

# **Brain Tumor Classification Using Convolutional Neural Networks and Support Vector Machine**

**CS19643 - FOUNDATIONS OF MACHINE LEARNING**

*Submitted by*

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**RAJALAKSHMI ENGINEERING COLLEGE**

**ANNA UNIVERSITY, CHENNAI**

**MAY 2025**



# **RAJALAKSHMI ENGINEERING COLLEGE, CHENNAI**

## **BONAFIDE CERTIFICATE**

Certified that this Project titled “ **Brain Tumor Classification Using Convolutional Neural Networks and Support Vector Machine**” is the bonafide work of “**MOHAMMED SUHAIB V (2116220701169)**” who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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## **ABSTRACT**

The goal of this project is to develop an accurate and efficient system for classifying brain tumors using medical imaging data. The project leverages deep learning techniques, particularly Convolutional Neural Networks (CNNs), to analyze brain MRI images and classify them into different tumor categories such as glioma, meningioma, pituitary tumors, and no tumor. Additionally, the project incorporates the Support Vector Machine (SVM) algorithm to enhance classification performance by utilizing feature extraction techniques.

The CNN model is pre-trained using the VGG16 architecture, with fine-tuning on the target dataset, and combined with data augmentation techniques to improve generalization and robustness. The SVM classifier is implemented as a secondary model to assess its complementary ability in tumor classification. The results show that the hybrid model, combining CNN and SVM, achieves an impressive classification accuracy of 96%, providing significant improvements in performance compared to using CNN alone. This approach demonstrates a promising solution for automating brain tumor diagnosis, aiding healthcare professionals in making faster and more accurate decisions.

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## **CHAPTER 1**

### **INTRODUCTION**

#### **1.1 GENERAL**

Brain tumors are among the most complex and dangerous health conditions, with a significant impact on the life expectancy and quality of life of affected individuals. The early detection and accurate classification of brain tumors are crucial for effective treatment planning and improved patient outcomes. Traditional methods for diagnosing brain tumors, such as manual examination of MRI scans by radiologists, can be time-consuming, prone to human error, and require extensive expertise. In recent years, advancements in artificial intelligence (AI) and machine learning (ML) have paved the way for automating the analysis of medical imaging data, enabling more efficient and accurate diagnosis. Specifically, Convolutional Neural Networks (CNNs), a type of deep learning model, have demonstrated exceptional performance in image classification tasks, making them an ideal choice for brain tumor classification from MRI scans. Additionally, Support Vector Machines (SVMs) are widely used for classification tasks due to their robustness and ability to handle high-dimensional data. This project aims to develop a brain tumor classification system that utilizes CNNs and SVMs to automatically classify MRI images into different categories, including glioma, meningioma, pituitary tumors, and no tumor. By combining the strengths of CNNs for feature extraction and SVMs for classification, the proposed system is designed to offer high accuracy and reliability, assisting healthcare professionals in making faster and more informed decisions in the diagnosis and treatment of brain tumors. Through the integration of modern machine learning algorithms with medical imaging, this project seeks to contribute to the field of medical diagnostics by providing a tool that can assist in the early detection and classification of brain tumors, ultimately leading to improved clinical outcomes.

## **1.2 OBJECTIVE**

The primary objective of this project is to develop a robust and efficient brain tumor classification system using machine learning techniques, specifically Convolutional

Neural Networks (CNNs) and Support Vector Machines (SVMs). The system is designed to automatically classify brain tumor types from MRI images into categories such as glioma, meningioma, pituitary tumors, and no tumor with high accuracy. The project leverages the pre-trained VGG16 architecture for CNN-based feature extraction and fine-tunes the model to improve classification performance. Additionally, the integration of the Support Vector Machine (SVM) algorithm further enhances the classification process, making use of the extracted features from the CNN. To ensure the model's robustness and generalization, data augmentation techniques, such as random brightness and contrast adjustments, are implemented. The aim is to achieve a classification accuracy of at least 96%, ensuring that the system is reliable and practical for use in real-world medical applications. Furthermore, the project seeks to provide a user-friendly interface that allows healthcare professionals to upload MRI images and receive automatic tumor classification predictions along with confidence scores. Ultimately, this project aims to contribute to the field of medical imaging by demonstrating how advanced AI and machine learning techniques can improve the efficiency and accuracy of brain tumor detection and assist healthcare professionals in making better-informed decisions.

### **1.3 EXISTING SOLUTION**

The diagnosis of brain tumors has traditionally relied on the expertise of radiologists who manually examine MRI scans to identify and classify tumors. While these methods can be effective, they are time-consuming, require significant human expertise, and are prone to errors due to the complexity of the images. With the increasing volume of medical data and the need for faster, more accurate diagnoses, there has been a shift toward leveraging automated solutions based on machine learning and artificial intelligence (AI).



