A

Major Project Presentation

on

COMPARATIVE ANALYSIS OF DEEP LEARNING ALGORITHMS FOR BRAIN TUMOR DIAGNOSIS

in

The Fullfilment

of

BACHELOR OF TECHNOLOGY

COMPUTER ENGINEERING(REGIONAL LANGUAGE)

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Contents

Introduction

- Brain tumors represent one of the most serious and life-threatening neurological conditions which demands early and precise diagnosis for determining the appropriate treatment strategy and improving clinical outcomes.

- In recent years, the application of artificial intelligence—particularly deep learning—has shown promising potential in transforming traditional diagnostics .

- This Project compares the effectiveness of four widely adopted pre-trained CNN architectures—VGG16, ResNet50, Xception, and EfficientNetB3 in identifying the classes of brain tumors using MRI scans.

Motivation

- Traditional diagnosis methods are slow, subjective, and prone to human error, making them less effective for the growing number of brain tumor cases.
- Deep learning models provide fast, consistent, and highly accurate analysis of MRI scans.
- These models support early detection and treatment planning, ultimately improving clinical outcomes.
- AI integration in medical imaging represents a major leap toward efficient, precise, and modern healthcare solutions.

Objectives

- To build a classification model that helps to detect and classify Brain Tumor.
- Compare four pre-trained CNN models including VGG16, RestNet, EfficientNetB3 and Xception for classification MRI images to accurately diagnose brain tumors.
- Evaluate the model's performance on a dataset comprising glioma, meningioma, and pituitary tumors.

Literature Review

- Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown significant promise in the field of brain tumor analysis.
- Several studies have explored different CNN architectures and methodologies to achieve high accuracy in classification and segmentation tasks .

Reference 1

Title	Detection and classification of brain tumor in MRI images using deep convolutional network
Conference / Journal Name	2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)
Year Of Publication	2020
Proposed Methodology	Deep CNN is employed to detect and classify brain tumors from MRI images through image preprocessing, feature extraction, and classification.
Dataset Samples	MR Image Dataset,mainly included 3 classes: Glioma, Meningioma and Pituitary tumor
Findings	Algorithm used : CNN Accuracy : 77.6%
Limitations	Generate high time computation when it deals with 50 and 100 deep layers

Reference 2

Title	Brain tumor classification using convolutional neural network
Conference / Journal Name	World Congress on Medical Physics and Biomedical Engineering
Year Of Publication	2018
Proposed Methodology	A CNN architecture was trained on T1-weighted CE-MRI images to classify tumors without prior segmentation, using basic convolution, pooling, and fully connected layers.
Dataset Samples	3064 T-1 weighted CE-MRI images.
Findings	Algorithm: Deep CNN Accuracy: 84.2%
Limitations	Different feature extraction methods are used that select non-essential and redundant feature sometimes.

Reference 3

Title	Machine learning and deep learning techniques to predict overall survival of brain tumor patients using MRI images
Conference / Journal Name	2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE)
Year Of Publication	2017
Proposed Methodology	The study predicts brain tumor survival using features from MRI data, with best accuracy (68.8%) from deep features and linear discriminant classifier.
Dataset Samples	Used glioma brain dataset provided BraTS challenge.
Findings	Algorithm: SVM, KNN and LR. Accuracy: 68.8%
Limitations	Conventional machine learning methods are used.

Reference 4

Title	Deep learning based multimodal brain tumor diagnosis
Conference / Journal Name	International MICCAI Brainlesion Conference
Year Of Publication	2017
Proposed Methodology	MvNet segments multimodal brain MRIs using multi-view fully convolutional residual networks across axial, coronal, and sagittal planes, while SPNet predicts patient survival using a CNN-based approach.
Dataset Samples	MRI scans of Glioblastoma (GBM/HGG) and lower-grade glioma(LGG)
Findings	Algorithm: Multi-view DNN Accuracy: 88%
Limitations	Time consuming process that generate similar result as CNN.

Reference 5

Title	Brain tumor segmentation using deep fully convolutional neural networks
Conference / Journal Name	Springer Nature
Year Of Publication	2018
Proposed Methodology	This study enhances U-Net with double convolutions, inception, and dense modules for 2D brain tumor segmentation, using ensemble learning across orientations and architectures to improve 3D Dice score performance without data augmentation.
Dataset Samples	BRATS15 and BRATS17 dataset
Findings	Algorithm: CNN architecture Accuracy: 88.20%
Limitations	Fully CNN may take high computation, it require HPC and GPU requirements.

Reference 6

Title	Learning contextual and attentive information for brain tumor segmentation
Conference / Journal Name	Springer Nature
Year Of Publication	2018
Proposed Methodology	The study uses deep learning with contextual and attention mechanisms to segment brain tumors, achieving high Dice scores on the BraTS 2018 dataset.
Dataset Samples	BRATS 2018 Challenge.
Findings	Algorithm: U-Nets were deepened by adding double convolution layers, emergence modules, and dense modules. Accuracy: 81.35
Limitations	Both CNN are conventional modules.

Reference 7

Title	Semantic segmentation using deep learning for brain tumor MRI via fully convolution neural networks
Conference / Journal Name	Springer Nature
Year Of Publication	2019
Proposed Methodology	A 3D CNN with a UNet architecture was trained on cropped MRI images for brain tumor segmentation, incorporating post-processing to refine results and manage memory constraints
Dataset Samples	BRATS 2017
Findings	Algorithm: UNET Architecture Accuracy: 89.60
Limitations	High computation with large epoch size.

