Mastisk Brain Tumour Detection

MASTISK

BRAIN TUMOR DETECTION SYSTEM

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Problem Statement

Brain tumors are abnormal growths of cells within the brain that can be life threatening if not detected and treated early.

Traditional diagnostic methods, such as MRI scans analyzed by radiologists, are time-consuming, prone to human error, and require specialized expertise.

This project aims to develop an automated brain tumor detection system using deep learning techniques.

By leveraging convolutional neural networks (CNNs) on medical imaging data, the model will enhance accuracy, reduce diagnostic time, and assist healthcare professionals in early and reliable tumor detection, ultimately improving patient outcomes.

MOTIVATION

•Brain tumors, a perilous form of cancer, affect individuals across all age groups.
•Early detection is vital for better patient outcomes, but traditional methods like eye analysis of MRI data have inherent limitations.
•The alarming 300% increase in brain tumor-related deaths over the past 30 years underscores the urgent need for timely identification.
•Untreated brain tumors can lead to fatal consequences, emphasizing the critical importance of accurate and non-invasive diagnostic methods.
•Magnetic Resonance Imaging (MRI) stands out as the most effective tool for diagnosing brain cancers.

Introduction

Mastisk is a deep learning-based system designed to detect and classify brain tumors from medical imaging data, such as MRI scans.

Mastisk leverages Convolutional Neural Networks (CNNs) and machine learning/deep learning techniques to automate the detection and classification process, improving accuracy and efficiency.

The system is capable of distinguishing between different types of brain tumors, such as gliomas, meningiomas, and pituitary tumors,

This project aims to explore the capabilities of ML (Models like SVM, KNN, random forest) and CNN techniques in accurately identifying brain tumors from MRI images.

Our Contributions

Overview

•Extending prior work, our study implements state-of-the-art ML and deep learning algorithms.

Results

•Improved accuracy, efficiency, and applicability in diverse scenarios.

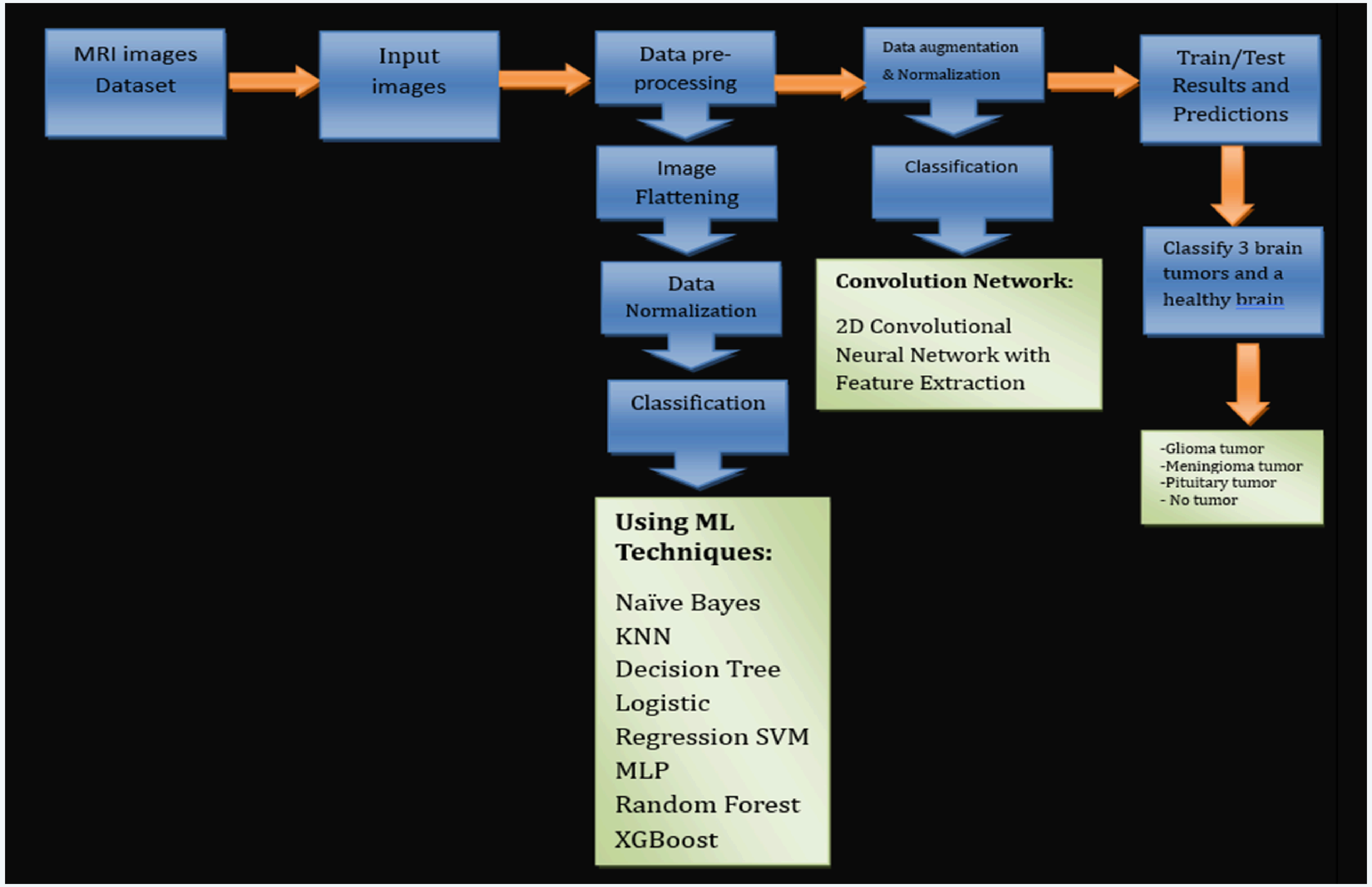
Comparison:

•Highlight key improvements or differences

•Make predictions

•Use visuals to enhance understanding

Proposed Methodology



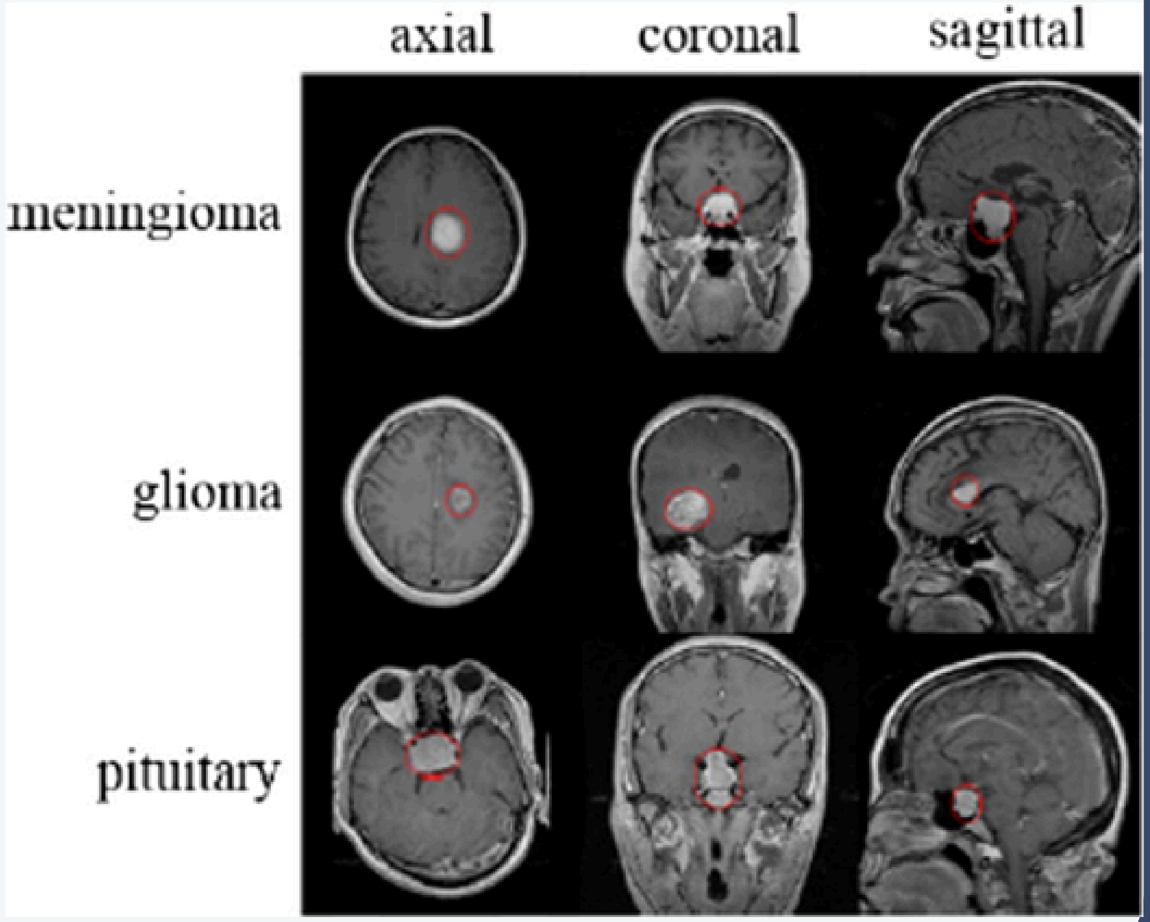
Dataset Overview

Dataset Information: Total Images: 3264 brain tumor (MRI) images
Dataset after up-sampling: 3788

•Data Split: Applied an 80-20 train-test split.
Train (3030) and Test (758)

Source: Publicly available dataset on Kaggle
https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri

MRI Images of Four Classes:
•No tumor (Healthy Brain)
•Meningioma Tumor
•Pituitary Gland Tumor
•Glioma Tumor



Machine Learning Models Used

- Naive Bayes: Limited performance suggesting simplicity may not capture complex data patterns effectively.

- KNN (K-Nearest Neighbors): Solid, balanced performance across metrics.

- Decision Tree: Balanced performance in accuracy, recall, precision, and F1.

- Logistic Regression: Consistent, robust performance. Simple and interpretable, suitable for various tasks.

- SVM (Support Vector Machine): Strong overall performance. Effective for both linear and non-linear patterns.

- MLP (Multi-Layer Perceptron): High accuracy and balanced metrics.

- Random Forest: Excellent overall performance with high metrics. The ensemble approach enhances robustness.

- XGBoost: Top-tier performance with high accuracy and balanced metrics. Gradient boosting optimizes generalization.

CNN MODELS/ARCHITECTURE USED

1- VGG-16 (Visual Geometry Group 16)

2-ResNet-50 (Residual Network)

3-Inception V3

4-DenseNet-121 (Densely Connected Convolutional Networks)

