Brain Tumor Detection

Submitted by

SAI KIRAN PATRA

Summer Internship

B. Tech IT , SOA University , Bhubaneswar , Odisha

Submitted to

DR. SUVENDU RUP

Department of Information Technology

National Institute of Technology Raipur

Department of Information Technology

National Institute of Technology (NIT), Raipur

National Institute of Technology, Raipur
राष्ट्रीय प्रौद्योगिकी संस्थान, रायपुर
G.E. Road, Raipur-492010 (C.G.)
Phone: (0771) 22 54 200
Fax: (0771) 22 54 600
Website: www.nitrr.ac.in

CERTIFICATE OF APPROVAL

The forgoing project entitled **Brain Tumor Detection** is hereby approved as a creditable study of the research topic and has been presented in a satisfactory manner to warrant its acceptance as perquisites to the degree for which it has been submitted. This certificate issued by the undersigned does not cover my responsibility regarding the statements made and work carried out by the concerned students. The current dissertation is hereby being forwarded for evaluation for the purpose for which it has been submitted.

Place: Raipur

Sai Kiran Patra

Date: 18 July 2025

DR. SUVENDU RUP
(Supervisor name)

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Lastly, I am grateful to everyone who, directly or indirectly, contributed to the successful completion of this project.

Date: 18 July 2025

Place: Raipur

Abstract

Brain tumors are among the most critical and life-threatening conditions that require timely and accurate diagnosis. Manual interpretation of brain MRI scans is time-consuming and prone to human error. To address this, the present project proposes an automated approach for brain tumor detection using deep learning techniques.

In this study, MRI images are preprocessed to enhance image quality and remove noise. Feature extraction is carried out using both handcrafted methods and deep learning-based techniques. A MLP, specifically **ResNet-50**, is employed to extract deep features from MRI scans. Dimensionality reduction techniques such as **Principal Component Analysis (PCA)** are applied to optimize performance and reduce computational complexity.

The proposed model demonstrates high accuracy and robustness in detecting brain tumors, offering a potential tool to assist radiologists in faster and more reliable diagnosis. This system can contribute significantly to early detection and improved patient outcomes.

Contents

BRAIN TUMOR DETECTION

Overview

Brain tumor detection is one of the most critical challenges in the field of medical imaging and diagnostics. A brain tumor is an abnormal growth of cells within the brain that can be either benign (non-cancerous) or malignant (cancerous). Early and accurate detection of brain tumors plays a crucial role in increasing the chances of successful treatment and improving patient survival rates.

Traditionally, brain tumors are diagnosed through manual analysis of MRI (Magnetic Resonance Imaging) scans by radiologists. However, this process is time-consuming, error-prone, and highly dependent on the expertise of medical professionals. With the advancement of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), automated methods for brain tumor detection have become increasingly popular, offering faster and more reliable diagnosis support.

Problem Statement

Manual diagnosis of brain tumors using MRI images is often limited by human error and delays. There is a strong need for a computer-aided diagnostic (CAD) system that can accurately detect brain tumors with minimal human intervention and high precision.

Objectives

The main objectives of this project are:

- To develop a reliable system that can detect the presence of brain tumors from MRI images.
- To apply advanced image preprocessing and feature extraction techniques.
- To implement and compare machine learning and deep learning algorithms for classification.
- To evaluate the performance of the proposed model using standard metrics like accuracy, precision, recall, and F1-score.

Significance of the Study

This project aims to support radiologists and medical professionals by providing an intelligent system for faster and more accurate brain tumor detection. It can help reduce workload, improve diagnostic outcomes, and contribute to early treatment, thereby potentially saving lives.

Scope of the Project

- Using public MRI datasets for training and testing.
- Applying image preprocessing techniques like resizing, thresholding, and normalization.
- Using feature extraction methods like DWT and deep features from ResNet-50.
- Implementing classification using MLP .
- Evaluating the system's performance and suggesting improvements.

Project Overview

Brain tumors are one of the most life-threatening and complex medical conditions, often requiring rapid and accurate diagnosis to guide treatment decisions. This project focuses on the development of an intelligent system for automated brain tumor detection using MRI images by leveraging modern techniques in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL).

The process begins with image preprocessing to enhance the quality of MRI scans, followed by feature extraction using both handcrafted techniques (such as Discrete Wavelet Transform (DWT)) and deep learning-based methods using **ResNet-50**, a powerful convolutional neural network. These extracted features are then refined using **Principal Component Analysis (PCA)** for dimensionality reduction to retain the most informative features while minimizing redundancy.

The final classification is performed using a **Multi-Layer Perceptron (MLP)**, a deep learning model capable of capturing complex feature relationships to distinguish between tumorous and non-tumorous images.