Dataset Description

Dataset Design: Collection & Composition

- Custom Dataset of ~20,000 brain MRI images curated from:
  - Research papers, public datasets, and medical imaging repositories
- Four Tumor Classes:
  - Glioma, Meningioma, Pituitary Tumor, No Tumor
- Images captured under varied conditions to improve generalization
- Data Split:
  - 80% Training (16,000 images)
  - 20% Testing (4,000 images)
- Format: Images resized to 512×512, grayscale or RGB
- Quality checks performed:
  - Duplicate removal, accurate labels, balanced class distribution

Dataset Description

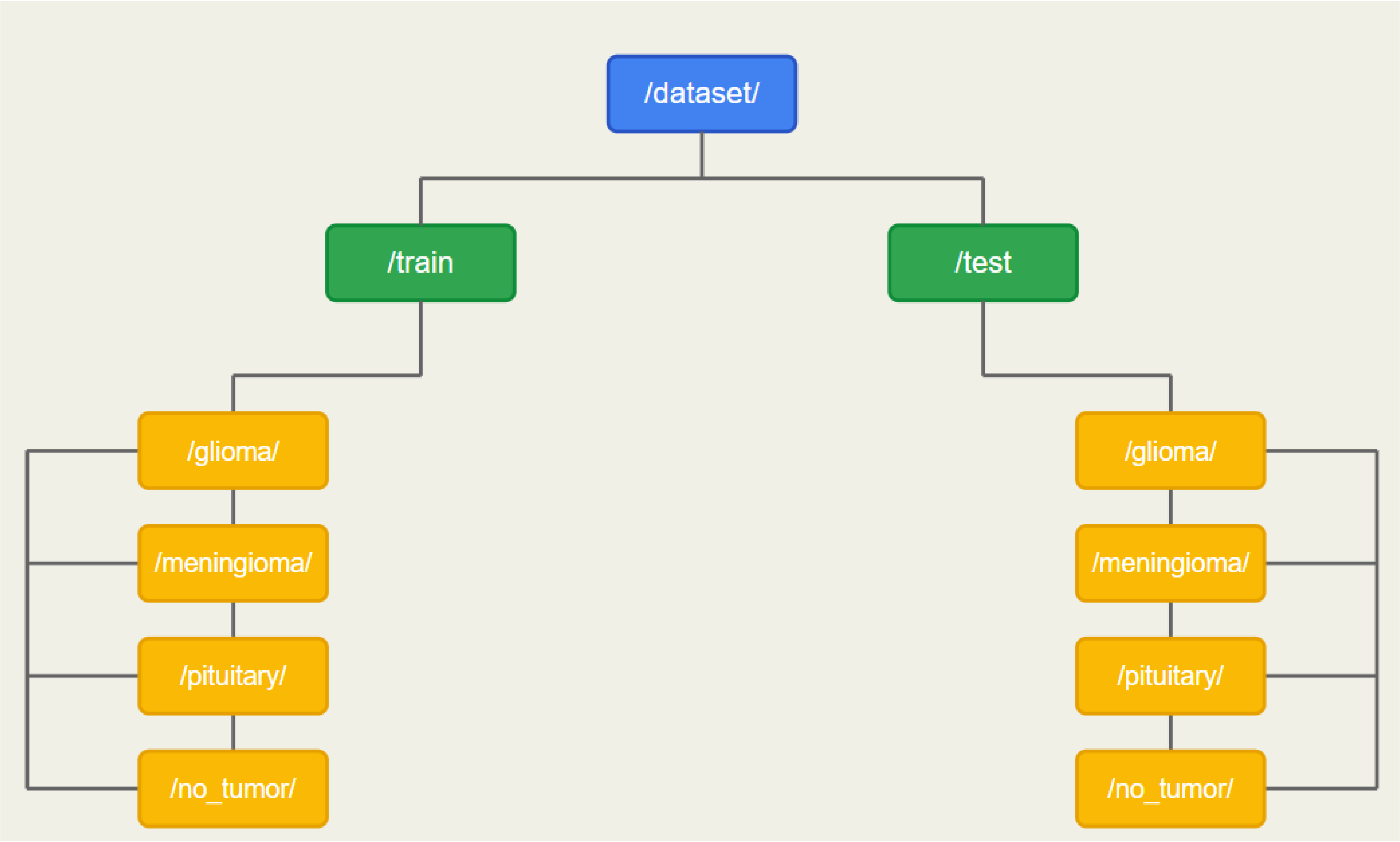


Fig 1: Brain tumor classification dataset Structure

Dataset Description

Dataset Organization & Visual Analysis

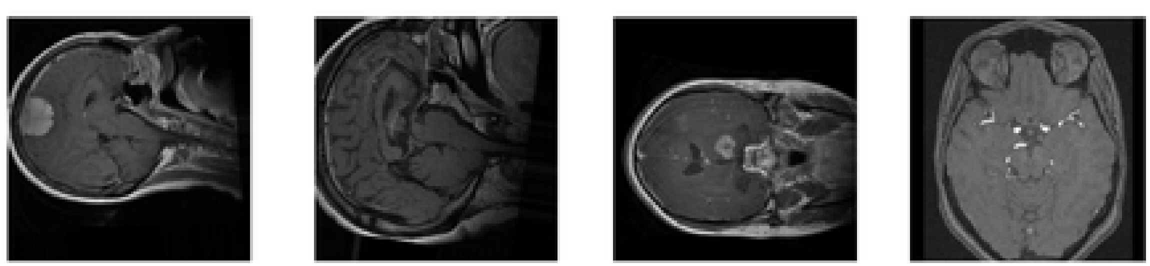
- Directory-based structure used for:
  - Easy preprocessing, label mapping, and integration with TensorFlow/PyTorch