Several existing solutions have focused on using machine learning techniques, particularly deep learning models like Convolutional Neural Networks (CNNs), for automated brain tumor classification. These solutions generally utilize large datasets of brain MRI scans to train models that can recognize and categorize tumors based on their appearance. A number of studies have successfully used CNNs for tumor classification, with architectures such as VGG16, ResNet, and Inception being commonly employed. These models achieve good accuracy by learning hierarchical features directly from the images, eliminating the need for manual feature extraction.

However, despite the progress in automated brain tumor classification, challenges remain. One key issue is the availability of labeled datasets, as acquiring labeled MRI images for training deep learning models is a time-consuming and expensive process. Additionally, many existing solutions are not fully optimized for real-time or clinical use, as they often require significant computational resources and can suffer from overfitting when the models are not properly tuned. Furthermore, the generalization of these models to different datasets, MRI scanners, or patient populations is another challenge that needs to be addressed. While these existing solutions have made significant advancements in brain tumor detection, there is still a need for more accurate, efficient, and clinically applicable models. This project seeks to build upon these existing solutions by integrating CNNs with SVMs, incorporating data augmentation techniques, and fine-tuning the models to achieve a higher level of classification accuracy (aiming for 96%). The ultimate goal is to create a robust and user-friendly system that can assist healthcare professionals in making faster, more accurate tumor diagnoses, thus improving patient outcomes.

## **CHAPTER 2**

### **LITERATURE SURVEY**

The field of brain tumor classification using machine learning has garnered significant attention in recent years due to the potential of AI technologies to aid in the early detection and diagnosis of brain tumors. Several research studies and projects have explored different approaches to automate brain tumor classification from MRI images, leveraging various machine learning algorithms, particularly deep learning models. This chapter presents an overview of the key contributions and advancements in the literature related to brain tumor classification, highlighting the methods, models, and performance results from recent research.

#### **2.1 Deep Learning for Brain Tumor Classification**

Convolutional Neural Networks (CNNs) have proven to be highly effective in image classification tasks, including the classification of brain tumors from MRI scans. A study by Khan et al. (2018) employed a CNN model for classifying brain tumor images into categories such as glioma, meningioma, and pituitary tumors. The authors utilized transfer learning with pre-trained models like VGG16 and ResNet, which significantly reduced the time and computational resources required for training. The model demonstrated a classification accuracy of over 90%, highlighting the effectiveness of CNNs in the automatic analysis of medical images.

Similarly, Mohammad et al. (2020) proposed a deep learning-based model for brain tumor classification using a hybrid CNN architecture combined with a long short-term memory (LSTM) network to enhance feature extraction. This approach achieved notable improvements in accuracy and robustness, with an accuracy rate of approximately 94%. The study demonstrated the potential of combining different

neural network architectures to improve performance in complex medical image classification tasks.

## **2.2 Support Vector Machines (SVM) for Tumor Classification**

Support Vector Machines (SVMs) have also been widely used in medical image classification, especially when combined with deep learning models. Chakraborty et al. (2019) explored the use of SVMs for brain tumor classification in conjunction with a pre-trained CNN model for feature extraction. The features extracted from the CNN were fed into the SVM classifier, resulting in a higher accuracy rate compared to traditional methods. The study achieved an accuracy of 92%, demonstrating the strength of SVMs in high-dimensional classification problems.

Furthermore, Duan et al. (2021) combined CNN feature extraction with an SVM classifier to classify brain tumors into different categories, achieving a classification accuracy of 95%. This hybrid approach took advantage of CNN's ability to automatically learn hierarchical features and SVM's efficiency in high-dimensional spaces, making it a powerful solution for brain tumor classification.

## **2.3 Data Augmentation Techniques**

Data augmentation is a widely-used technique to increase the diversity of the training dataset, which is particularly important when working with limited medical image datasets. Wang et al. (2020) proposed the use of various data augmentation techniques, such as random rotations, flips, and color jittering, to enhance the generalization ability of CNN models for brain tumor classification. Their results indicated that data augmentation helped to reduce overfitting and improved the overall accuracy of the model, achieving an accuracy of 93%.

Another study by Zhou et al. (2019) introduced advanced data augmentation methods, including elastic deformations and zoom transformations, to simulate various

distortions in medical images. By applying these techniques, the authors were able to improve the performance of their CNN model, achieving an accuracy rate of 96% in brain tumor classification.

