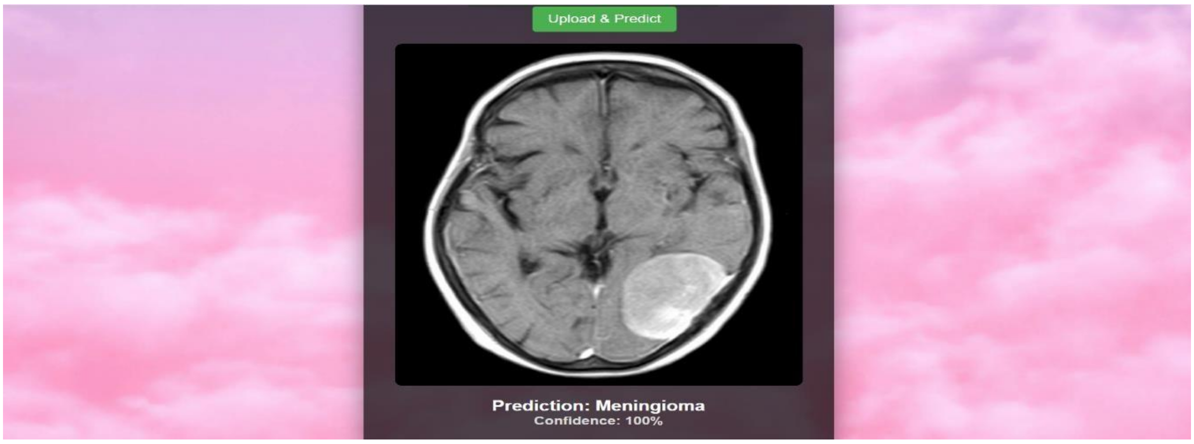


Figure 18

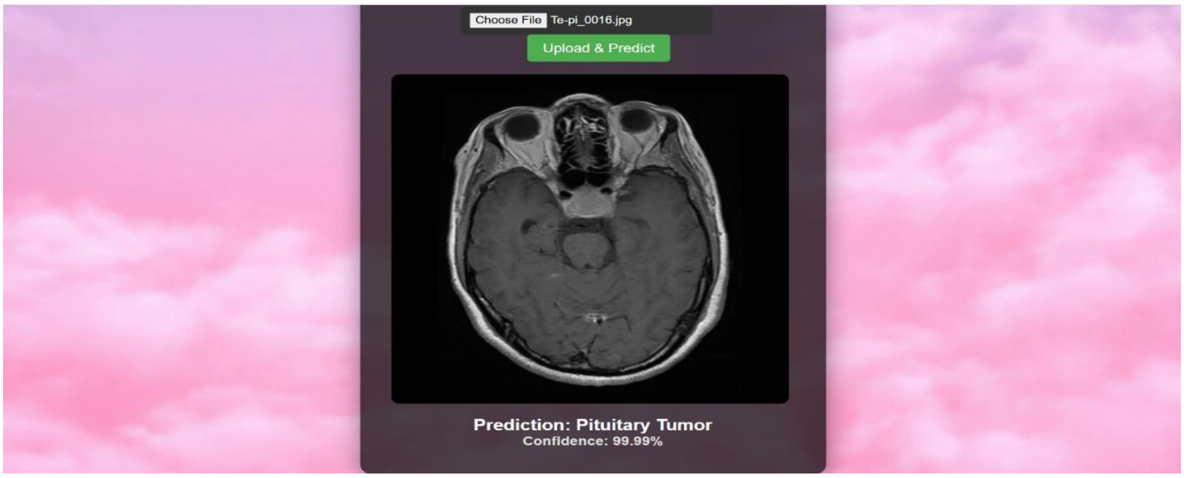


Figure 19

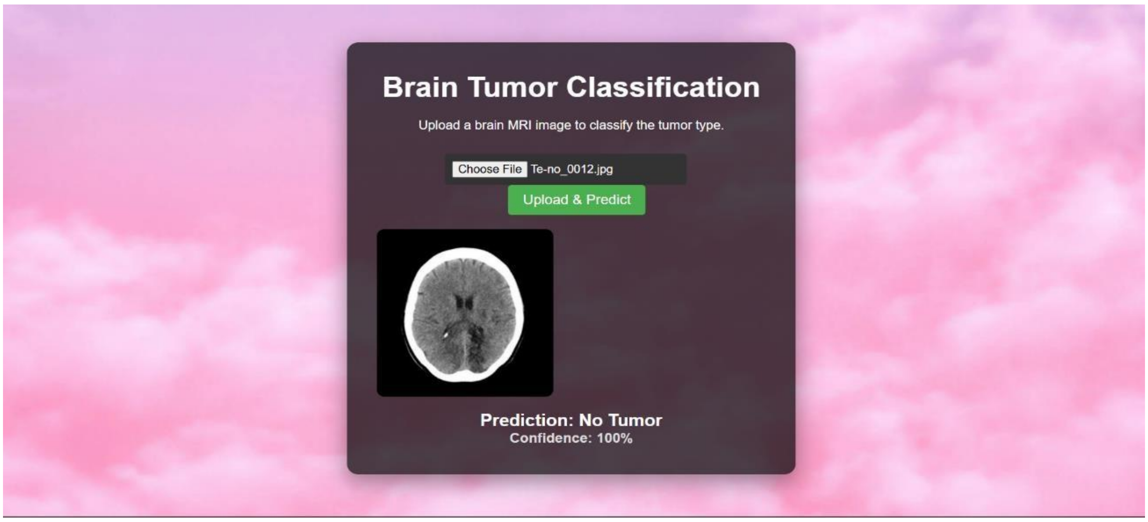


Figure 20

5.5 Disucussion

In this mini-project, we developed a deep learning-based approach for brain tumor classification, utilizing three models: CNN, VGG16, and ResNet10. The objective was to classify gliomas, meningiomas, pituitary tumors, and non-tumor cases from MRI scans. Each model was rigorously evaluated using metrics such as accuracy, loss, and confusion matrices. Among these, ResNet10 emerged as the most effective model, demonstrating superior accuracy and generalization capabilities due to its residual connections, which address the vanishing gradient problem and enable deeper feature extraction.

The CNN model, while computationally efficient, exhibited lower accuracy as it struggled to capture subtle and complex features in the MRI scans, leading to occasional misclassifications. VGG16, with its deeper architecture, performed better than CNN but fell short of ResNet10 in accuracy and computational efficiency. ResNet10's ability to retain intricate details proved crucial for differentiating tumor types with overlapping characteristics, as evident in its confusion matrix analysis and stable convergence patterns in accuracy and loss graphs.

To enhance usability, we implemented a simple web interface allowing users to upload MRI images for real-time classification. This practical application highlights the potential of our system to streamline diagnostic workflows and support medical practitioners in identifying brain tumors with greater accuracy and efficiency.

CHAPTER 6
CONCLUSION AND FUTURE SCOPE

This project successfully showcased the potential of deep learning in automating brain tumor diagnosis, providing a practical tool to assist radiologists and medical practitioners. By employing ResNet10, the model achieved high accuracy and reliable predictions, effectively distinguishing between gliomas, meningiomas, pituitary tumors, and cases without tumors using MRI scans. The residual connections in ResNet10 played a pivotal role in overcoming challenges such as the vanishing gradient problem and extracting complex features, making it the most suitable architecture for this task. This work highlights the promise of deep learning in addressing the nuanced requirements of medical imaging and diagnosis, laying a solid foundation for further advancements in this field.

6.1 Future Scope