- Dataset hierarchy supports efficient loading and training

- Integrity Ensured via:
  - Manual review, label validation, class balancing

- Visual Distribution:
  - Bar Graphs and Pie Charts used to verify class balance

- Diverse features in images: contrast, intensity, and orientation variations



Meningioma   Pituitary   Glioma   No Tumor

Dataset Description

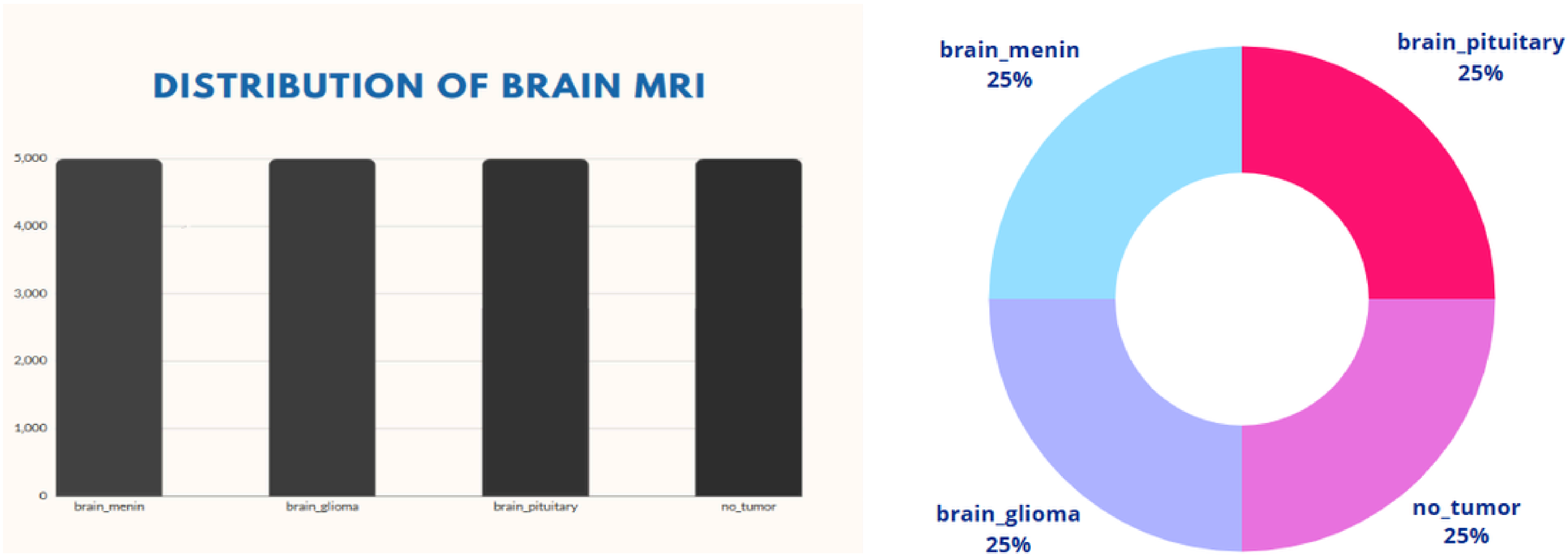


Fig 2: Graphical Distribution of images over four classes

Proposed Methodology

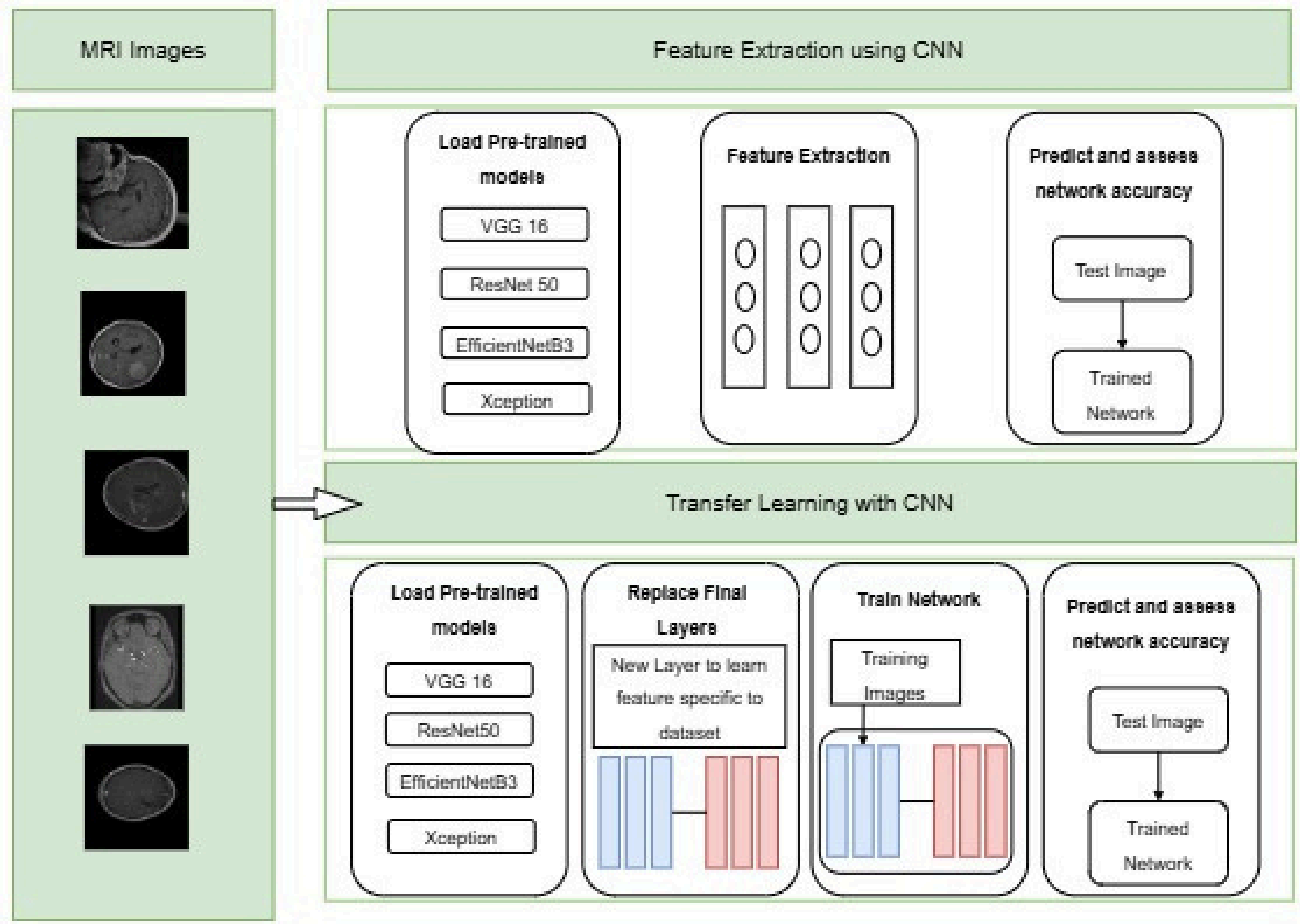


Fig 3: Architecture Diagram

Proposed Methodology

SYSTEM ARCHITECTURE WORKFLOW

- **Image Acquisition** – 20,000 MRI images collected from public sources (Kaggle); optional real-time capture and upload interface; categorized into four tumor types.

- **Preprocessing** – Images resized (128×128), normalized, split (80:20), and converted to NumPy arrays for model input.

- **Feature Extraction** – Transfer learning with EfficientNetB3, VGG16, ResNet50, and Xception; CNN layers extract spatial and semantic features.

- **Model Training** – CNN + dense layers trained using Adam optimizer, early stopping, and validation monitoring.

- **Evaluation** – Accuracy, Precision, Recall, F1-score, and confusion matrix used for performance assessment.

Proposed Methodology

Algorithm 1 – Feature Extraction using CNN

- **Step 1:** Acquire 20,000 brain MRI images from dataset.
- **Step 2:** Preprocess each image:
  Resize to 128×128
  Normalize pixel values for standardization.
- **Step 3:** Feed into pre-trained CNN model (EfficientNetB3, VGG16, ResNet50, Xception)
- **Step 4:**
  Apply convolutional layers to extract spatial features
  Use pooling to reduce dimensionality
  Pass through deeper layers for abstract feature learning
- **Step 5:** Flatten final output into 1D feature vector, creating a feature representation of the image.

Proposed Methodology

Algorithm 2 – Classification via Transfer Learning

- **Step 1:** Modify pre-trained CNNs with a new classification head for 4 classes: Glioma, Meningioma, Pituitary Tumor, No Tumor
- **Step 2:** Fine-tune model using Adam optimizer
- **Step 3:** Train on 80% of dataset; test on 20% unseen data
- **Step 4:** Predict tumor class from MRI images
- **Step 5:** Evaluate with:
  Accuracy, Precision, Recall, F1-Score
  Confusion Matrix

