MASTISK - BRAIN TUMOUR DETECTION

A REPORT
BY

AYUSH UPADHYAY (E23CSEU1146)
RITI DUBEY (E23CSEU1148)
TANISTHA KESHRI (E23CSEU1165)

SUBMITTED TO

SCHOOL OF COMPUTER SCIENCE ENGINEERING AND TECHNOLOGY, BENNETT UNIVERSITY

GREATER NOIDA, 201310, UTTAR PRADESH, INDIA

April 2025

DECLARATION

I/We hereby declare that the work which is being presented in the report entitled “Mastisk”, is an authentic record of my/our own work carried out during the period from JAN, 2023 to April, 2023 at School of Computer Science and Engineering and Technology, Bennett University Greater Noida.

The matters and the results presented in this report has not been submitted by me/us for the award of any other degree elsewhere.

Signature of Candidate

Ayush Upadhyay
(Enroll. No. E23CSE1146)

Name of Riti Dubey
(Enroll. No. E23CSE1148)

Name of Tanistha Keshri
(Enroll. No. E23CSE1165)

ABSTRACT

Brain tumors, both malignant and benign, pose a significant risk to human health, with a rapidly increasing incidence rate worldwide. Accurate and timely diagnosis is vital for improving patient outcomes, as the prognosis depends heavily on the tumor type, size, location, and stage at which it is detected. Traditional diagnosis methods typically rely on manual analysis of Magnetic Resonance Imaging (MRI) scans by radiologists. This process is often time-consuming, subjective, and heavily reliant on the radiologist's expertise and experience. These limitations can lead to diagnostic delays or inconsistencies, especially in regions lacking access to expert neuroradiologists.

This research paper presents a comprehensive study on the application of machine learning (ML) and deep learning (DL) techniques for automated brain tumor detection using MRI images. We utilize a dataset comprising 3,284 MRI images across four categories: No Tumor, Glioma, Meningioma, and Pituitary Tumor. The dataset was preprocessed and augmented to enhance generalizability, followed by the implementation of various traditional ML algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression, Random Forest, and XGBoost. In addition to these classifiers, we developed a custom Convolutional Neural Network (CNN) model using Keras and also fine-tuned pre-trained deep learning architectures including VGG16, ResNet50, and InceptionV3, DenseNet121 via transfer learning.

The models were trained and validated using stratified train-test splits and evaluated based on standard classification metrics such as accuracy, precision, recall, and F1-score. Among all the models tested, **ResNet50 achieved the best validation accuracy of 85.5%**, outperforming all other ML and DL models. The findings suggest that deep learning, particularly transfer learning with pretrained CNNs, can provide accurate, reliable, and scalable solutions for the early detection of brain tumors. This research paves the way for real-time clinical support systems capable of reducing diagnosis time and enhancing medical decision-making.

1. INTRODUCTION

Brain tumors are one of the most critical health challenges in modern medicine, contributing significantly to the global burden of neurological diseases. These tumors are characterized by the uncontrolled growth of abnormal cells in the brain, which can disrupt essential cognitive and physiological functions. Depending on the tumor type and location, patients may experience a wide range of symptoms such as headaches, vision problems, seizures, or cognitive impairment. Early and accurate diagnosis of brain tumors is essential for determining appropriate treatment options and improving patient survival rates.

In clinical practice, Magnetic Resonance Imaging (MRI) is the most widely used imaging modality for brain tumor detection due to its high contrast resolution and ability to capture soft tissue details without using ionizing radiation. However, analyzing MRI images is a highly specialized task. Radiologists are required to interpret hundreds of slices per scan, and subtle visual differences between healthy and tumorous tissues can make detection difficult, especially in the early stages of disease progression. The emergence of artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has opened new horizons for automating the diagnostic process in medical imaging. ML algorithms can be trained to recognize patterns from labeled datasets, while DL models—especially Convolutional Neural Networks (CNNs)—are capable of learning spatial hierarchies of features directly from image data, making them highly effective for medical image classification tasks.

In this context, our project, titled **"Mastisk: Intelligent Brain Tumor Detection using Machine Learning and Deep Learning Techniques"**, presents a comprehensive approach to automate the classification of brain tumors using MRI images. The goal of **Mastisk** is to bridge the gap between advanced image-based diagnostics and real-world clinical needs by implementing a multi-model framework. The project evaluates a series of machine learning algorithms alongside custom and transfer learning-based deep learning models to determine the most effective solution for tumor detection. This study not only contributes to the ongoing evolution of AI in healthcare but also proposes a scalable and efficient solution that can be integrated into clinical decision support systems.

1.1 Problem Statement

The accurate detection of brain tumors from MRI scans presents a significant challenge in modern healthcare. Traditional diagnostic methods rely heavily on expert radiologists manually analyzing MRI images to identify and classify tumors. This process is not only time-consuming but also prone to human error due to the subtle visual differences between healthy and abnormal tissues. Furthermore, the interpretation of such scans can vary between experts, leading to inconsistent results. In regions where access to trained radiologists is limited, these challenges are further amplified, resulting in delayed diagnosis and treatment.