About The CNN Models/Architecture

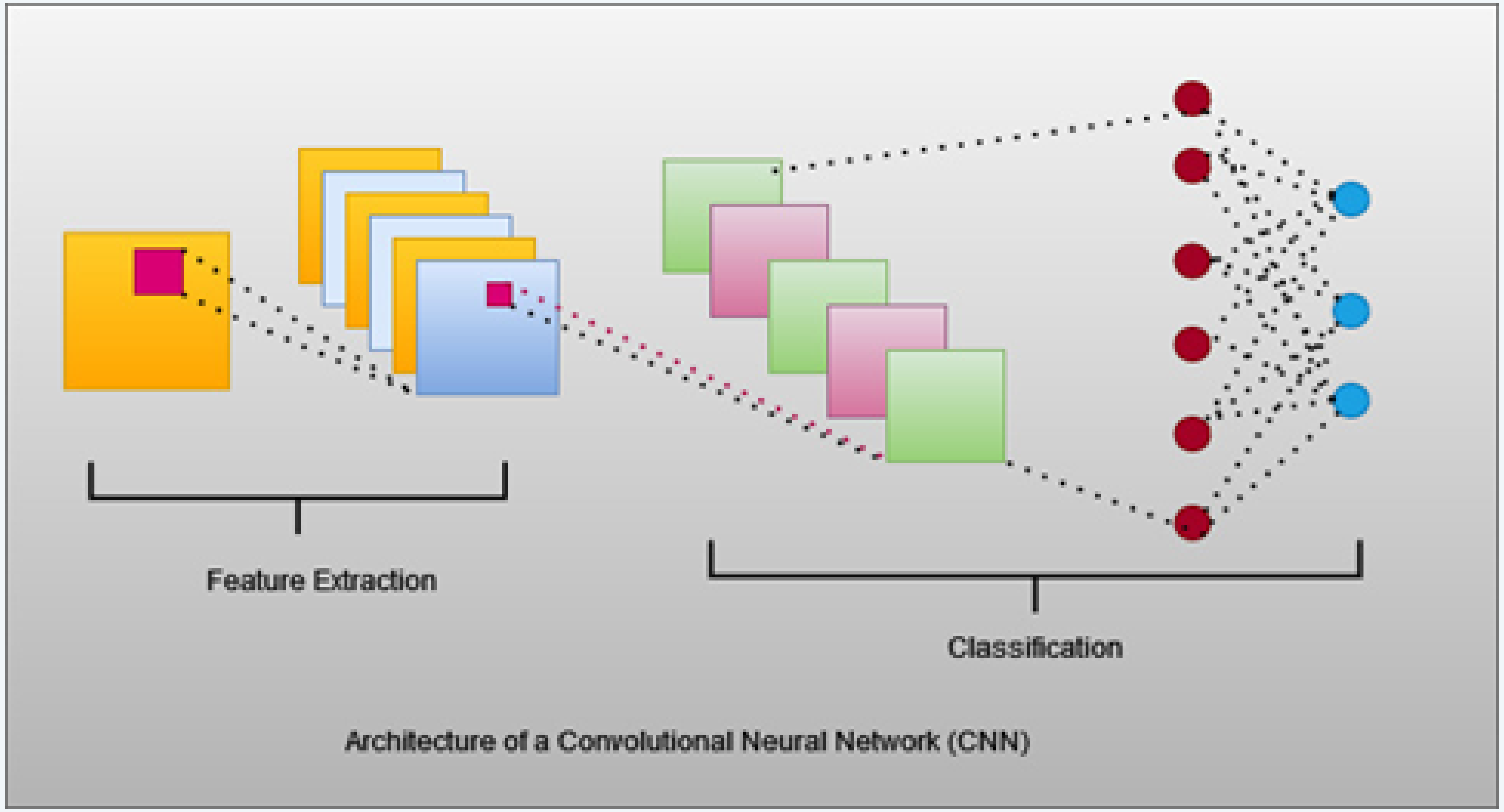
1- VGG-16 (Visual Geometry Group 16): VGG-16 is characterized by its deep architecture with 16 weight layers. It is renowned for its simplicity and uniformity, employing 3x3 convolutional filters throughout the network.

2-ResNet-50 (Residual Network): ResNet-50 introduces the concept of residual learning, mitigating the vanishing gradient problem in deep networks.

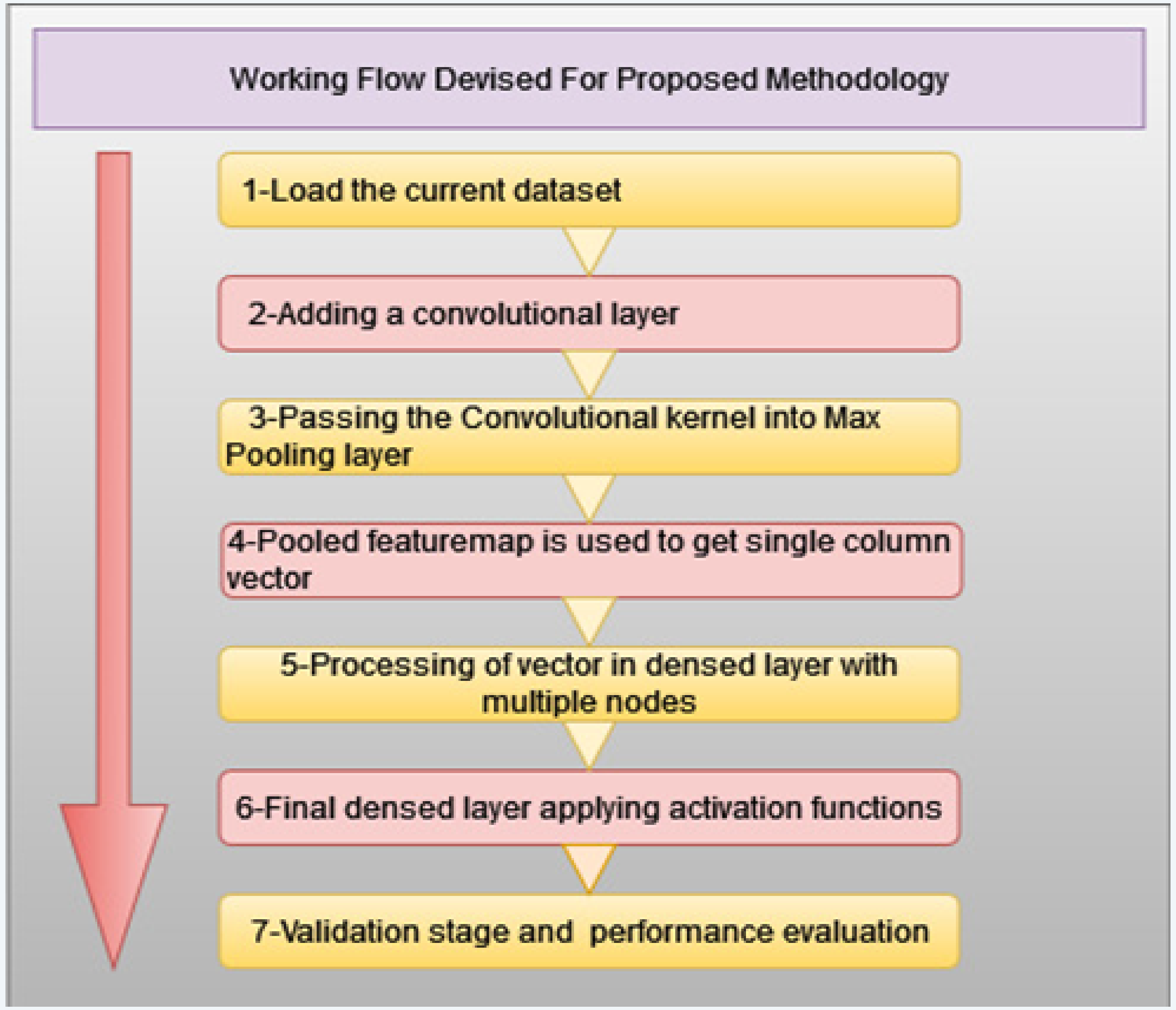
3-Inception V3: Inception V3 employs a unique architecture with multiple parallel paths for feature extraction. It incorporates 1x1, 3x3, and 5x5 convolutions

4-DenseNet-121 (Densely Connected Convolutional Networks): DenseNet-121 features dense connectivity, where each layer receives input from all previous layers.