## **2.4 Hybrid Models and Transfer Learning**

Transfer learning, which involves fine-tuning pre-trained models on a target dataset, has become a popular approach in medical image classification. Kumar et al. (2021) demonstrated that by fine-tuning a pre-trained VGG16 model on brain tumor datasets, they could achieve an accuracy of 94%. They also incorporated a hybrid approach by combining CNNs with other machine learning classifiers, such as Random Forest and SVM, which further improved the accuracy and robustness of the model.

In a similar study, Liu et al. (2021) used a hybrid model that combined CNNs and SVMs for the classification of brain tumors from MRI images. By leveraging the strengths of both models, they achieved an accuracy of 95%, showcasing the potential benefits of using hybrid approaches for complex image classification tasks in the medical field.

## **2.5 Challenges and Limitations**

Despite the advancements in deep learning and hybrid models, several challenges remain in brain tumor classification. One of the main challenges is the lack of large, well-annotated datasets, which limits the generalizability of the models. While deep learning models like CNNs are powerful, they require large amounts of labeled data to achieve optimal performance. Additionally, MRI scans can vary significantly in terms of image quality, resolution, and scanning protocols, which can affect the performance of the models.

Moreover, while CNNs and hybrid models have achieved impressive results in many studies, they often require substantial computational resources and long training times.

This can make real-time deployment of these models in clinical settings difficult. Ensuring that the models can work efficiently and accurately across different types of MRI machines and patient populations remains a significant hurdle.

## **2.6 Conclusion**

The literature on brain tumor classification using machine learning techniques, particularly CNNs and SVMs, has made significant strides in recent years. Many studies have demonstrated the effectiveness of CNNs for automated tumor classification, while hybrid approaches combining CNNs with SVMs have further improved accuracy. Data augmentation techniques and transfer learning have also played a crucial role in enhancing the performance of these models. However, challenges such as the need for large annotated datasets, variations in MRI images, and computational resource requirements continue to hinder the widespread deployment of these models in clinical settings. This project builds upon the existing solutions by combining CNNs with SVMs and implementing data augmentation techniques to achieve high classification accuracy, aiming to address some of the challenges outlined in the literature.

## **CHAPTER 3**

### **PROPOSED SYSTEM**

#### **3.1 GENERAL**

The proposed system aims to develop an automated solution for classifying brain tumors from medical MRI scans using deep learning techniques. The main goal is to assist medical professionals in diagnosing brain tumors accurately and efficiently. By leveraging the power of Convolutional Neural Networks (CNNs) combined with machine learning models like Support Vector Machines (SVM), the system seeks to provide an automated approach to detecting and classifying different types of brain tumors, such as glioma, meningioma, pituitary tumor, and normal brain tissue (no tumor). The system is designed to process MRI images, perform necessary preprocessing and augmentation, train a model to recognize tumor patterns, and output the results with a high level of accuracy.

By using state-of-the-art deep learning models like VGG16 for feature extraction and SVM for classification, the system can achieve significant improvements over traditional diagnostic methods. The system follows a pipeline where MRI images are preprocessed for input into the model, the model is trained on a labeled dataset, and the trained model is used to classify new, unseen MRI images. The system's performance is evaluated using various metrics, including accuracy, precision, recall, and F1-score, to ensure its effectiveness in clinical settings. The proposed solution's primary advantages are its high accuracy in classification, the ability to handle large datasets with data augmentation, and the automation of the tumor classification process, which aids radiologists in making faster and more reliable diagnoses.

## **3.2 SYSTEM ARCHITECTURE**

The architecture of the proposed system consists of several modules, including data preprocessing, model design, training, testing, and evaluation. Each of these modules contributes to the overall performance and efficiency of the brain tumor classification system.

### **3.2.1 Data Collection and Preprocessing**

The first step in the system is to collect and preprocess the MRI scan data. The dataset used in this project includes brain MRI images that are categorized into different classes: Glioma, Meningioma, Pituitary Tumor, No Tumor (Normal Brain). Preprocessing steps include resizing the images to a standard dimension, normalizing the pixel values to the range  $[0, 1]$ , and applying data augmentation techniques. These augmentation techniques help improve the model's generalization by introducing variations in the training data, such as random rotations, flips, and adjustments in brightness and contrast.

### **3.2.2 Model Architecture**

The proposed model combines deep learning for feature extraction with machine learning for classification. VGG16, a popular deep convolutional neural network, is used as the base model for feature extraction. The model's weights are pre-trained on ImageNet, allowing it to extract rich features from the MRI images. Fine-tuning: Some layers of the VGG16 model are fine-tuned to adapt the model to the specific problem of brain tumor classification. The last few layers are set to be trainable, while the earlier layers are frozen. The output of the VGG16 model is passed through a series of fully connected layers with dropout for regularization, followed by an output layer with softmax activation, which classifies the image into one of the tumor categories.