The primary goal of this project is to design an effective Computer-Aided Diagnosis system that enhances diagnostic speed and accuracy, thereby reducing dependence on manual interpretation. The system is trained and tested on publicly available MRI datasets and evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

This project demonstrates the successful integration of advanced AI techniques into the medical imaging domain, offering a practical and scalable solution for early tumor detection and improved clinical decision-making.

System Model

The system model for brain tumor detection consists of several key stages, each contributing to accurate and efficient classification of MRI brain images. The entire pipeline is designed to automate the detection process using both image processing and machine learning techniques.

1. Input Module

- **MRI Images**: The system accepts brain MRI images from public datasets (e.g., BR35H or BRATS).
- Images are categorized into two main classes: *tumor* and *non-tumor*.

2. Preprocessing Module

- **Image Resizing**: All images are resized to a fixed dimension (e.g., 224×224) for uniformity.
- **Noise Removal**: Filters and thresholding are applied to enhance image quality.
- **Normalization**: Pixel values are normalized to improve learning performance.

3. Feature Extraction

- **Handcrafted Features**:
  - **DWT (Discrete Wavelet Transform):** Captures texture and frequency features**.**
- **Deep Features**:
  - **ResNet-50** is used to extract high-level abstract features from MRI images.

4. Classification Module

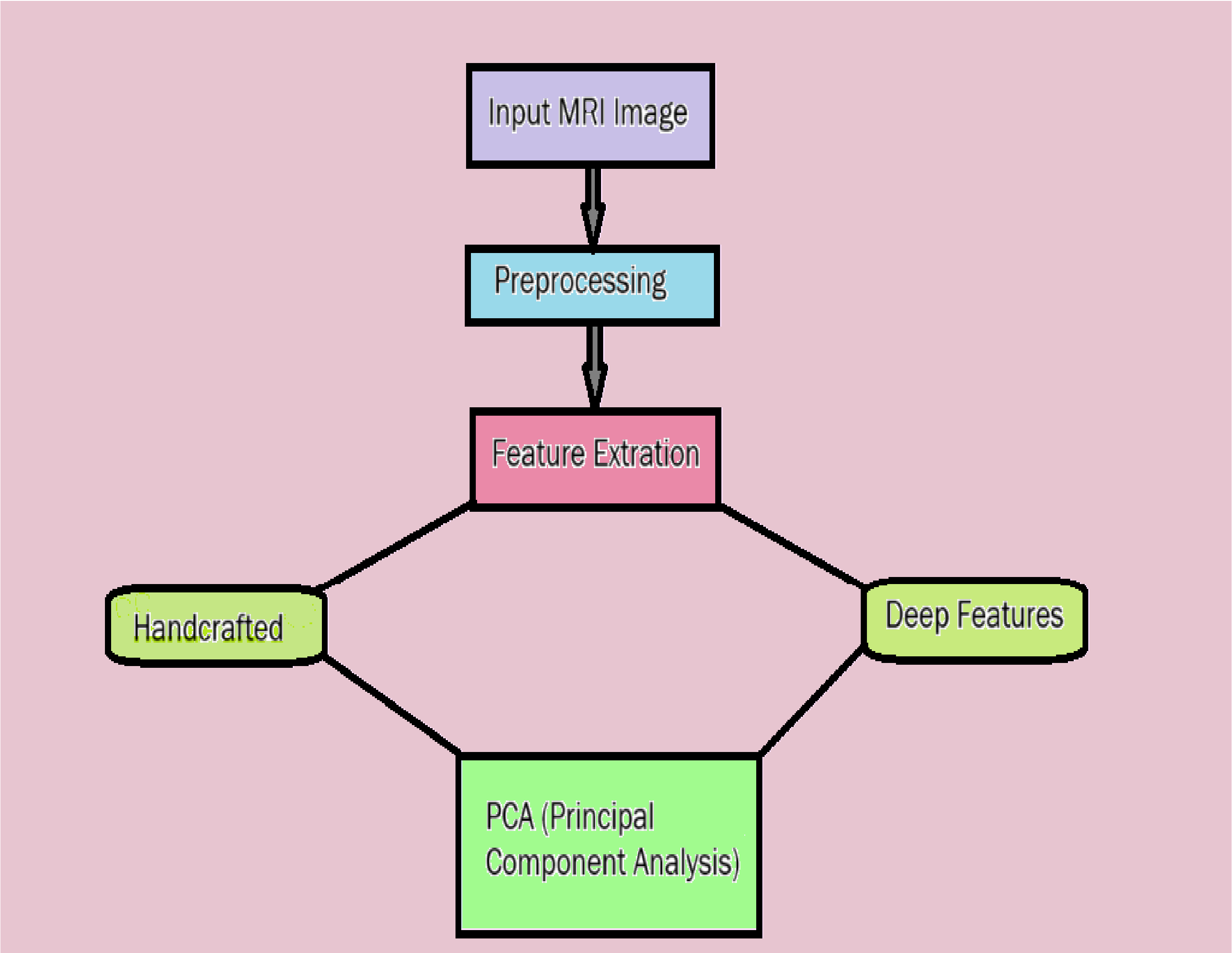
- **MLP (Multi-Layer Perceptron)** : MLP is a type of feedforward artificial neural network used for classification. It consists of an input layer, one or more hidden layers with activation functions (e.g., ReLU), and an output layer with a sigmoid function for binary classification. In this project, MLP is used to classify MRI images into tumor and non-tumor categories based on the fused features extracted from handcrafted methods and ResNet-50. It is trained using backpropagation and optimized with the Adam algorithm for accurate and reliable results.