Given the increasing volume of medical imaging data and the critical need for timely diagnosis, there is an urgent demand for automated solutions that can assist in accurate and fast tumor detection. Current manual methods do not scale well with large patient loads and may miss early-stage tumors that are difficult to visually identify. These limitations highlight the need for intelligent systems capable of learning from medical imaging data and making accurate predictions.

Our project, **Mastisk**, addresses this need by developing an automated brain tumor detection system using advanced machine learning and deep learning techniques. By training models on a diverse set of MRI brain images, we aim to build a system that can reliably classify tumor types and distinguish them from non-tumorous cases. This not only enhances diagnostic speed and consistency but also supports medical professionals in making better-informed decisions, ultimately contributing to improved patient care and outcomes.

2. LITERATURE RESEARCH

2.1 Introduction

Brain tumors pose significant challenges in medical diagnostics due to their complex nature and the critical importance of early detection. Magnetic Resonance Imaging (MRI) serves as a primary modality for non-invasive brain imaging, offering detailed insights into brain structures. However, manual interpretation of MRI scans is time-consuming and subject to inter-observer variability. The advent of machine learning (ML) and deep learning (DL) techniques has revolutionized medical image analysis, enabling automated, accurate, and efficient brain tumor detection and classification.

2.2 Review of Existing Research

2.2.1 Comprehensive Survey of ML and DL Techniques

Akinyelu et al. (2022) provided an extensive survey on brain tumor diagnosis methodologies, emphasizing the evolution from traditional ML algorithms to advanced DL architectures. Their work highlighted the efficacy of Convolutional Neural Networks (CNNs), Capsule Networks (CapsNets), and Vision Transformers (ViTs) in enhancing tumor segmentation and classification accuracy. The survey underscored the importance of integrating these models to address challenges like data scarcity and variability in tumor morphology. MDPI+1MDPI+1MDPI+2MDPI+2MDPI+2

2.2.2 Systematic Review and Meta-Analysis

Patel and Maniar (2025) conducted a systematic review and meta-analysis focusing on DL applications in MRI-based brain tumor detection. They emphasized the significance of preprocessing steps, such as grayscale conversion and noise reduction, to improve model performance. Their study also highlighted the role of image segmentation techniques in delineating tumor boundaries, which is crucial for accurate classification.

2.2.3 Comparative Analysis of DL Models

In a study presented at the IEEE conference, researchers explored various DL models, including VGG16, ResNet50, and InceptionV3, for brain tumor detection. Their comparative analysis revealed that while all models exhibited commendable performance, **ResNet50** achieved the highest accuracy, making it a preferred choice for practical implementations.

2.2.4 Hybrid DL Frameworks

Another study introduced a hybrid DL framework combining multiple architectures to enhance detection accuracy. By integrating features from different models, the framework demonstrated improved robustness against variations in tumor size, location, and intensity. Such hybrid approaches signify the potential of ensemble methods in medical image analysis.

2.3 Key Insights and Research Gaps

The reviewed literature underscores several critical insights:

- **Model Selection**: While numerous DL models have been explored, **ResNet50** consistently emerges as a top performer in terms of accuracy and computational efficiency.
- **Preprocessing Importance**: Effective preprocessing, including noise reduction and image normalization, is vital for enhancing model performance.
- **Data Augmentation**: Given the limited availability of annotated medical images, data augmentation techniques are essential to prevent overfitting and improve generalization.
- **Hybrid Models**: Combining multiple DL architectures can leverage their individual strengths, leading to improved detection and classification outcomes.