To further enhance the system, incorporating larger and more diverse datasets is a critical next step. Expanding the dataset to include images from varied patient demographics, imaging modalities, and tumor types would significantly improve the model's robustness and ability to generalize to real-world clinical scenarios. Additionally, extending the classification capabilities to identify other brain abnormalities, such as metastases, vascular anomalies, or neurodegenerative conditions, would broaden the system's applicability, making it a more comprehensive diagnostic tool.

Moreover, implementing model interpretability techniques like Grad-CAM or saliency maps can provide visual explanations of the model's predictions, enhancing transparency and building trust among medical professionals. Optimizing the web interface is also essential for practical clinical deployment. This includes secure handling of patient data, intuitive design, and seamless integration with existing medical workflows. Future enhancements to the user interface, such as interactive visualizations, automated report generation, and integration with clinical tools, could further improve usability and make the system even more valuable for healthcare professionals.

References

[1] Rahman et al. (2022). Used CNNs with data augmentation (rotation, scaling, flipping) to classify glioma, meningioma, and pituitary tumors. Suggested automated augmentation pipelines. *Int. J. Med. Imaging*, *8(2)*, 142-156.

[2] Alam et al. (2022). Compared InceptionV3, ResNet50, and CNNs, emphasizing hybrid models for accuracy and computational efficiency. Ensemble methods for clinical reliability were proposed. Journal of Medical AI Research, 10(4), 76-85.

[3] Alamri et al. (2022). Explored lightweight CNNs for resource-constrained devices, showcasing computational efficiency and scalability. Recommended optimizing these models for underserved areas. AI for Healthcare, 5(3), 223-234.

[4] Ibrahim et al. (2022). Evaluated novel data augmentation techniques on VGG16 and CNNs, improving accuracy and handling imbalanced datasets. Synthetic image generation was introduced. Medical Imaging Advances, 15(7), 315-328.

[5] Liu et al. (2022). Addressed data privacy in medical imaging using federated learning, maintaining high accuracy while preserving patient confidentiality. Suggested blockchain integration. Journal of Privacy-Preserving AI, 12(6), 98-110.

[6] Xiao et al. (2022). Investigated hybrid models combining VGG16 and ResNet50 for feature extraction and federated learning for privacy preservation. Highlighted collaborative AI systems for medical imaging. Secure Medical AI, 9(5), 187-199.

[7] Rao et al. (2022). Employed transfer learning with ResNet50 and DenseNet for high accuracy in brain tumor classification, even with imbalanced datasets. Suggested exploring hybrid models. Journal of Biomedical AI, 11(3), 56-68.