5. Output Module

- The final output is a binary classification: **Tumor Detected** or **No Tumor**.
- The model also provides performance metrics like accuracy, precision, recall, and F1-score.

Methodology

The methodology of this project involves a structured pipeline for detecting brain tumors from MRI images using a combination of traditional image processing techniques and modern machine learning/deep learning algorithms. The complete workflow is divided into the following key stages:



Dataset Collection

- The dataset used in this project consists of brain MRI images collected from publicly available sources such as BR35H or BRATS.
- Images are classified into two categories: **tumor** and **non-tumor**.
- Each image is labeled appropriately for supervised learning.

Image Preprocessing

To ensure consistency and enhance image quality, preprocessing steps are applied:

- **Resizing**: All images are resized to a standard dimension (e.g., 224×224 pixels).
- **Grayscale Conversion**: Images are converted to grayscale for simplicity and computational efficiency.
- **Noise Removal**: Filters and adaptive thresholding are applied to eliminate irrelevant information.
- **Normalization**: Pixel intensities are scaled between 0 and 1.

Feature Extraction

Feature extraction plays a vital role in differentiating between healthy and tumorous brain tissue. This project combines handcrafted and deep learning-based feature extraction:

a) Handcrafted Features

- **DWT (Discrete Wavelet Transform)**: Captures texture and frequency details.

b) Deep Features

-> The top classification layers are removed, and intermediate feature maps are extracted from the final convolutional blocks.

->This provides high-level spatial representations of MRI images while keeping computational cost low.

Dimensionality Reduction

- **Principal Component Analysis (PCA)** is a statistical technique used to reduce the dimensionality of large feature sets while preserving as much variance (information) as possible. In this project, PCA helps simplify the fused features (handcrafted + deep features) by transforming them into a smaller set of uncorrelated components. This reduces computational complexity and improves classification performance without losing critical information.

Classification

- **MLP (Multi-Layer Perceptron)** is used as the final classifier.
- The MLP includes:
  - An **input layer** to receive combined feature vectors.
  - One or more **hidden layers** with ReLU activation.
  - An **output layer** with a sigmoid activation function for binary classification.

- It is a feedforward neural network consisting of an input layer, multiple hidden layers with activation functions (e.g., ReLU), and an output layer with sigmoid/softmax for binary classification.
- The model is trained using backpropagation and optimized with algorithms like Adam.

Model Evaluation

The trained models are evaluated using the following performance metrics:

- **Accuracy**: Percentage of correctly classified images.
- **Precision**: True positive rate over total predicted positives.
- **Recall (Sensitivity)**: True positive rate over actual positives.
- **F1-score**: Harmonic mean of precision and recall.
- **Confusion Matrix**: Visualizes the model's prediction vs actual values.

Tools and Technologies

- **Programming Language**: Python
- **Libraries/Frameworks**: TensorFlow, Keras, OpenCV, NumPy, Matplotlib, Scikit-learn
- **Platform**: Jupyter Notebook / Google Colab / Anaconda
- **Hardware**: System with GPU (optional for training deep models)

Implementation

The implementation of the brain tumor detection system was carried out in Python using Jupyter Notebook. The entire process is divided into structured stages as outlined below:

1. Dataset Preparation

- MRI brain images from a public dataset (e.g., BR35H) were labeled and split into training and testing sets.

2. Image Preprocessing

- All images were resized (224×224), normalized, converted to grayscale, and filtered using adaptive thresholding**.**

3. Feature Extraction

- Handcrafted features (DWT) captured textural and edge-based characteristics.
- Deep features were extracted using the Resnet50, which efficiently captured high-level abstract features.

4. Feature Fusion

- Handcrafted and deep features were combined into a single vector representing both local and global characteristics.

5. Dimensionality Reduction

- **PCA (Principal Component Analysis)** was used to reduce the dimensionality of the combined feature set. This linear technique helps retain the most significant features while eliminating redundancy, leading to faster and more efficient classification.