CNN MODEL STRUCTURE



Working Methodology For CNN



ML MODEL RESULTS

Results

The models exhibited varying degrees of performance.

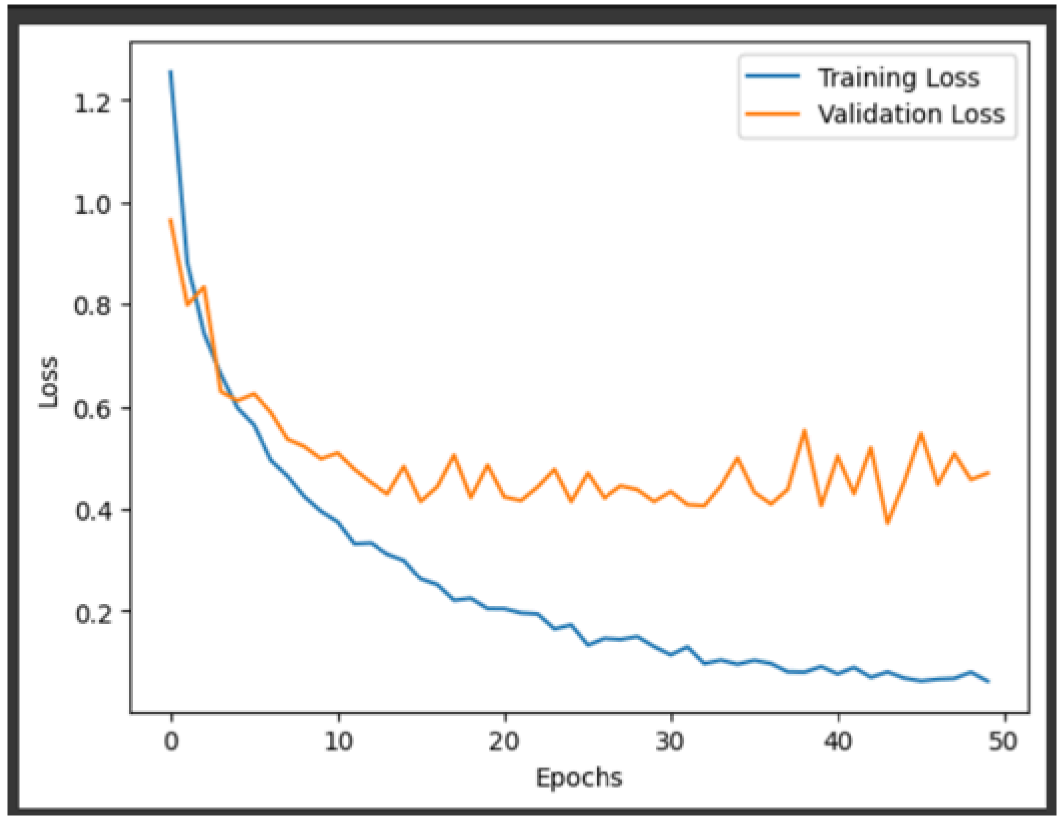
Below is a summary table outlining the Precision, Recall, F1-score, and Accuracy for each model:

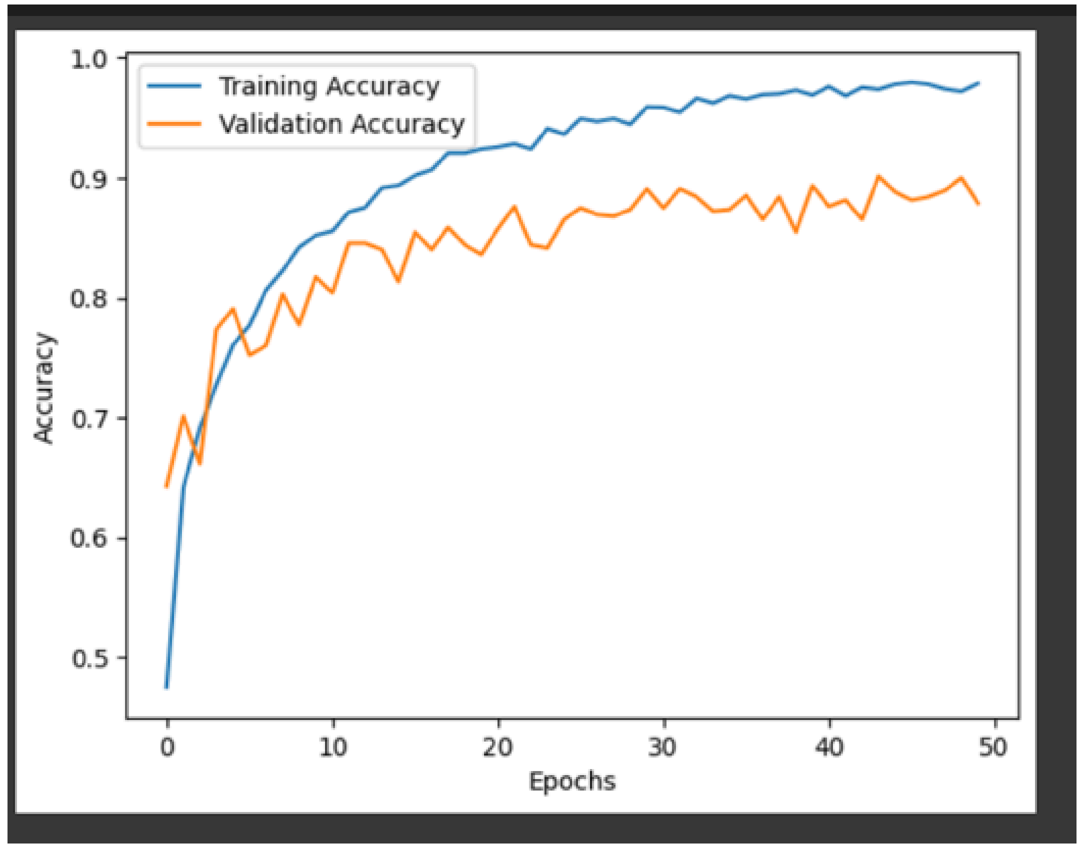
Model	Precision	Recall	F1Score	Accuracy
Support Vector Machine (SVM)	0.87	0.87	0.87	0.87
Naive Bayes Classifier	0.53	0.51	0.48	0.51
Decision Tree Classifier	0.81	0.81	0.81	0.81
Random Forest Classifier	0.90	0.90	0.90	0.90
K-NearestNeighbors (KNN)	0.85	0.85	0.84	0.85
Logistic Regression	0.83	0.84	0.83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