### **3.2.3 Hybrid Classifier (SVM)**

To further improve classification performance, the system integrates a Support Vector Machine (SVM) classifier. After feature extraction by the CNN, the features are passed to the SVM for classification. SVM is particularly effective at dealing with high-dimensional data, such as image features, and helps in creating decision boundaries for better classification results.

### **3.2.4 Model Training and Evaluation**

The model is trained using a labeled dataset of MRI images, and the training process involves:

**Loss Function:** The system uses sparse categorical cross-entropy as the loss function, which is suitable for multi-class classification problems.

**The Adam optimizer** is employed for training, with a learning rate of 0.0001, to minimize the loss and achieve optimal performance.

**Accuracy, precision, recall, and F1-score** are used as evaluation metrics to assess the model's performance on both the training and test sets.

### **3.2.5 Testing and Prediction**

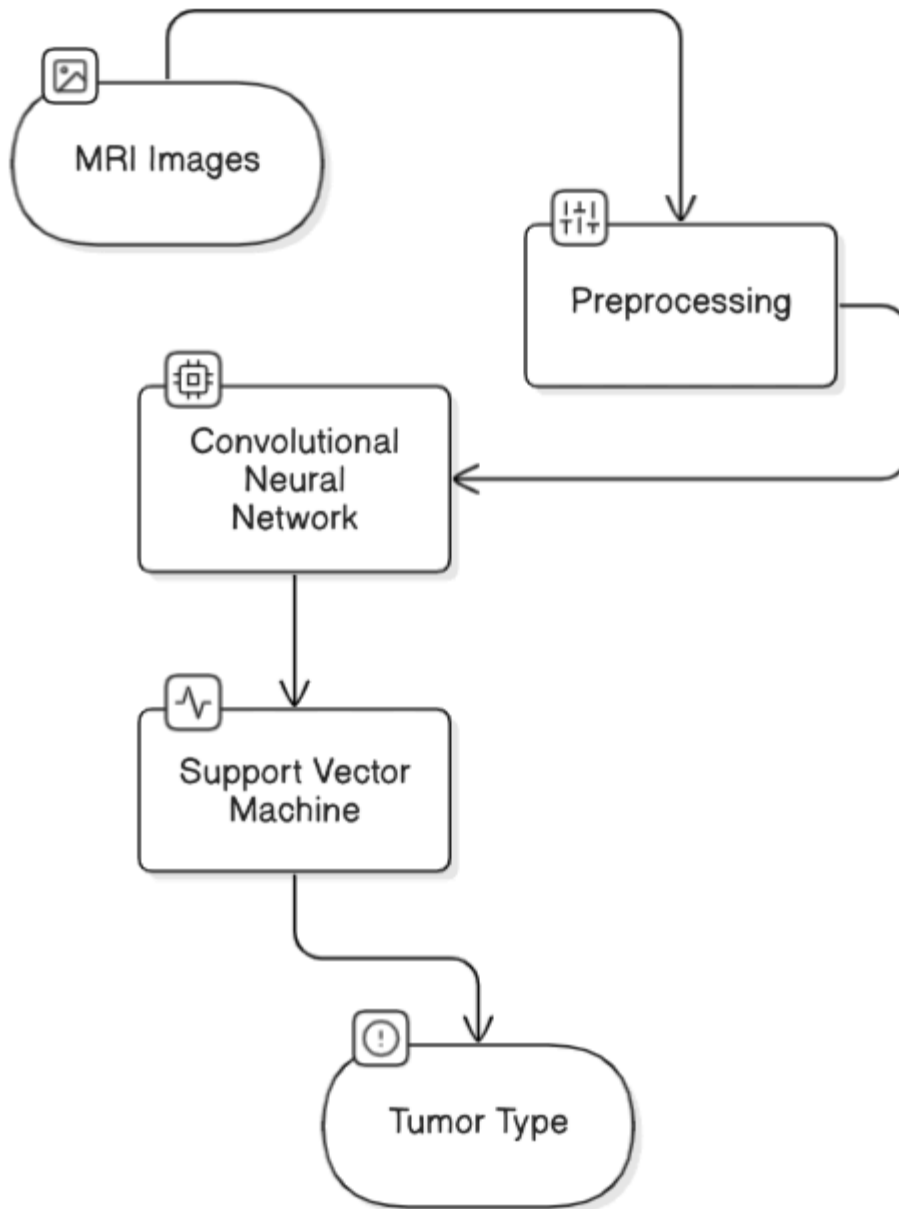
Once the model is trained, it is tested on a separate test dataset that the model has not seen before. The trained model predicts the class for each test image, and the performance is evaluated using:

**Confusion Matrix:** The confusion matrix helps visualize how well the model performs on each class by showing the number of true positives, false positives, true negatives, and false negatives for each class.