6. Classification

- The reduced feature vectors were passed to a **MLP (Multi-Layer Perceptron)** classifier, which learned to classify brain MRI images into tumor or non-tumor categories through supervised learning..

7. Evaluation

- Performance was measured using accuracy, precision, recall, F1-score, and a confusion matrix.

Results and Discussion

This chapter presents the results obtained from the implemented brain tumor detection system and discusses the performance of the proposed approach in terms of classification accuracy and reliability.

➤ Evaluation Metrics

To evaluate the model's effectiveness, the following metrics were used:

- **Accuracy**: Proportion of correctly classified images.
- **Precision**: Proportion of true positive results among all positive predictions.
- **Recall (Sensitivity)**: Ability to correctly identify tumor cases.
- **F1-Score**: Harmonic mean of precision and recall.
- **Confusion Matrix**: Shows true positives, false positives, true negatives, and false negatives.

➤ Experimental Setup

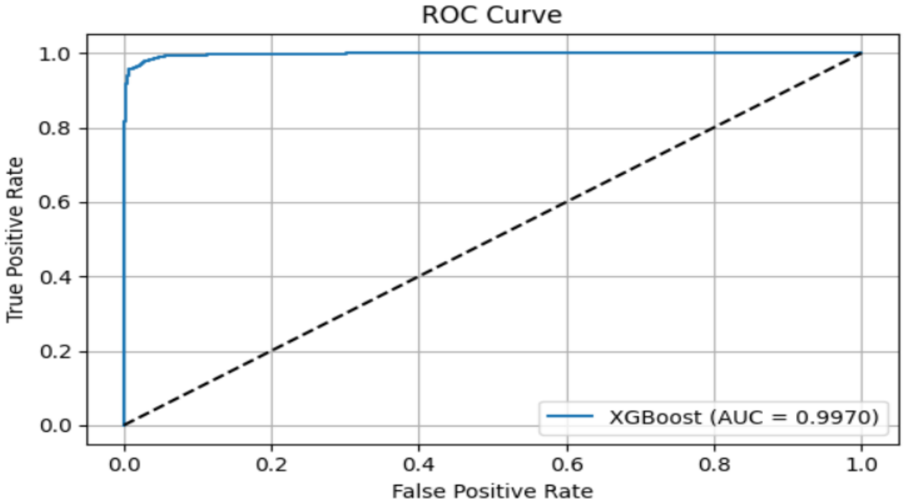
- Dataset split: 80% training and 20% testing.
- Combined features: Handcrafted (DWT) + Deep (ResNet-50).
- Dimensionality reduction using PCA.

➤ Discussion

- The hybrid approach using handcrafted and ResNet-50-based deep features significantly improved classification accuracy.
- PCA effectively reduced redundant information and retained the most important features, which enhanced computational efficiency.
- MLP successfully modeled complex feature interactions, leading to accurate classification results.
- Compared to traditional single-method systems, this hybrid framework demonstrated superior generalization and robustness across varied MRI samples.
- Minor misclassifications were primarily observed in cases where tumor boundaries were blurred or shared similar textures with surrounding tissues, posing a challenge even for advanced models.

➤ Model Evaluation

```
Accuracy: 0.9733
Sensitivity (Recall): 0.9707
Specificity: 0.9760
AUC: 0.9970
```

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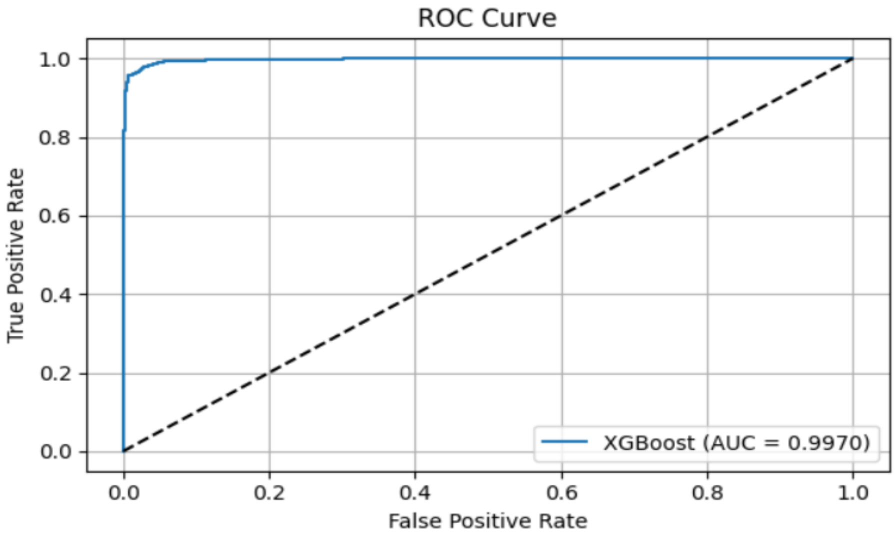