CNN Model Results

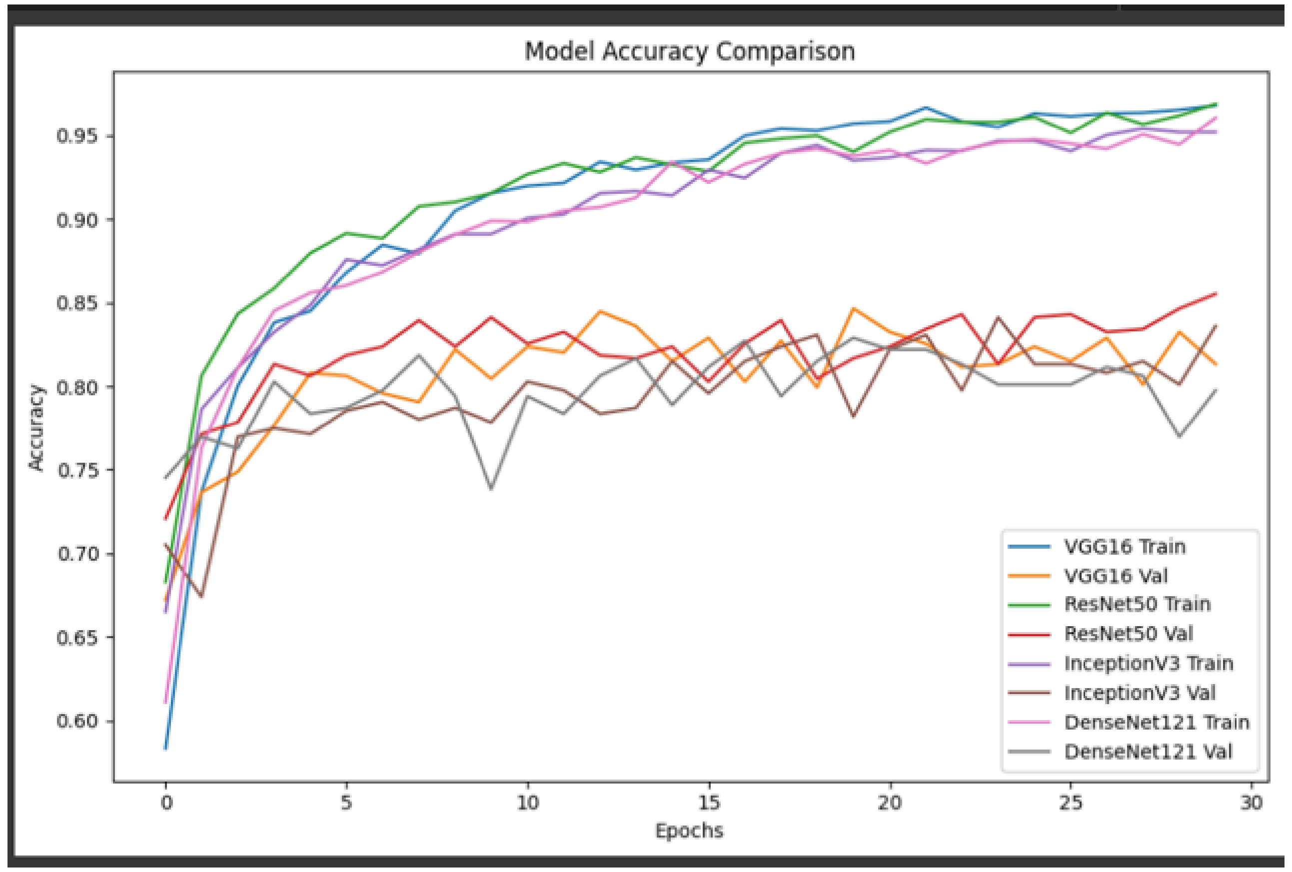
Model	Accuracy
Custom CNN Model	0.886 (validation accuracy)
VGG16 (Transfer Learning)	0.846
ResNet50 (Transfer Learning)	0.855
InceptionV3 (Transfer Learning)	0.841
DenseNet121 (Transfer Learning)	0.829