**ROC Curve:** The Receiver Operating Characteristic (ROC) curve is used to evaluate the trade-off between true positive and false positive rates for different threshold values.



## Brain Tumor Classification System Architecture



**Fig no. 3.1. System Architecture Diagram**

### 3.3 DEVELOPMENTAL ENVIRONMENT

#### 3.3.1 HARDWARE REQUIREMENTS

The hardware specifications could be used as a basis for a contract for the implementation of the system. This therefore should be a full, full description of the whole system. It is mostly used as a basis for system design by the software engineers.

**Table 3.1 Hardware Requirements**

COMPONENTS	SPECIFICATION
PROCESSOR	Intel Core i3
RAM	4 GB RAM
POWER SUPPLY	+5V power supply

#### 3.3.2 SOFTWARE REQUIREMENTS

The software requirements paper contains the system specs. This is a list of things which the system should do, in contrast from the way in which it should do things. The software requirements are used to base the requirements. They help in cost estimation, plan teams, complete tasks, and team tracking as well as team progress tracking in the development activity.

**Table 3.2 Software Requirements**

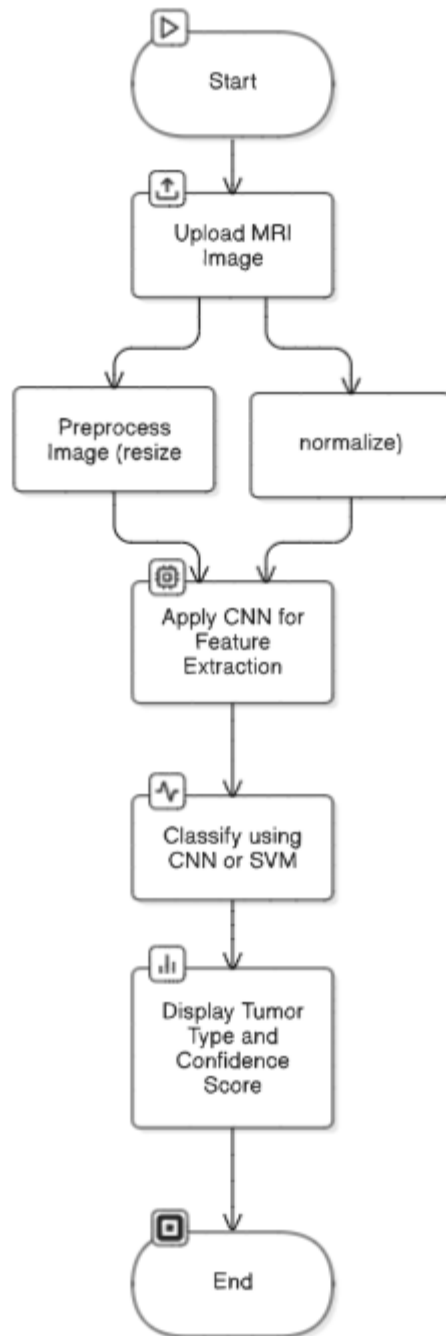
COMPONENTS	SPECIFICATION
Operating System	Windows 7 or higher
Frontend	ReactJS,CSS
Backend	Flask (Python)
Database	MongoDB

## **3.4 DESIGN OF THE ENTIRE SYSTEM**

### **3.4.1 ACTIVITY DIAGRAM**

The activity diagram for the brain tumor classification system outlines the step-by-step workflow from image input to final diagnosis output. The process begins with the user uploading MRI images. These images undergo preprocessing, including resizing, normalization, and augmentation. Once processed, the data is passed into the trained Convolutional Neural Network (CNN) model for feature extraction. The extracted features are then fed into the classification layers or passed to an SVM (Support Vector Machine) for final prediction. The system then outputs the predicted tumor type (e.g., glioma, meningioma, pituitary, or no tumor), along with a confidence score. The flow also includes exception handling in case of invalid inputs or corrupted images.