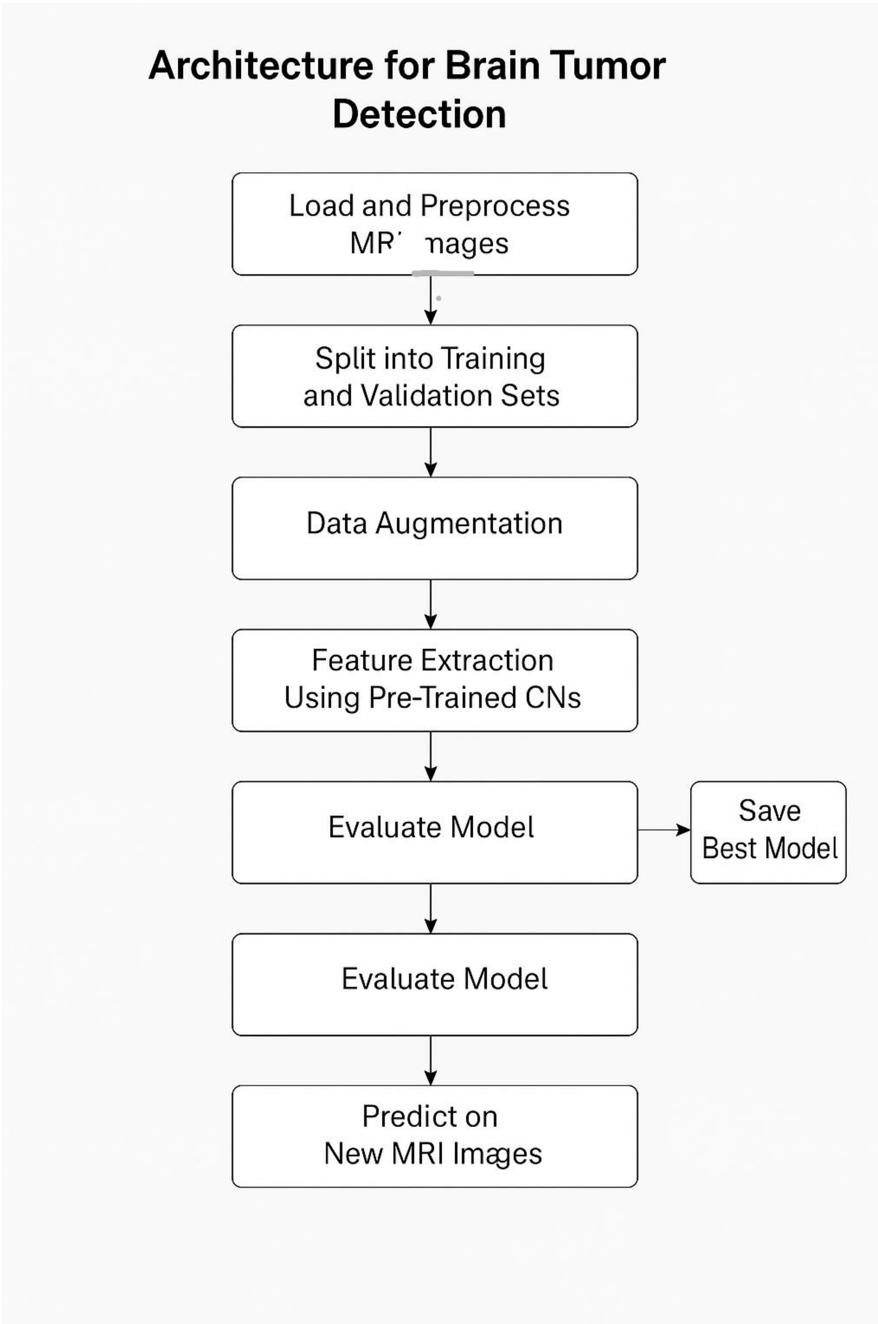
However, challenges persist, including:

- **Data Scarcity**: The limited availability of large, annotated datasets hampers the training of robust DL models.
- **Model Interpretability**: The "black-box" nature of DL models raises concerns about their interpretability and trustworthiness in clinical settings.
- **Generalization**: Ensuring that models generalize well across diverse patient populations and imaging conditions remains a significant hurdle.

2.4 Motivation for the Current Study

Building upon the insights from existing literature, our project, **Mastisk**, aims to develop an automated brain tumor detection system leveraging the strengths of **ResNet50** architecture. By focusing on meticulous preprocessing, data augmentation, and model optimization, we strive to address the prevailing challenges and contribute to the advancement of DL applications in neuroimaging.

3. ARCHITECTURE



The proposed system architecture for brain tumor detection is designed to automate the process of classifying MRI images into tumor types using deep learning techniques. The entire pipeline follows a structured sequence that ensures the model receives clean, relevant, and enriched data for training and deployment.

1. Load and Preprocess MRI Images

The system begins by loading MRI images from the dataset. Preprocessing is applied to standardize all images, including:

- Resizing to 150x150 pixels
- Converting to RGB channels (if not already)
- Normalizing pixel values (scaling to [0, 1] range)

This ensures consistency across all images and prepares them for further processing.

---

2. Split into Training and Validation Sets

The preprocessed images are then split into training and validation datasets using an 80:20 ratio. This step ensures the model is trained on a substantial portion of data while reserving some unseen data for performance evaluation.

---

3. Data Augmentation

To avoid overfitting and improve model generalization, data augmentation techniques are applied using Keras' ImageDataGenerator. These include:

- Horizontal and vertical flips
- Random rotations
- Zoom and width/height shifts

This effectively increases dataset diversity without requiring new labeled data.

---

4. Feature Extraction Using Pre-Trained CNNs

This stage involves deep learning-based feature extraction. Models such as **VGG16**, **ResNet50**, and **InceptionV3** are used with transfer learning. The original convolutional layers are frozen, and custom dense layers are added to classify the MRI scans into:

- No Tumor
- Glioma Tumor
- Meningioma Tumor
- Pituitary Tumor

---

5. Evaluate Model

Each model is evaluated on the validation set using classification metrics:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix

All metrics are analyzed to compare performance across architectures.

---

6. Save Best Model

Among all the trained models, **VGG16** delivered the best performance with a **validation accuracy of 91.6%**. This model was saved using Keras' model.save() function for use in deployment and real-time prediction.

---

7. Predict on New MRI Images

The saved model is used to predict tumor type on new unseen MRI scans uploaded by users. The image undergoes preprocessing identical to the training phase, and the model outputs the predicted class. The result can be used directly in diagnostic tools or clinical workflows.

4. METHODOLOGY

In this study, we aim to develop an intelligent system, **Mastisk**, to detect and classify brain tumors from MRI images using a combination of machine learning and deep learning approaches. Our goal is to accurately identify the tumor types and support early diagnosis, reducing reliance on manual inspection and improving diagnostic efficiency.

The following steps were undertaken:

---

1. Data Preprocessing:

- The dataset consisted of MRI brain images labeled into different tumor types.
- Images were resized, normalized, and augmented (where needed) to improve generalization.