Proposed Methodology

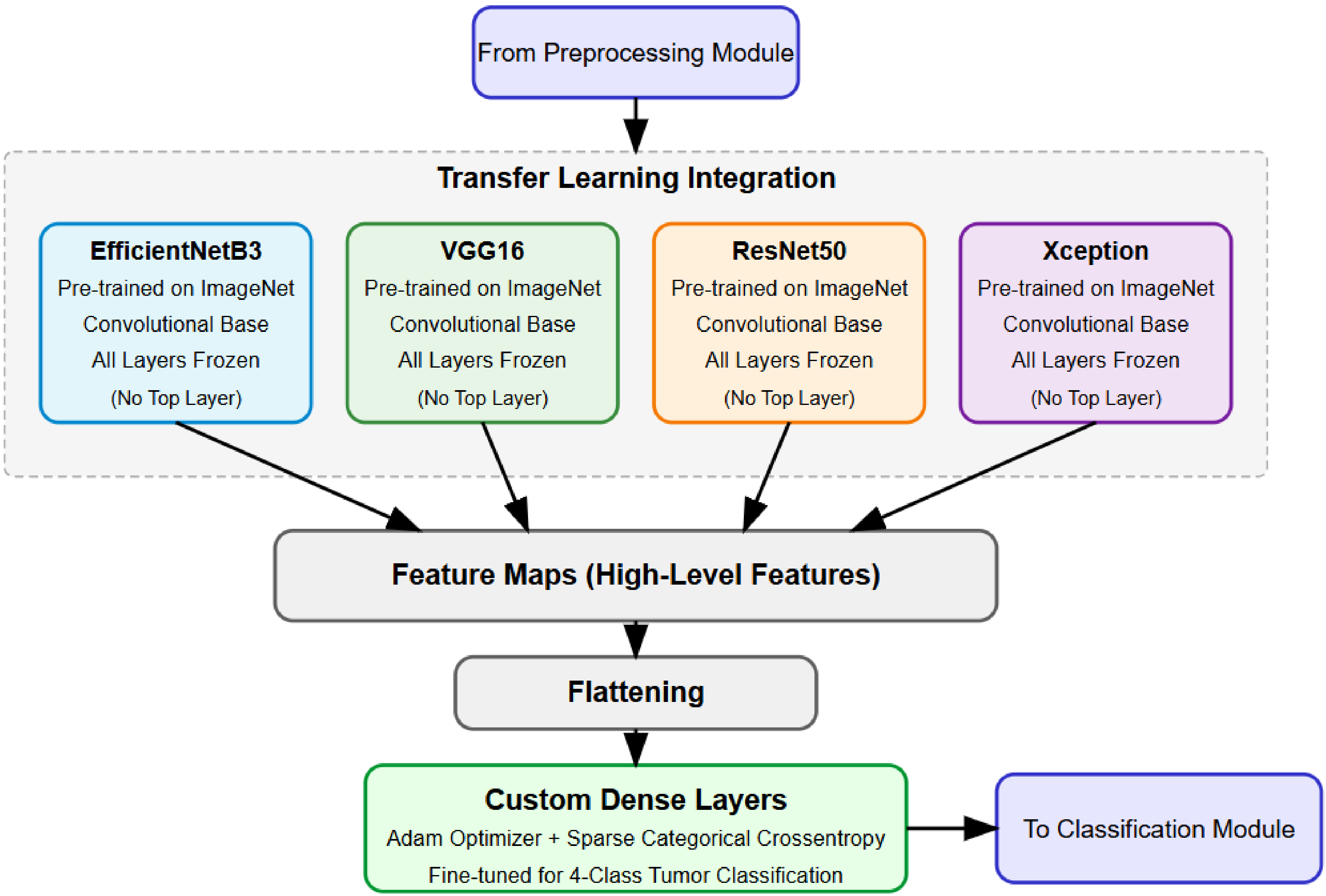


Fig 4: Brain MRI Feature Extraction Module

Results

Model Evaluation & Performance Metrics:

- Evaluated VGG16, ResNet50, Xception, EfficientNetB3 for brain tumor classification.
- EfficientNetB3 achieved highest accuracy (97.62%), followed by Xception (97.57%).
- Strong performance across accuracy, precision, recall, and F1-score.
- EfficientNetB3 showed best performance in terms of both accuracy and training efficiency.

Results

Model	Accuracy
EfficientNetB3	97.62%
ResNet50	96.93%
VGG16	97.15%
Xception	97.57%