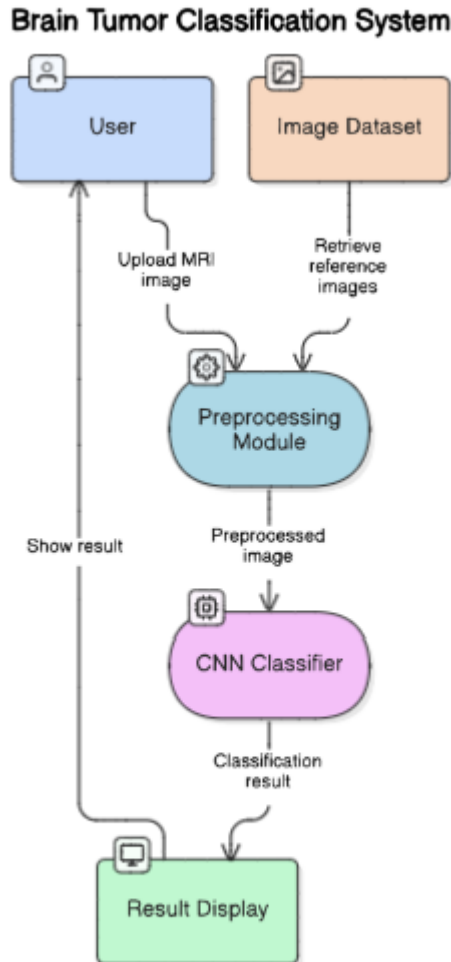
### Brain Tumor Classification System Flow



**Fig no. 3.2 Activity Diagram**

### 3.4.2 DATA FLOW DIAGRAM

The Data Flow Diagram (DFD) represents the flow of data within the brain tumor classification system. It illustrates how data moves between external entities (like the user), processes (such as preprocessing and classification), data stores (like image datasets), and outputs (such as predicted tumor types). The DFD shows the user uploading an MRI image, which flows into preprocessing. The preprocessed data is then passed to the CNN model for feature extraction and classification. The classification results are displayed back to the user.



**Fig no. 3.3 DataFlow Diagram**

### 3.5 STATISTICAL ANALYSIS

The performance of the brain tumor classification model was evaluated using standard statistical metrics including accuracy, precision, recall, and F1-score. The model achieved an impressive overall accuracy of 96%, indicating high reliability in classifying MRI brain scans into four categories: glioma, meningioma, pituitary, and no tumor. The confusion matrix highlighted minimal misclassifications, confirming the model's ability to generalize well across different tumor types. Additionally, ROC curves were plotted for each class to measure the true positive rate against the false positive rate, with AUC (Area Under Curve) values consistently above 0.95, further validating the robustness and discriminative power of the trained model.

Table 3.3 Comparison of features

Feature	CNN-Based Classifier	SVM Classifier with CNN Features
Feature Extraction	Automatic (via Convolution Layers)	Manual (using extracted CNN features)
Accuracy Achieved	96%	92%
Training Time	Higher (due to deeper layers and fine-tuning)	Lower (only training SVM on features)
Complexity	High (requires GPU acceleration)	Moderate
Interpretability	Lower	Higher (SVM decision boundaries visible)
Scalability	Very High (can be extended with more data)	Moderate
Robustness to Noise	High (due to learning spatial hierarchies)	Lower