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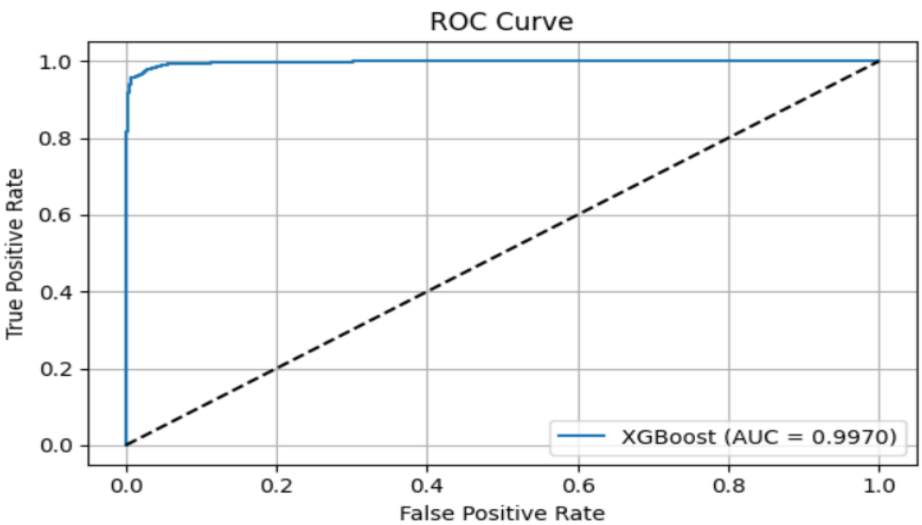