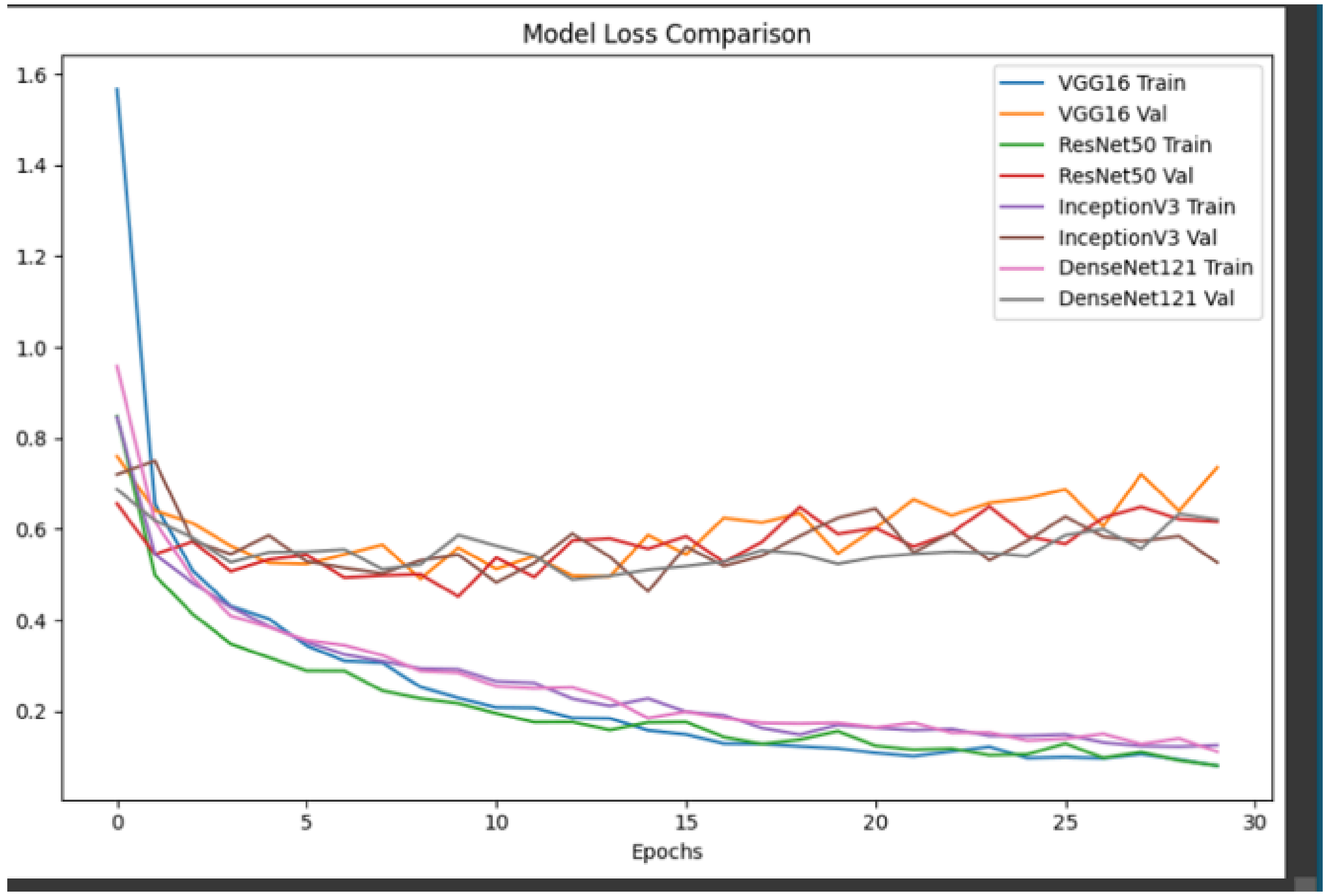
Plot of Custom CNN Model





Plot of CNN Architecture





SUMMARY

Machine Learning Models:
•Naive Bayes and KNN showed lower performance.
•Decision Tree, Logistic Regression, SVM, MLP, Random Forest, and XGBoost demonstrated varying levels of accuracy.
•Top performers were Random Forest and XGBoost.

Convolutional Neural Network (CNN):
•Achieved a high accuracy
•Outperformed traditional ML models on image data.
Architectures

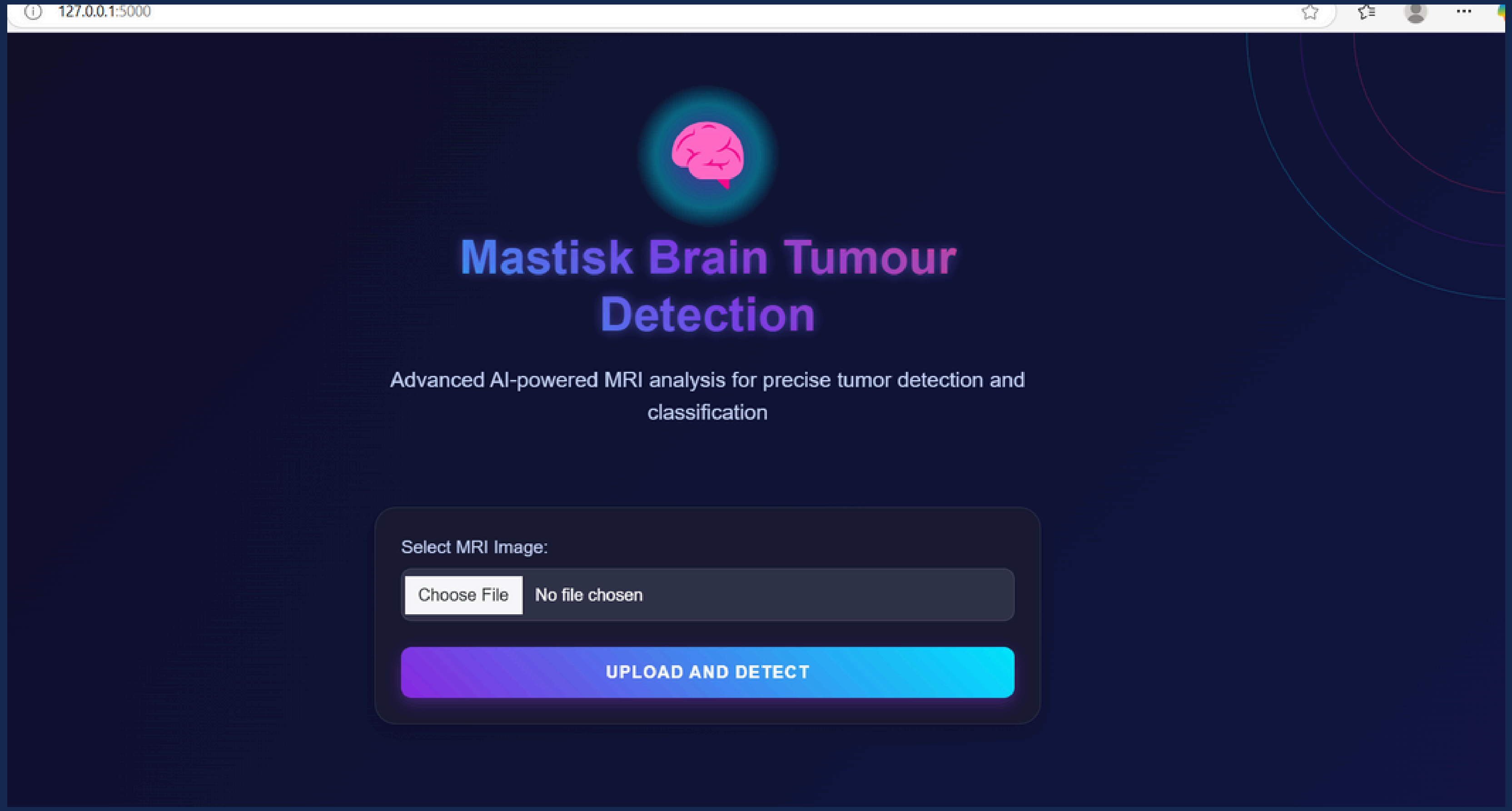
- Resnet Performed The Best ahead og VGG16, Inception V3, DenseNet121