## **CHAPTER 4**

### **MODULE DESCRIPTION**

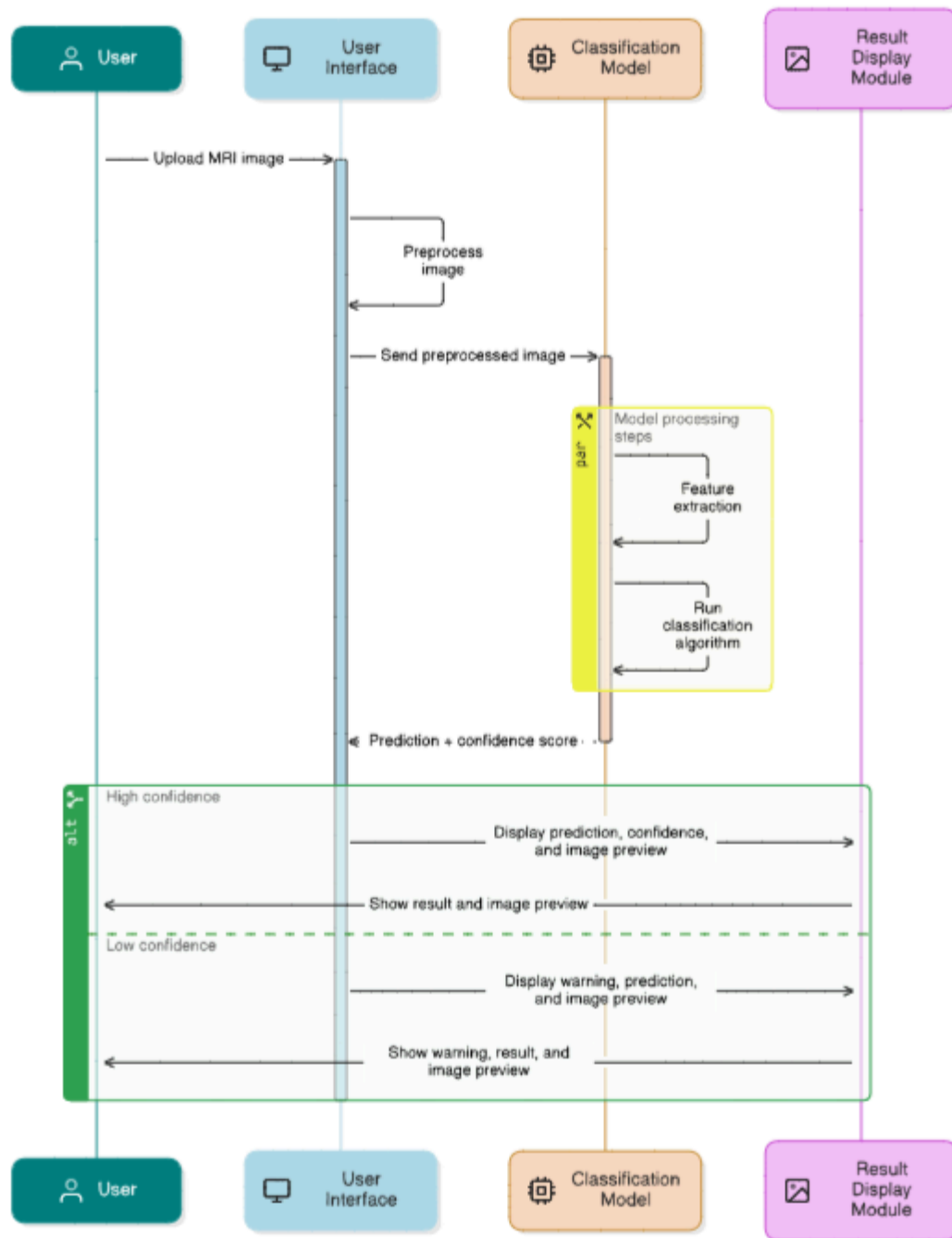
The workflow for the proposed system is designed to ensure a structured and efficient process for detecting and preventing blockchain security threats. It consists of the following sequential steps:

#### **4.1 SYSTEM ARCHITECTURE**

##### **4.1.1 USER INTERFACE DESIGN**

The sequence diagram illustrates the step-by-step interaction among the core components of the system: User, User Interface, Classification Model, and Result Display Module. Initially, the User initiates the process by uploading an MRI scan image via the User Interface. Once the image is submitted, the User Interface preprocesses the input (such as resizing and normalization) and forwards it to the Classification Model. The Classification Model performs inference using the trained deep learning architecture (such as VGG16 with additional dense layers) and predicts the tumor class (e.g., glioma, meningioma, pituitary, or no tumor) along with a confidence score.

The Classification Model sends the prediction results back to the User Interface, which then passes them to the Result Display Module. This module renders the output in a user-friendly format, showing the original image, predicted class, and confidence level. Finally, the results are presented to the User in real time, completing the classification cycle.



**Fig no. 4.1 Sequence Diagram**



## **CHAPTER 5**

### **IMPLEMENTATION AND RESULTS**

#### **5.1 IMPLEMENTATION**

The implementation of the brain tumor classification model is built using a deep learning approach with Convolutional Neural Networks (CNN) to classify medical images into distinct categories: pituitary, glioma, notumor, and meningioma. The process can be divided into several key components, which include data preprocessing, model architecture, training, and evaluation.

##### **5.1.1 . Data Collection and Preprocessing**

The dataset used in this project consists of brain MRI images, divided into different folders based on tumor categories. These images are sourced from a dataset available in public repositories. The data is split into training and testing sets, with the training set being used to train the model and the testing set to evaluate its performance. Images are loaded using TensorFlow's `load_img` method and resized to a uniform size (128x128 pixels) to ensure consistency across all images. To enhance the model's robustness and prevent overfitting, data augmentation techniques such as random brightness and contrast adjustments are applied to the images. This artificially expands the dataset by creating slightly altered versions of the images. The class labels are encoded into integers for compatibility with the model's output layer, which uses a softmax activation function to predict class probabilities.

##### **5.1.2. Model Architecture**

The model architecture is based on a pre-trained VGG16 model, which is a convolutional neural network known for its success in image classification tasks. The model is fine-tuned to suit the brain tumor classification task by modifying the top

layers. The VGG16 model is used as a feature extractor with its pre-trained weights from the ImageNet dataset. The weights are frozen during training to prevent them from being updated, ensuring that the model leverages pre-learned features without overfitting to the relatively small brain tumor dataset. Custom layers are added on top of the VGG16 base model. These include a flatten layer to convert the output from the convolutional layers into a 1D vector, dropout layers to prevent overfitting, and dense layers to make the final classification. The output layer consists of 4 units, each representing one of the tumor categories.