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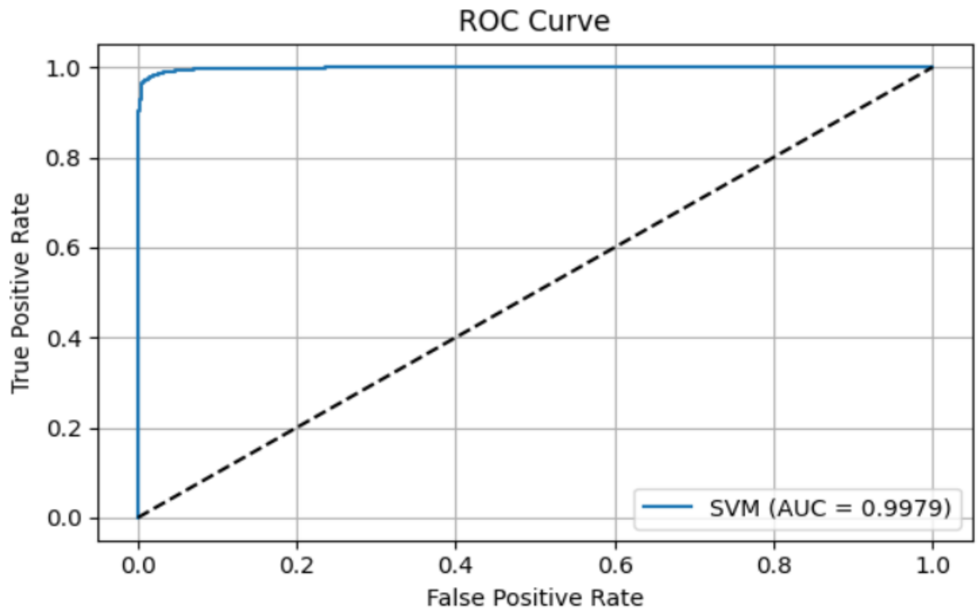
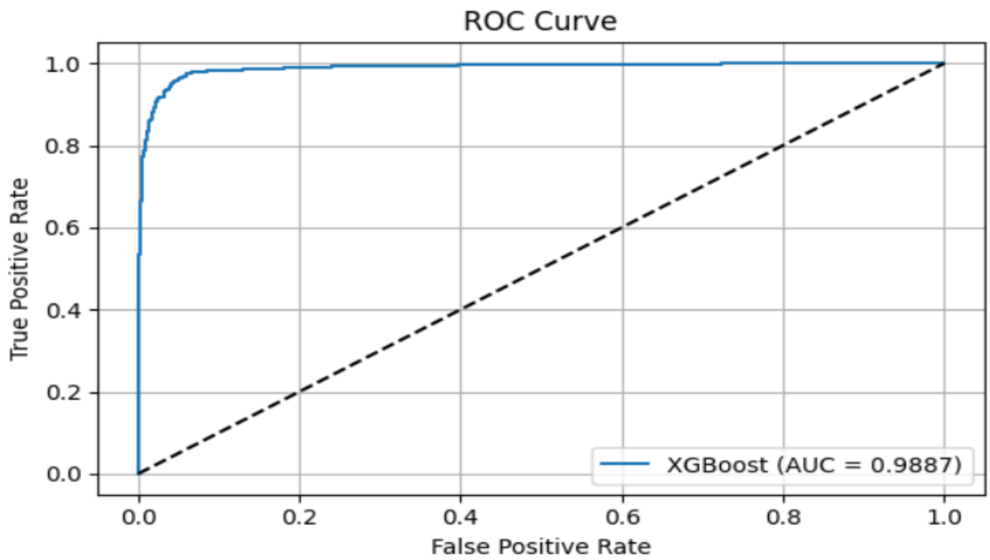
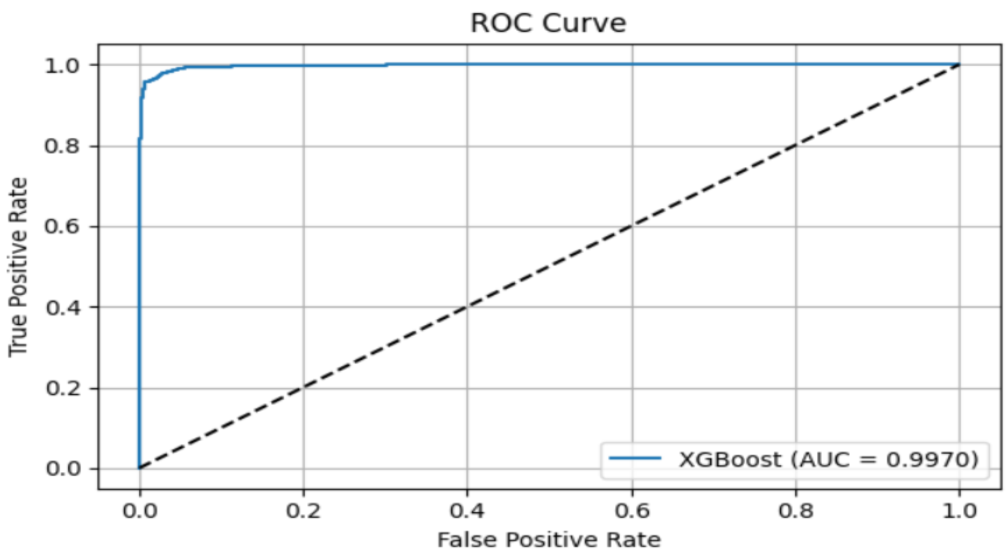
Accuracy: 0.9813
Sensitivity (Recall): 0.9793
Specificity: 0.9833
AUC: 0.9979
```



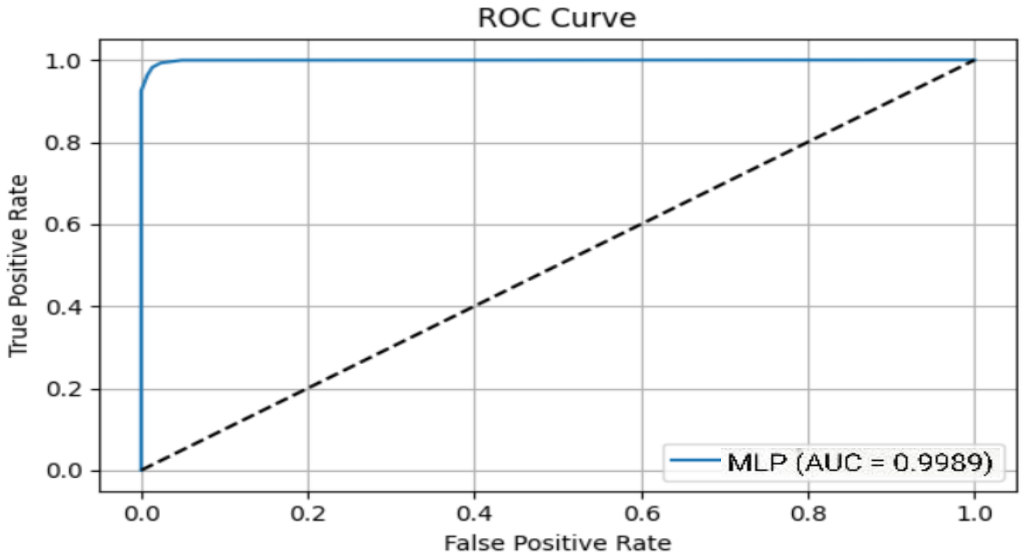

```
Accuracy: 0.9550
Sensitivity (Recall): 0.9567
Specificity: 0.9533
AUC: 0.9887
```