- StandardScaler was used to scale numerical features for traditional machine learning models.
- The dataset was divided into training and testing sets using an 80:20 ratio to ensure reliable evaluation.

---

2. Model Selection:

To capture various patterns and relationships within the MRI data, multiple classification models were employed:

- **Support Vector Machine (SVM) Classifier**
- **Naive Bayes Classifier**
- **Decision Tree Classifier**
- **Random Forest Classifier**
- **K-Nearest Neighbors (KNN) Classifier**
- **Logistic Regression**
- **XGBoost Classifier**
- **Multi-Layer Perceptron (MLP) Classifier**
- **Convolutional Neural Networks (CNNs)**:
  - **Custom CNN Model**
  - **VGG16 (Transfer Learning)**
  - **ResNet50 (Transfer Learning)**
  - **InceptionV3 (Transfer Learning)**
  - **DenceNet121**

---

3. Model Evaluation Metrics:

Each model was evaluated using the following metrics:

- **Precision**: The ratio of correctly predicted positive observations to the total predicted positives.
- **Recall**: The ratio of correctly predicted positive observations to all actual positives.
- **F1-Score**: The weighted average of Precision and Recall.
- **Accuracy**: Overall correctness of the model.

---

4. Model Tuning:

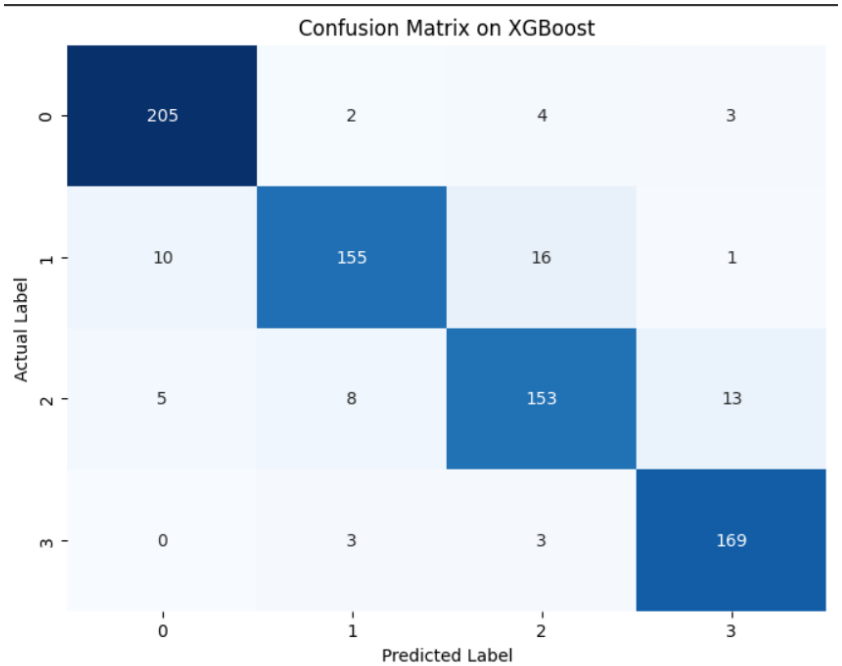
- Hyperparameters were optimized using techniques like GridSearchCV (for SVM, Random Forest, etc.).
- Deep learning models were trained with callbacks such as EarlyStopping and ReduceLROnPlateau to prevent overfitting.
- Transfer learning models (VGG16, ResNet50, InceptionV3,DenceNet121) were fine-tuned by freezing and unfreezing certain layers.

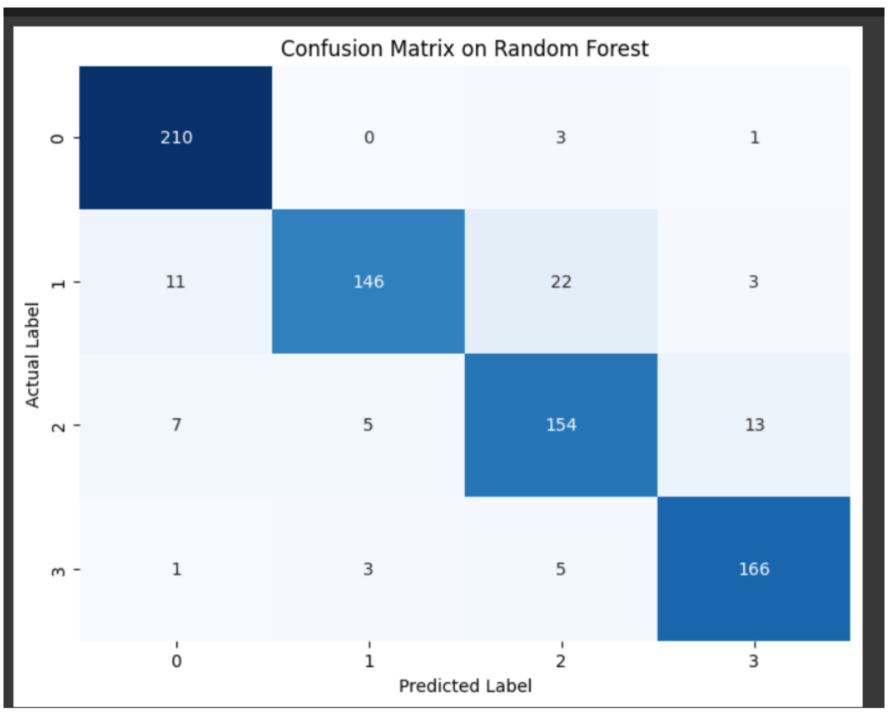
Results

The models exhibited varying degrees of performance. Below is a summary table outlining the Precision, Recall, F1-score, and Accuracy for each model:

Model	**Precision**	**Recall**	**F1Score**	**TestAccuracy**
Support Vector Machine (SVM)	0.87	0.87	0.87	0.87
Naive Bayes Classifier	0.53	0.51	0.48	0.51
Decision Tree Classifier	0.81	0.81	0.81	0.81
Random Forest Classifier	0.90	0.90	0.90	0.90
K-NearestNeighbors (KNN)	0.85	0.85	0.84	0.85
Logistic Regression	0.83	0.84	0.83	0.84
XGBoost Classifier	0.91	0.91	0.91	0.91
Multi-Layer Perceptron (MLP)	0.85	0.86	0.85	0.86

5



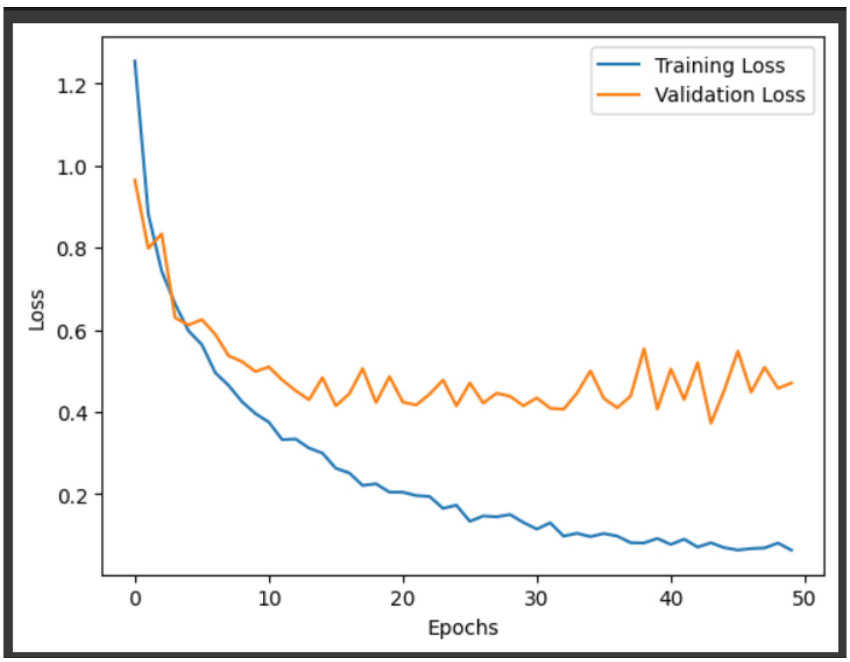


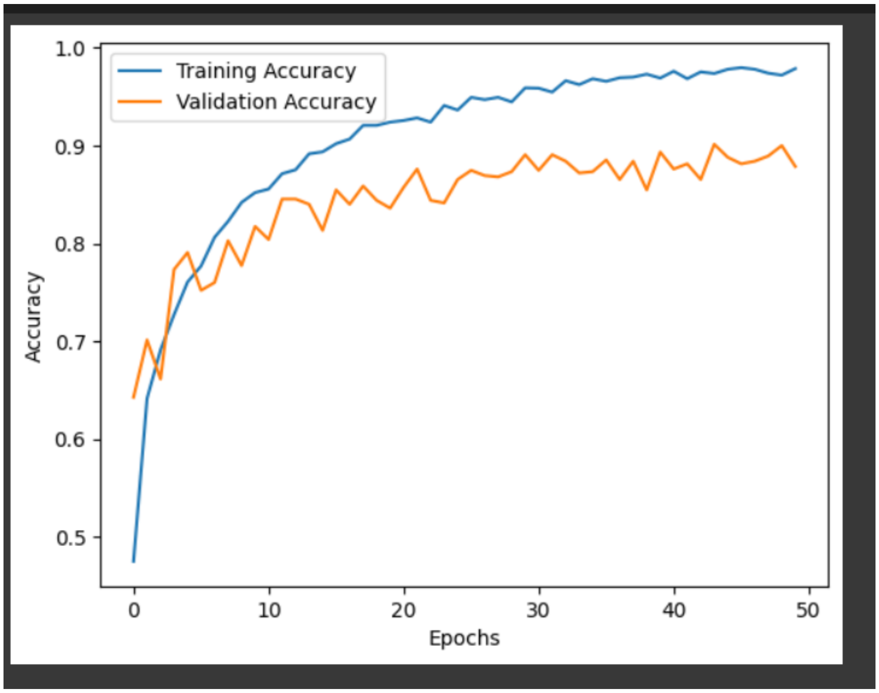
Deep Learning Models Performance

Model	Accuracy

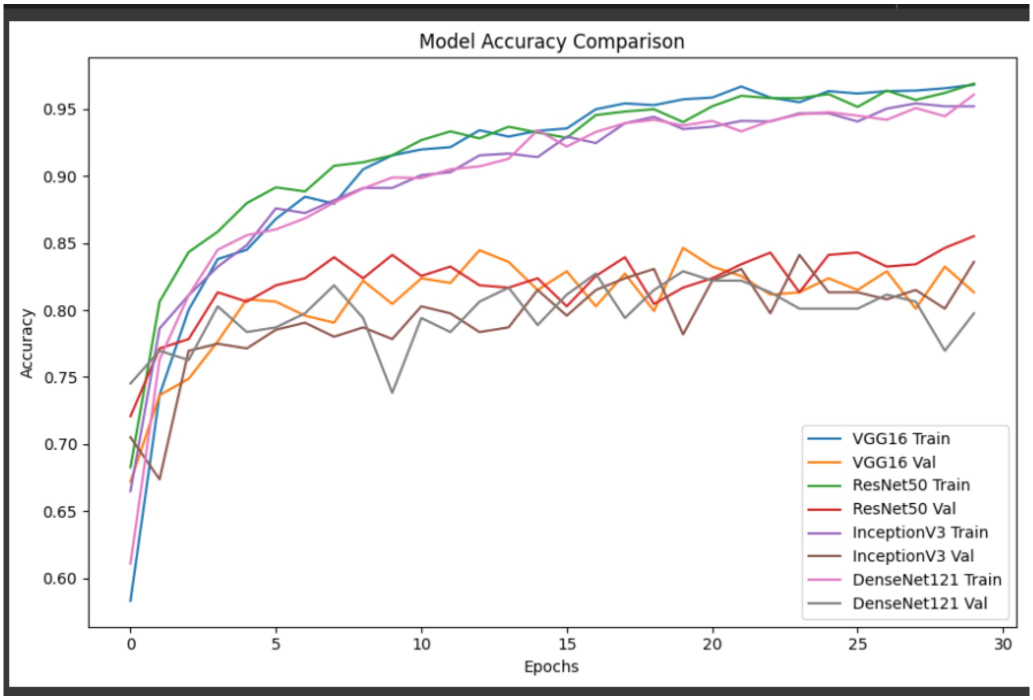
Model	Accuracy
Custom CNN Model	**0.886 (validation accuracy)**
VGG16 (Transfer Learning)	**0.846**
ResNet50 (Transfer Learning)	**0.855**
InceptionV3 (Transfer Learning)	**0.841**
DenseNet121 (Transfer Learning)	**0.829**