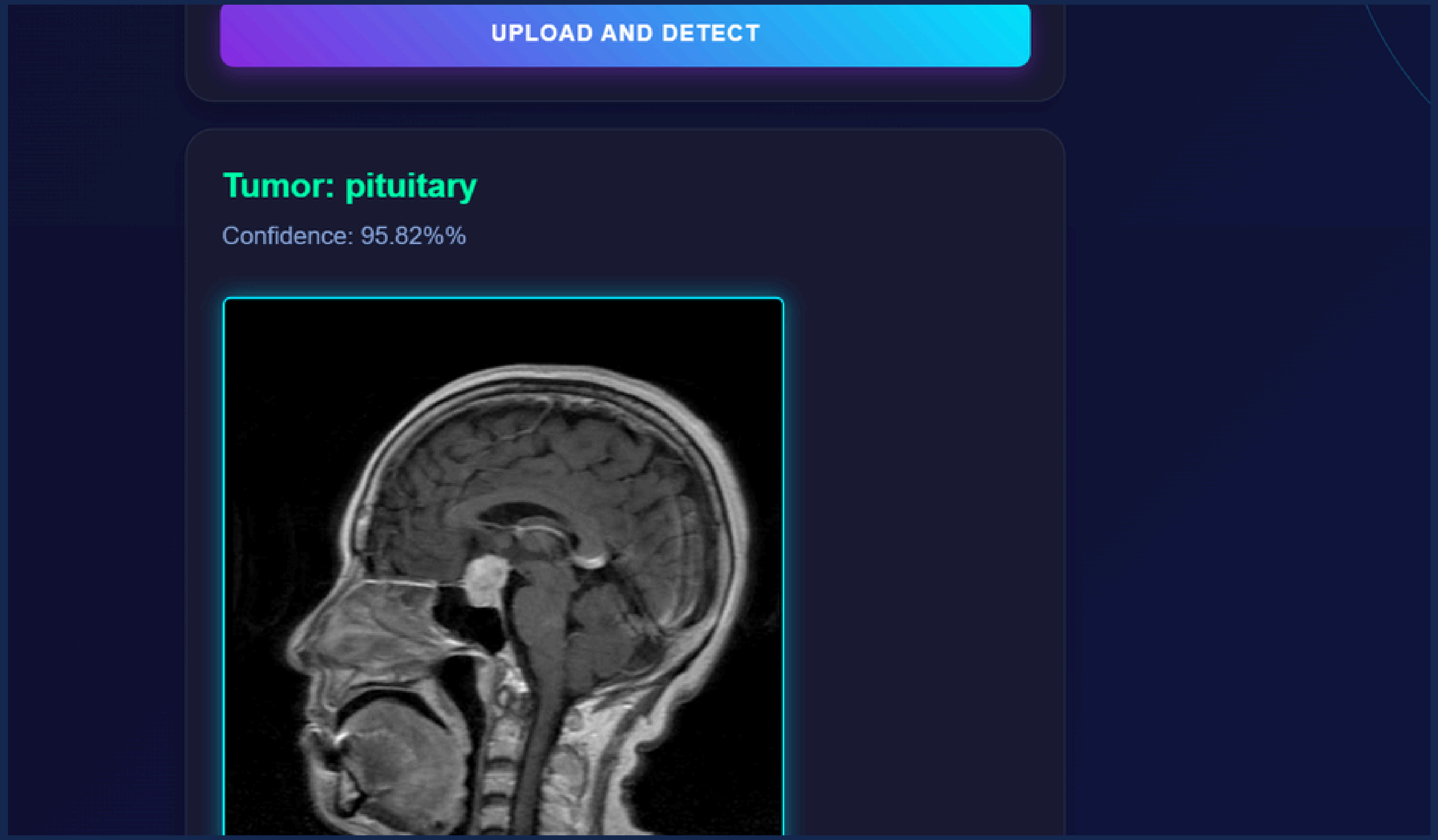
CONCLUSION

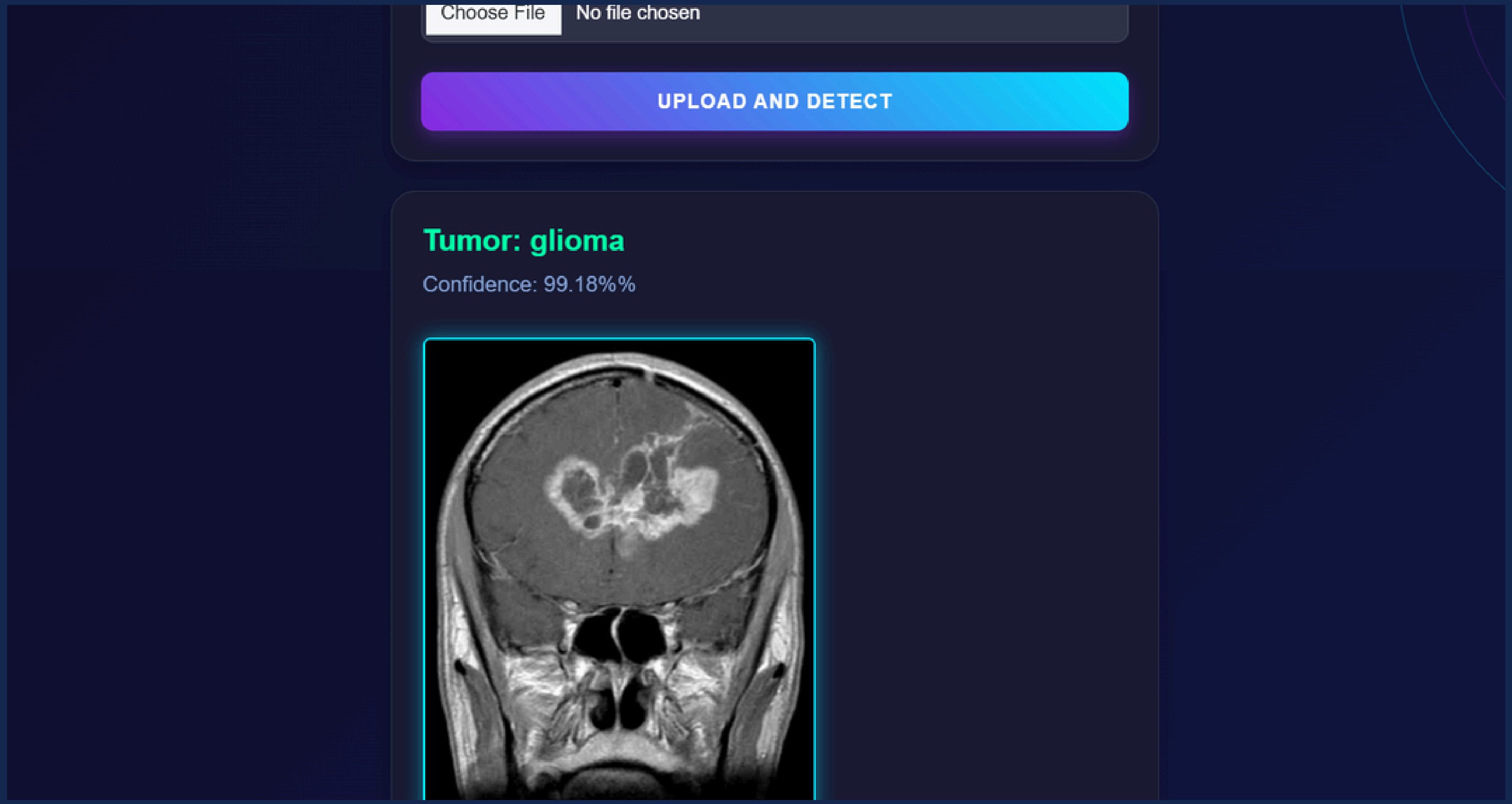
- We worked on different models to estimate the best performing model
- Trained ML Models and CNN Models to understand the working behind of the models
- Designed A Working model for Tumor Detection