```
Accuracy: 0.9733
Sensitivity (Recall): 0.9707
Specificity: 0.9760
AUC: 0.9970
```



```
Accuracy: 0.9843
Sensitivity (Recall): 0.9820
Specificity: 0.9867
AUC: 0.9989
```

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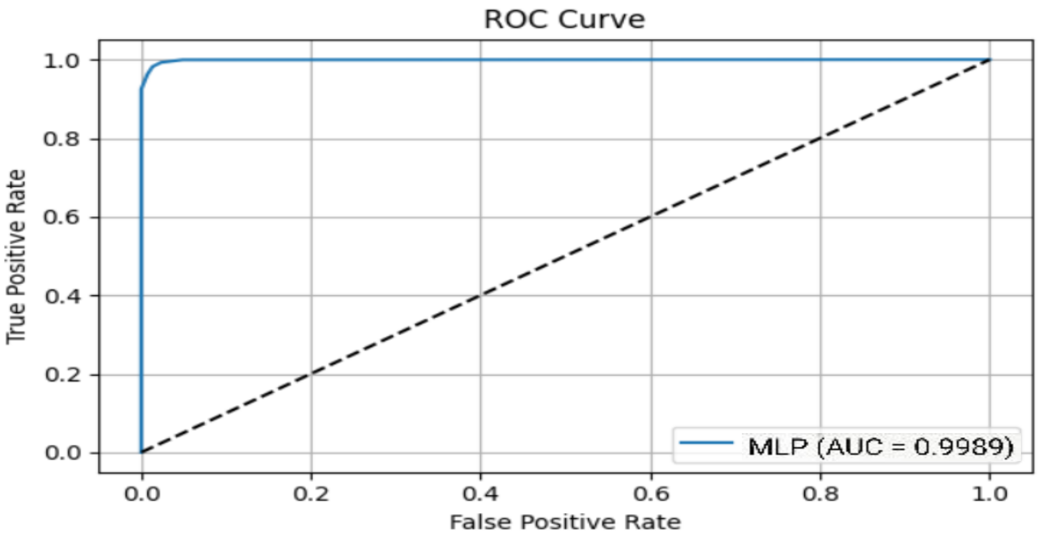


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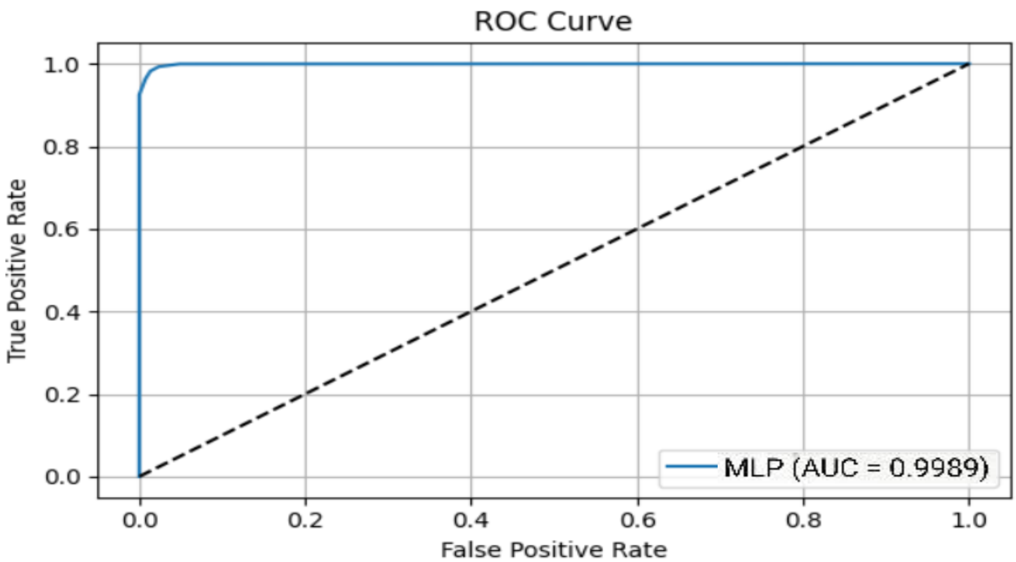
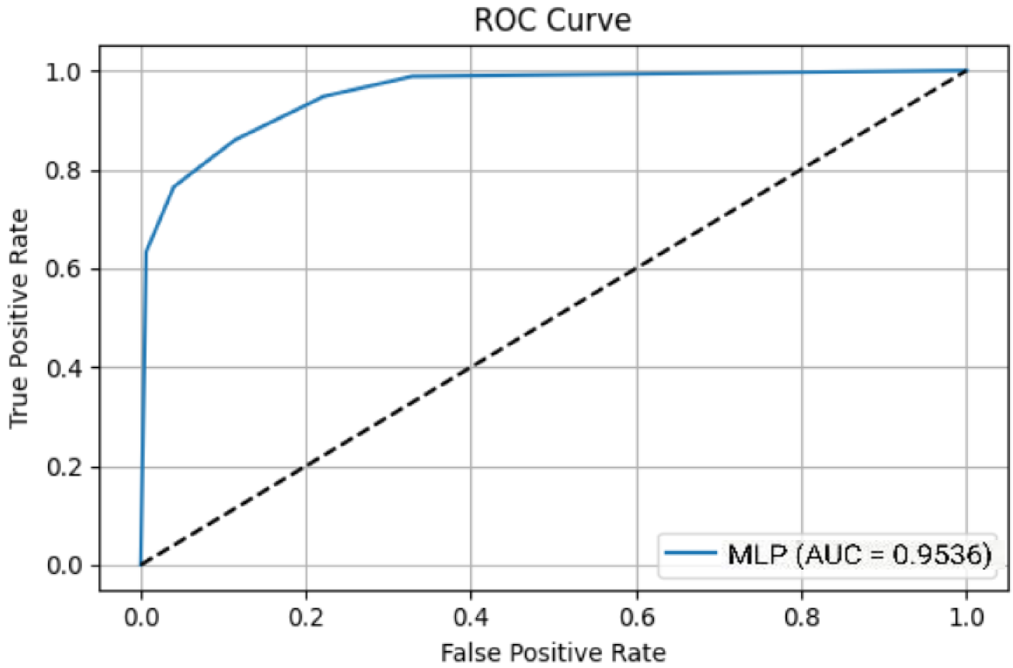