Table 1: Comparative Analysis of CNN Models

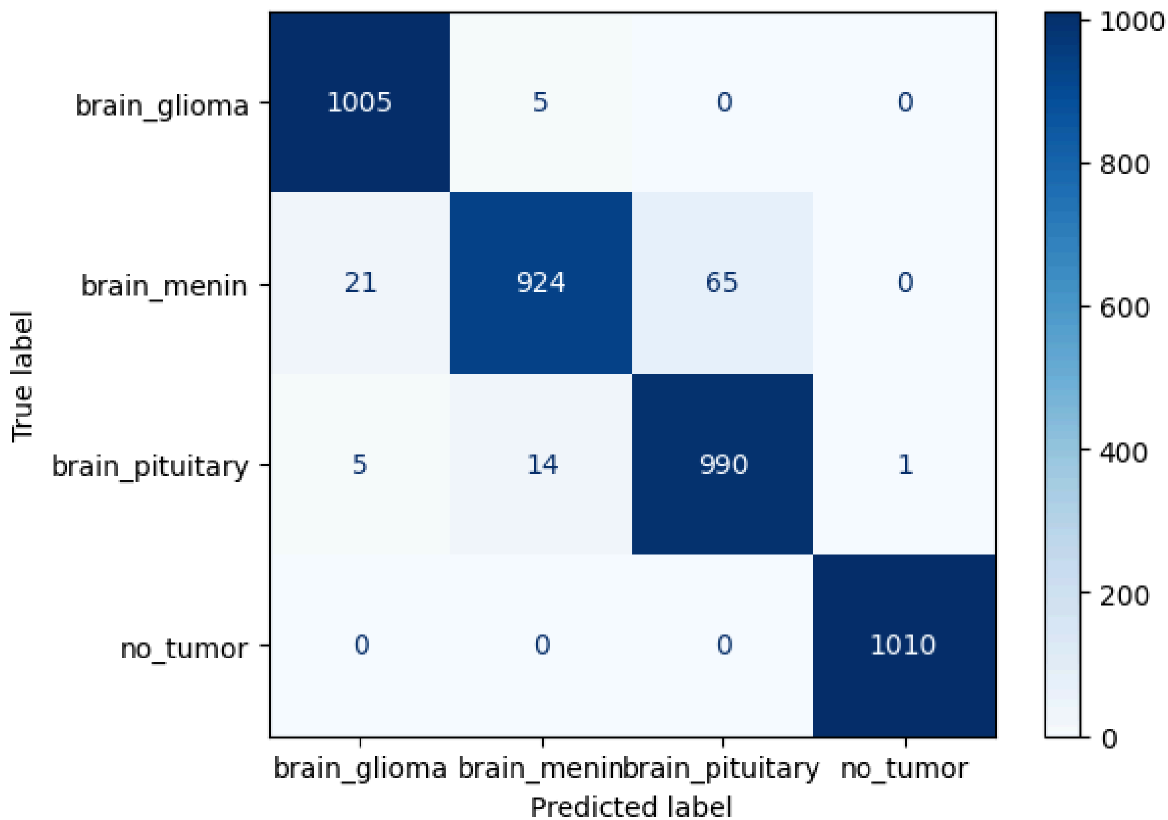
Results

Key Insights:

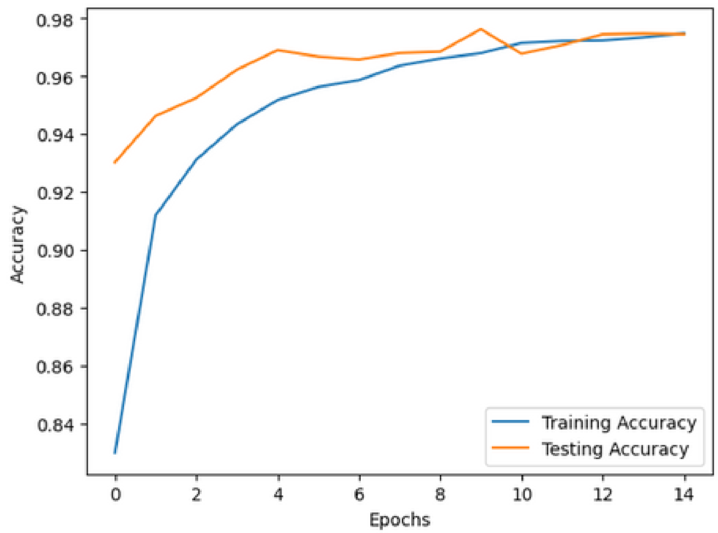
- EfficientNetB3 converged faster due to optimized parameters.
- All models validated effectively on unseen data, showing strong generalization.
- Results support EfficientNetB3 for real-time medical imaging integration.

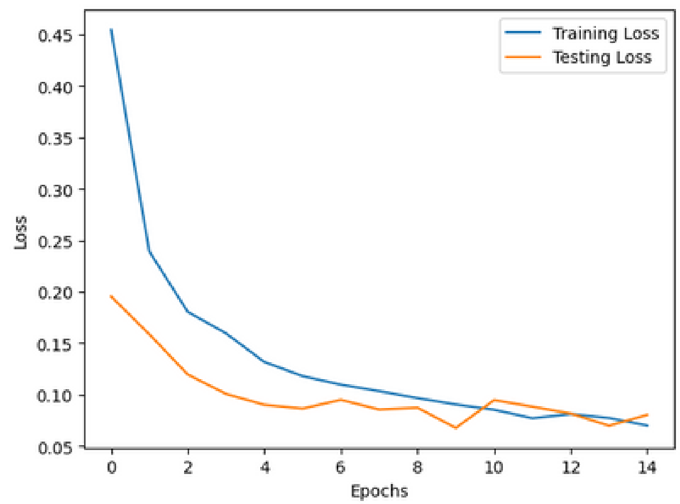
Graphs / Screenshots

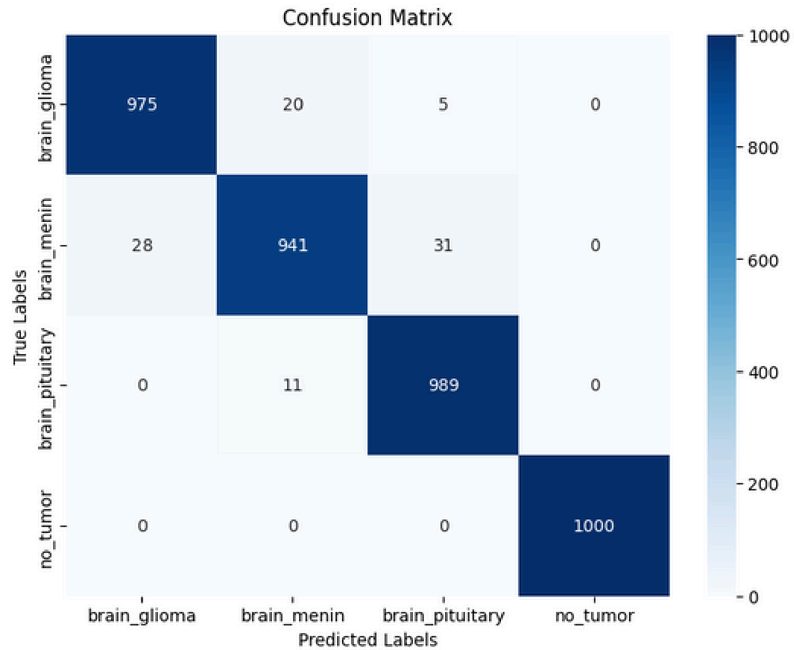
Xception Results:



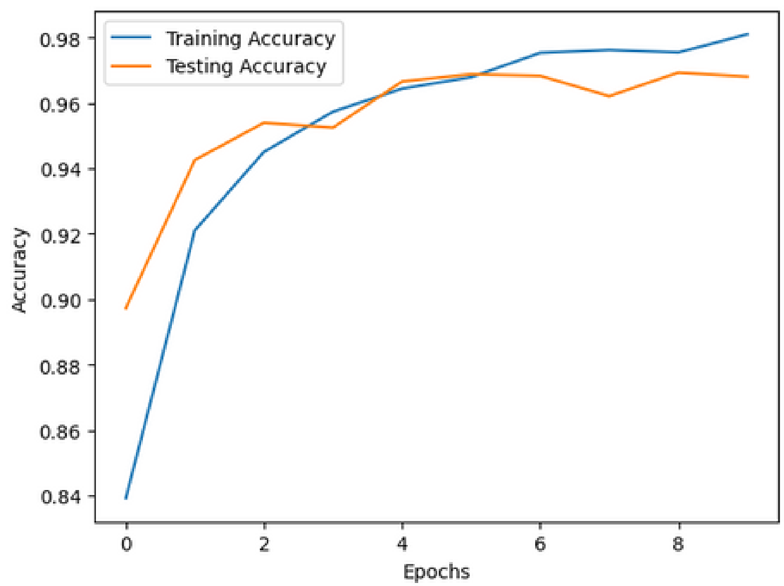
EfficientNetB3 Results:

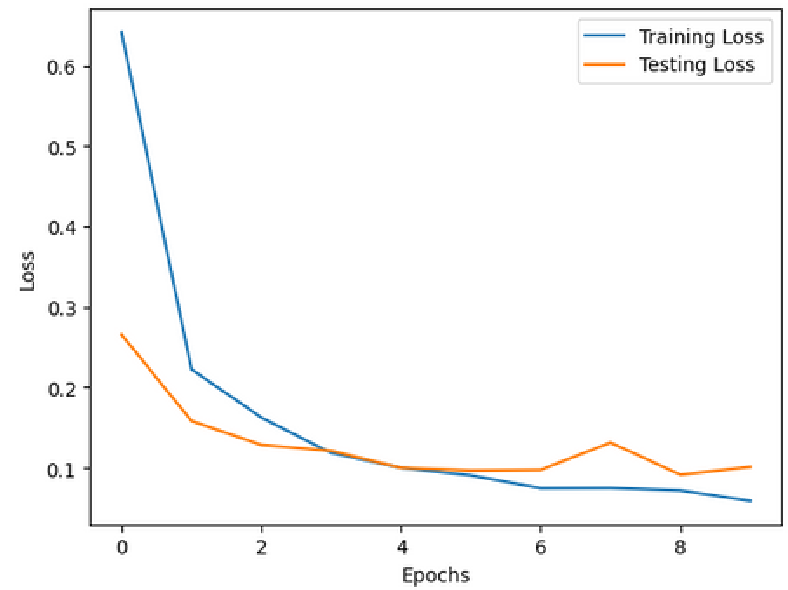


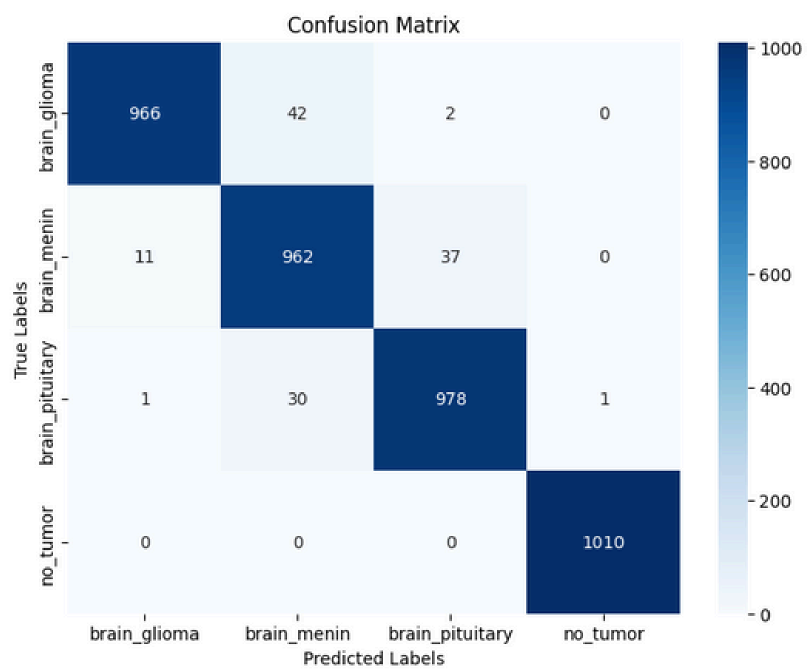




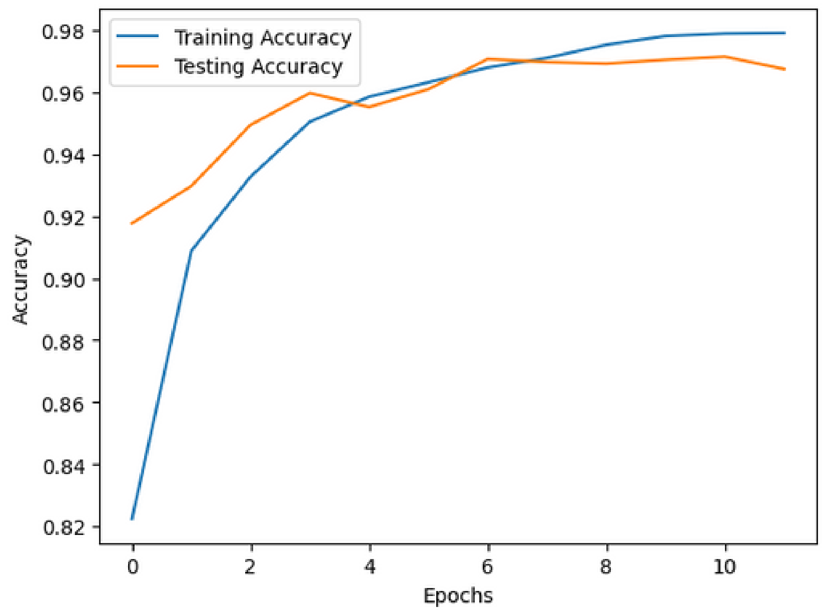
ResNet50 Results:

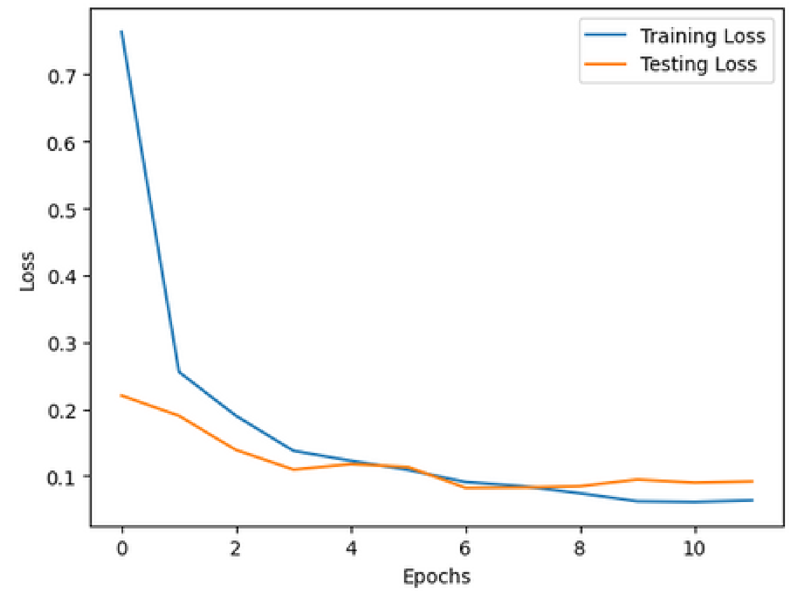


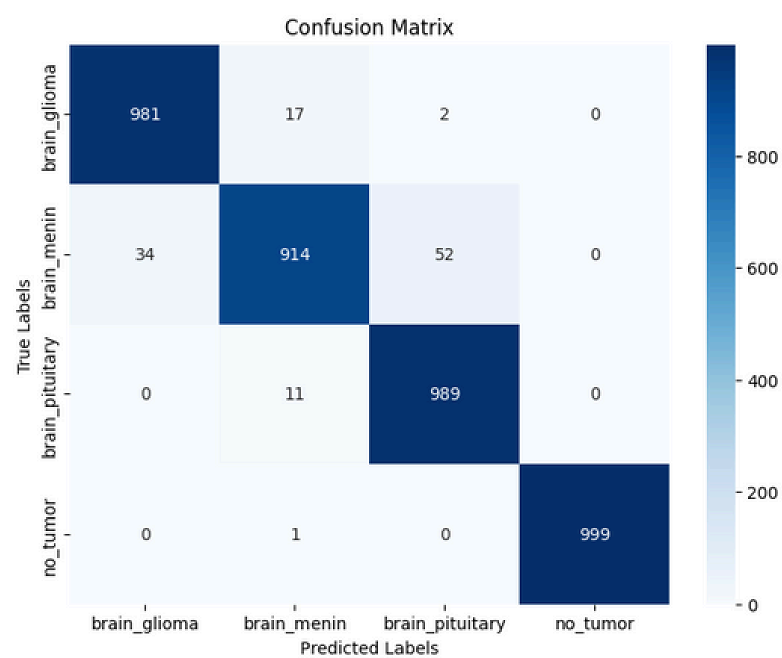




VGG16 Results:







Conclusion

- The project aimed to classify brain MRI images into four categories wherein Comparative analysis of four pre-trained models namely VGG16, ResNet50, EfficientNetB3, and Xception were done.
- EfficientNetB3 achieved the highest accuracy at 97.62%, followed by VGG16 (97.15%) and ResNet50 (96.93%).
- Models were trained and evaluated under identical conditions using transfer learning on Google Colab and Evaluation was done using accuracy scores, classification reports, and confusion matrices.
- EfficientNetB3 showed the best performance due to its advanced architecture and parameter efficiency.
- The study highlights the potential of these models to support faster and more accurate brain tumor diagnosis.

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Thank you