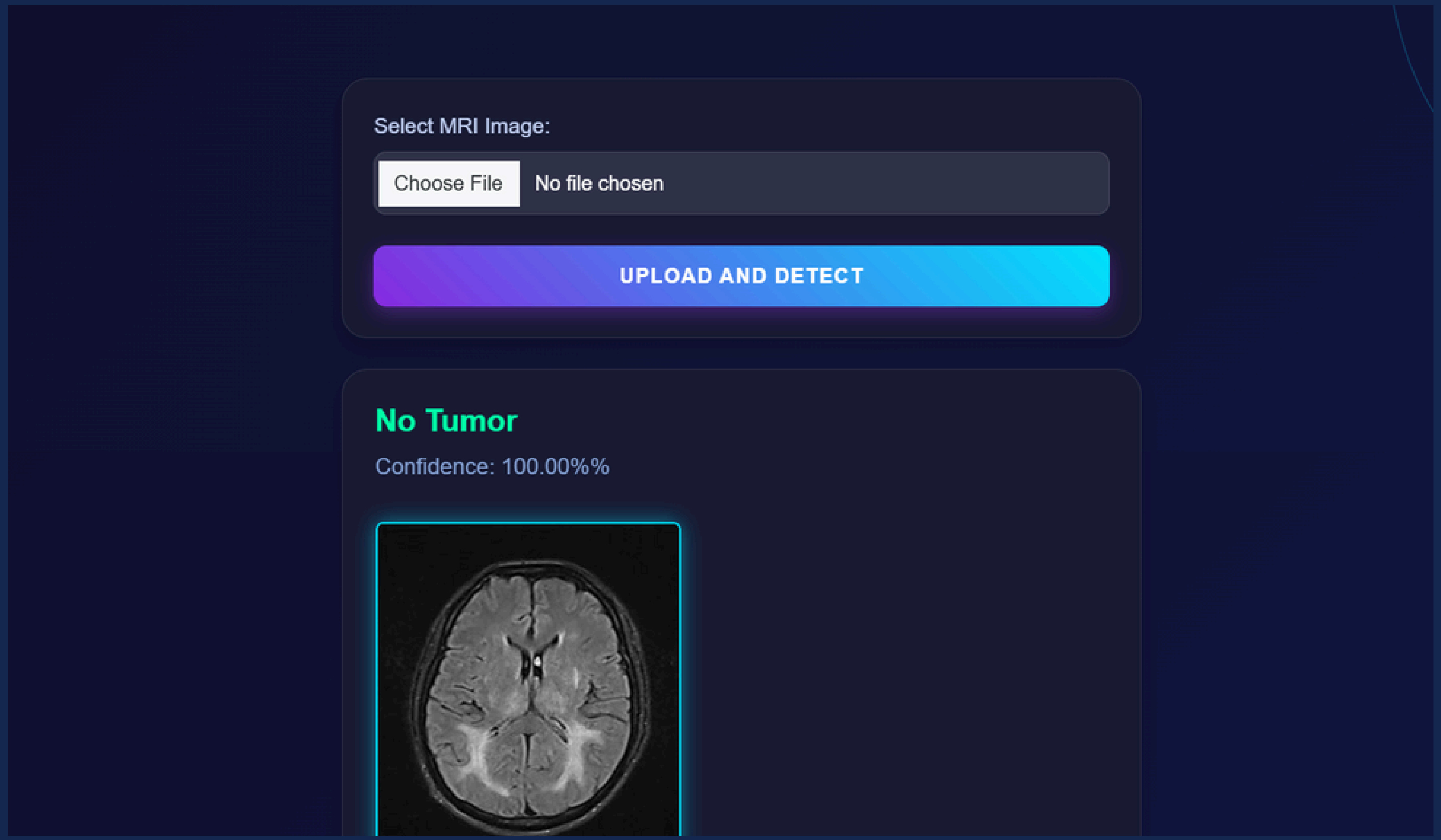
FUTURE SCOPE

- To work on more different models
- To Work on Textual Dataset including image ones mapping the change in concentrations of important factors with the brain data


127.0.0.1:5000
Mastisk Brain Tumour Detection
Advanced AI-powered MRI analysis for precise tumor detection and classification
Select MRI Image:
Choose File
No file chosen
UPLOAD AND DETECT


UPLOAD AND DETECT
Tumor: pituitary
Confidence: 95.82%%


Choose File
No file chosen
UPLOAD AND DETECT
Tumor: glioma
Confidence: 99.18%%


Select MRI Image:
Choose File
No file chosen
UPLOAD AND DETECT
No Tumor
Confidence: 100.00%%

THANK YOU