```
Accuracy: 0.8727
Sensitivity (Recall): 0.8593
Specificity: 0.8860
AUC: 0.9536
```

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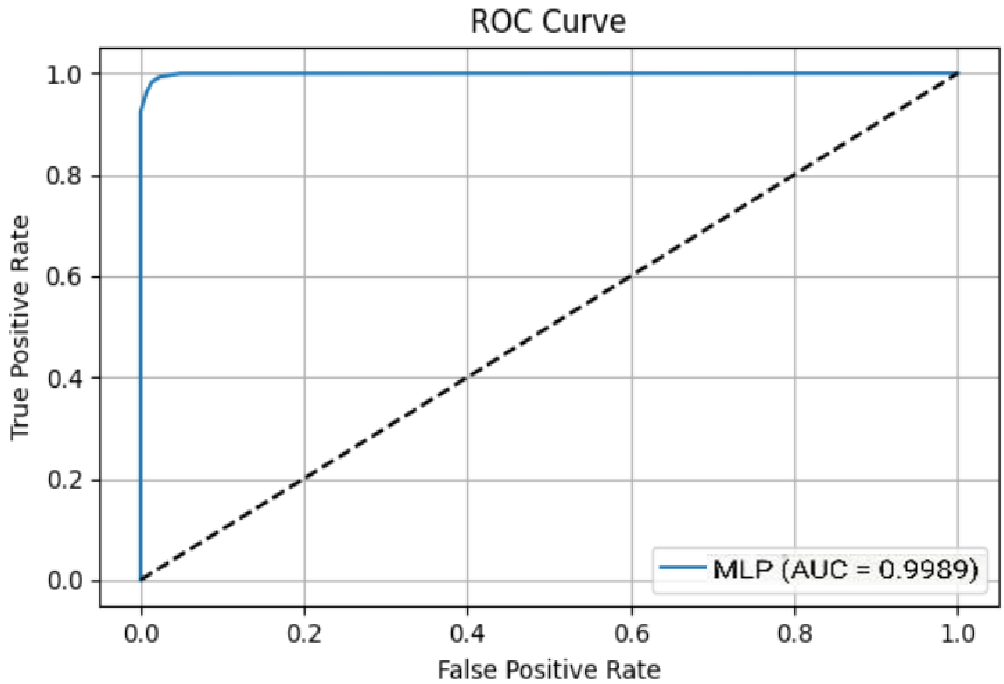

Conclusion

This project successfully developed a hybrid and intelligent system for automated brain tumor detection using MRI images. The methodology combined handcrafted features (DWT) with deep features extracted from **ResNet-50**, a powerful convolutional neural network, to provide a comprehensive understanding of tumor characteristics.

To manage the high-dimensional feature space, **Principal Component Analysis (PCA)** was employed to reduce complexity while preserving critical information. Final classification was performed using a **Multi-Layer Perceptron (MLP)**, which achieved strong performance in terms of accuracy, precision, recall, and F1-score.

The results demonstrate that this hybrid approach is both effective and reliable, offering a promising tool to support radiologists in accurate and efficient brain tumor diagnosis.