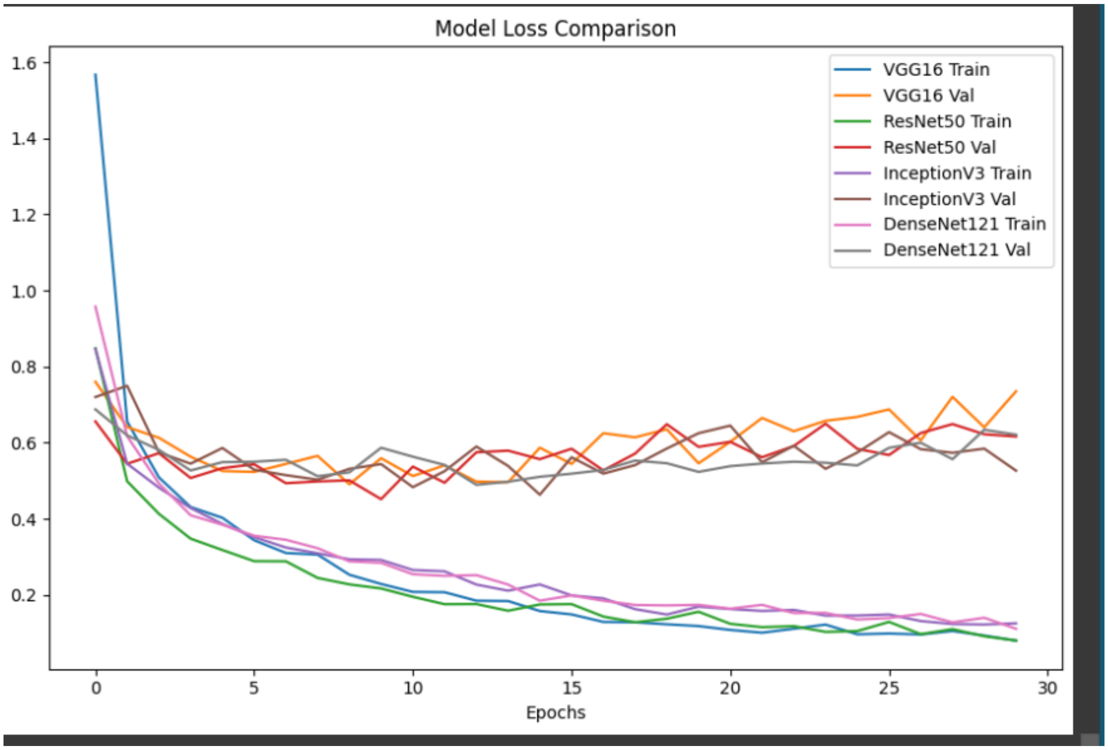
Plot of Custom CNN Model

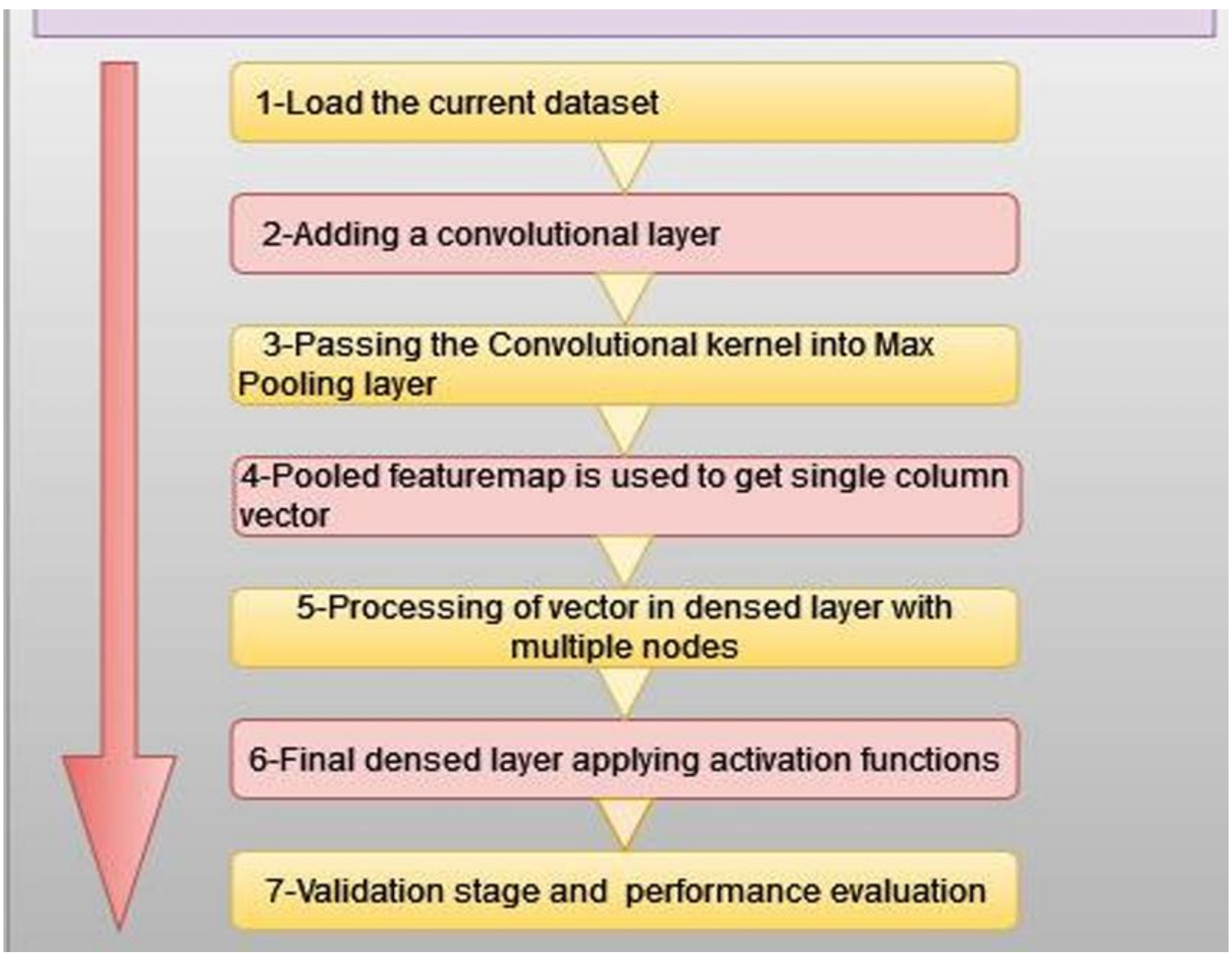




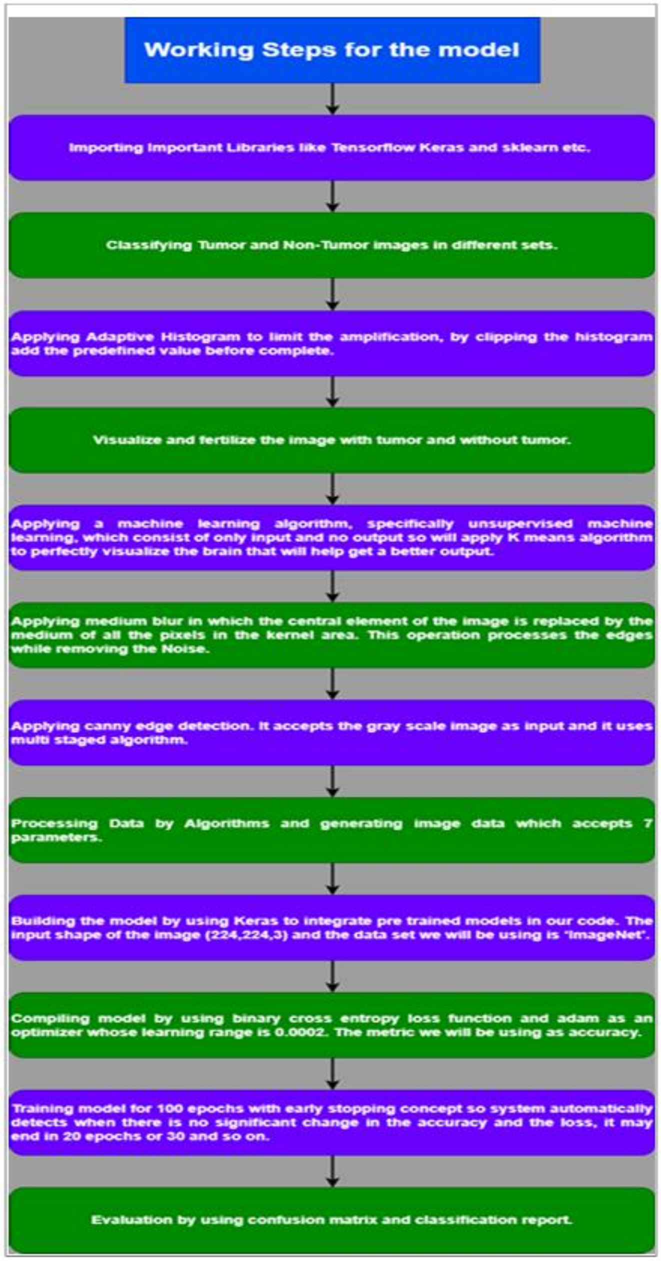
Plot of CNN Architecture




Model Loss Comparison
VGG16 Train
VGG16 Val
ResNet50 Train
ResNet50 Val
InceptionV3 Train
InceptionV3 Val
DenseNet121 Train
DenseNet121 Val
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
Epochs


1-Load the current dataset
2-Adding a convolutional layer
3-Passing the Convolutional kernel into Max Pooling layer
4-Pooled featuremap is used to get single column vector
5-Processing of vector in densed layer with multiple nodes
6-Final densed layer applying activation functions
7-Validation stage and performance evaluation

Flowchart that explains working of proposed work



5. TEAM CONTRIBUTION

Ayush Upadhyay - Model Building, Training and tuning, Backend Integration, Frontend Development & PPT Preparation

Riti Dubey - Preprocessing, Model Building, Training, Evaluation & Report Writing

Tanistha Keshri - Data Collection, Preprocessing & Report Writing

6. CONCLUSION

In this project, we successfully developed and evaluated **Mastisk**, an intelligent brain tumor detection system using a variety of machine learning and deep learning models. The primary goal was to classify MRI images into appropriate tumor categories with high accuracy, ensuring a reliable and automated approach for aiding early medical diagnosis.