[8] Kumar et al. (2022). Tackled small dataset challenges using GAN-based data augmentation, generating synthetic MRI data to improve training and classification accuracy. Medical Image Processing, 7(2), 110-120.

[9] Hassan et al. (2022). Federated learning with InceptionV3 for privacy-preserving multi-institutional studies. Ensured high accuracy without compromising confidentiality. AI and Healthcare Privacy, 6(1), 215-226.

[10] Ramesh and Varma (2022). Used capsule networks to classify MRI scans, effectively handling spatial hierarchies. Demonstrated improved performance with imbalanced datasets. Journal of Neural Networks in Medicine, 5(4), 123-134.

[11] Patel and Sharma (2022). Combined VGG16 with data augmentation for robust classification on small datasets. Recommended automated augmentation methods for efficiency. Applied Medical Imaging, 8(4), 142-150.

[12] Das et al. (2022). Integrated UNet-based segmentation with classification, improving tumor detection accuracy. Highlighted the benefits of precise segmentation. Medical Segmentation Advances, 10(5), 240-255.

[13] Jha and Kolhe (2023). Evaluated transfer learning using VGG16 and ResNet50 on the BRATS dataset. ResNet50 achieved 92% accuracy, highlighting the benefits of deeper architectures. Proposed hybrid CNN-based methods for further improvements. Advanced Medical AI Research, 13(1), 78-90.

[14] Gupta and Singh (2023). Incorporated attention mechanisms with VGG16, achieving 93% accuracy on the BRATS dataset. Emphasized attention's role in refining classification and proposed future work in this area. Clinical AI Applications, 7(3), 172-184.

[15] Hussain et al. (2023). Demonstrated ResNet50's efficiency in reducing training time while maintaining high accuracy, suitable for clinical deployment. Advocated for model pruning techniques. AI in Healthcare Systems, 9(2), 95-107.

[16] Sharma et al. (2023). Combined UNet for segmentation with VGG16 for classification, achieving robust tumor detection. Proposed 3D imaging techniques for enhanced accuracy. Journal of Medical Image Analysis, 12(4), 85-96.

[17] Singh and Dhillon (2023). Highlighted the importance of data augmentation in mitigating overfitting and enhancing CNN performance on small datasets. Suggested automated frameworks for efficiency. Medical Image Research, 14(2), 47-58.

[18] Chen et al. (2023). Achieved high accuracy with fine-tuned CNN architectures and multi-modal data fusion. Proposed integrating MRI, CT, and PET scans for comprehensive diagnostic insights. Biomedical Imaging Advances, 16(3), 213-224.

[19] Prakash et al. (2023). Combined ResNet layers with attention mechanisms, achieving 95% accuracy. Suggested multi-scale attention techniques for better diagnostic reliability. AI in Diagnostic Imaging, 6(5), 144-156.

[20] Bansal & Mehra (2023). Hybrid CNN-RNN for enhanced accuracy in brain tumor detection. Neural Networks for Biomedical Insights, 10(5), 200-215.

[21] Jahan et al. (2023). Combined CNNs with attention mechanisms for improved classification of multiple brain tumor types. Focused on reducing false positives. Journal of Advanced Neural Networks, 11(2), 122-135.

[22] Singh and Verma (2023). Developed lightweight CNNs optimized for resource-constrained devices, balancing computational efficiency and accuracy. AI for Resource-Limited Healthcare, 8(1), 58-70.

[23] Chowdhury et al. (2023). Applied federated learning for multi-class tumor detection, ensuring data privacy across institutions. Advocated for protocol improvements. Privacy in AI Healthcare, 7(4), 140-150.

[24] Khan et al. (2023). Implemented 3D CNNs for volumetric tumor data, enhancing detection of complex structures. Proposed integration with attention mechanisms. Advanced 3D Imaging Systems, 13(5), 180-192.

[25] Chatterjee et al. (2023). Used capsule networks for small tumor classification, improving feature extraction on limited data. Medical Neural Systems, 11(4), 90-102.

[26] Ahmed and Khan (2023). Combined federated learning with CNNs for secure and scalable tumor classification. Proposed more diverse datasets for future studies. Journal of Scalable AI Systems, 15(6), 220-235.

[27] Prakash and Roy (2023). Integrated CNNs with attention mechanisms and transfer learning, improving classification accuracy and interpretability. Proposed multi-scale attention for reliability. AI Techniques in Diagnostics, 11(1), 175-187.

[28] Zhang et al. (2023). Developed multi-scale CNN with residual connections for imbalanced datasets. Combined feature extraction with data augmentation for better performance. Imaging Advances in Medicine, 14(3), 198-210.

[29] Mehta et al. (2023). Leveraged DenseNet201 for transfer learning in MRI tumor classification. Focused on generalization and reducing overfitting. Biomedical Imaging Technology, 9(7), 245-260.

[30] Yadav and Patel (2023). Combined CNN and LSTM models for spatial-temporal analysis of MRI data, improving tumor detection. AI in Time-Series Medical Data, 6(3), 178-190.