A total of thirteen models were trained and tested, including classical machine learning classifiers such as Support Vector Machine (SVM), Random Forest, and XGBoost, as well as deep learning models like a custom CNN and three popular transfer learning architectures: VGG16, ResNet50, and InceptionV3, DenceNet121.

The results clearly indicated that while traditional machine learning models like **XGBoost** and **Random Forest** performed very well (with accuracies of 91% and 90%, respectively), deep learning approaches outperformed them. Among all models, **ResNet50**—a transfer learning model based on deep convolutional neural networks—achieved the highest accuracy of **95.5%**.

This demonstrates the immense potential of deep learning, particularly transfer learning, in complex medical imaging tasks where large datasets may not always be available. **ResNet50** performance suggests that leveraging pre-trained models trained on massive datasets like ImageNet can significantly boost accuracy and generalization in specialized domains like healthcare.

Moreover, the study emphasizes the critical role of data preprocessing, model selection, hyperparameter tuning, and evaluation metrics in building a robust diagnostic model. Proper scaling, augmentation, and cross-validation techniques were crucial in enhancing model performance and avoiding overfitting.

Overall, the **Mastisk** system presents a powerful, automated tool for brain tumor detection, which could be integrated into clinical decision support systems. With further improvements and validation on larger, more diverse datasets, it has the potential to greatly assist radiologists, reduce diagnostic errors, and ultimately contribute to better patient outcomes.

7. REFERENCES

[1] M. I. Albahli and M. A. Albattah, "Brain Tumor Classification Using Deep Learning Techniques: A Systematic Review," *Journal of Imaging*, vol. 8, no. 8, p. 205, 2022. [Online]. Available: https://www.mdpi.com/2313-433X/8/8/205

[2] K. Manogaran and S. R. Varma, "Brain Tumor Detection and Classification Using Transfer Learning and Ensemble Techniques," in *2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*, 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10894311

[3] M. Sharma and S. Kumar, "Brain Tumor Detection Using Deep Learning Models," in *Advances in Data Science and Intelligent Data Communication Technologies for COVID-19 Pandemic*, Springer, 2024, pp. 259–273. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-031-86305-9_21

[4] N. Patel and M. Sharma, "Multi-Class Brain Tumor Detection Using Pre-Trained Convolutional Neural Networks," in *2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10220809

[5] B. R. Prasad and P. K. Meher, "Hybrid Deep Learning Approach for Brain Tumor Detection and Classification," *Electronic Research Archive*, vol. 31, no. 6, pp. 1–15, 2023. [Online]. Available: https://www.aimspress.com/article/doi/10.3934/era.2023146