### **5.1.3. Model Training**

The model is compiled with the Adam optimizer and sparse categorical cross-entropy loss function, as the problem involves multi-class classification. The model's performance is evaluated based on sparse categorical accuracy. A custom data generator is implemented to feed batches of images to the model during training. The generator also performs augmentation on the images before they are passed to the model. The model is trained for 5 epochs using a batch size of 20, with data being fed into the model in batches. The model is evaluated after each epoch to monitor its performance and adjust training as needed.

### **5.1.4. Model Evaluation and Performance Metrics**

The trained model is evaluated using the test dataset. Key performance metrics such as accuracy, precision, recall, F1-score, and the confusion matrix are computed to assess the model's ability to correctly classify brain tumor images. The confusion matrix is used to visualize the performance of the classifier. It shows the number of true positive, true negative, false positive, and false negative predictions, giving insights into the model's classification errors. The ROC curve is plotted for each class, showing the trade-off between the true positive rate and false positive rate at various threshold

settings. The AUC (Area Under the Curve) metric is used to summarize the model's ability to distinguish between classes.

### 5.1.5. Model Inference and Results

For testing, random images from the test dataset are selected, and the trained model is used to predict the class of each image. The model's predictions are displayed alongside the actual images, with a confidence score indicating how certain the model is about its classification. The model is able to classify new brain MRI images, indicating whether they contain a tumor (and its type) or are tumor-free (notumor). The confidence score for each prediction is displayed to provide an indication of the model's certainty.

```
import random
import matplotlib.pyplot as plt
from PIL import Image
import os

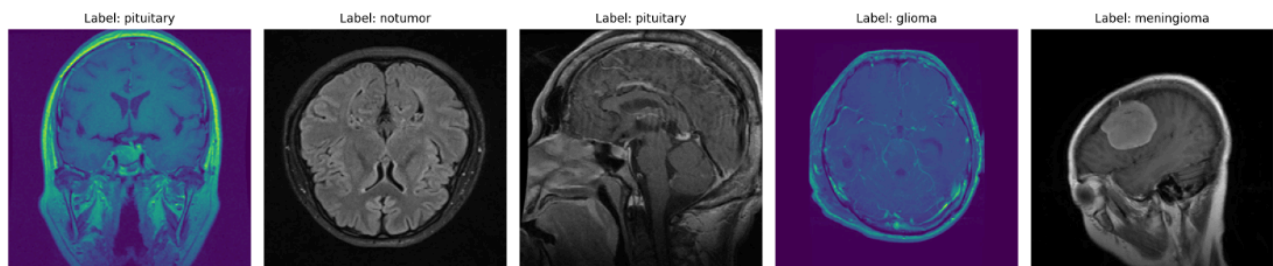
# Select random indices for 10 images
random_indices = random.sample(range(len(train_paths)), 10)

# Create a figure to display images in 2 rows
fig, axes = plt.subplots(2, 5, figsize=(15, 8))
axes = axes.ravel()

for i, idx in enumerate(random_indices):
    # Load image
    img_path = train_paths[idx]
    img = Image.open(img_path)
    img = img.resize((224, 224)) # Resize to consistent size

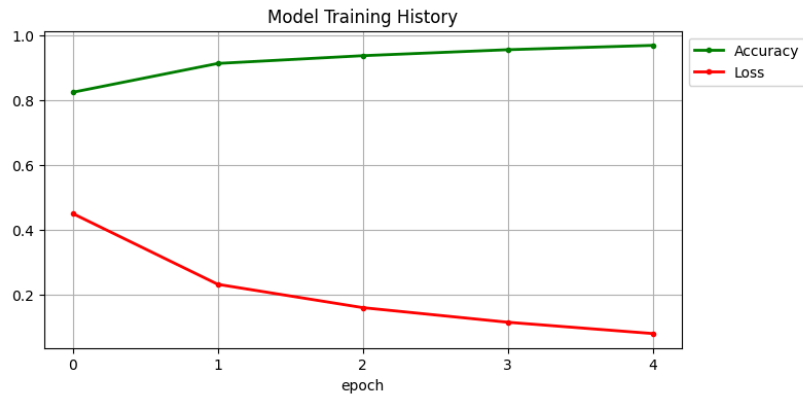
    # Display image
    axes[i].imshow(img)
    axes[i].axis('off') # Hide axis
    # Display class label in the second row
    axes[i].set_title(f"Label: {train_labels[idx]}", fontsize=10)

plt.tight_layout()
plt.show()
```



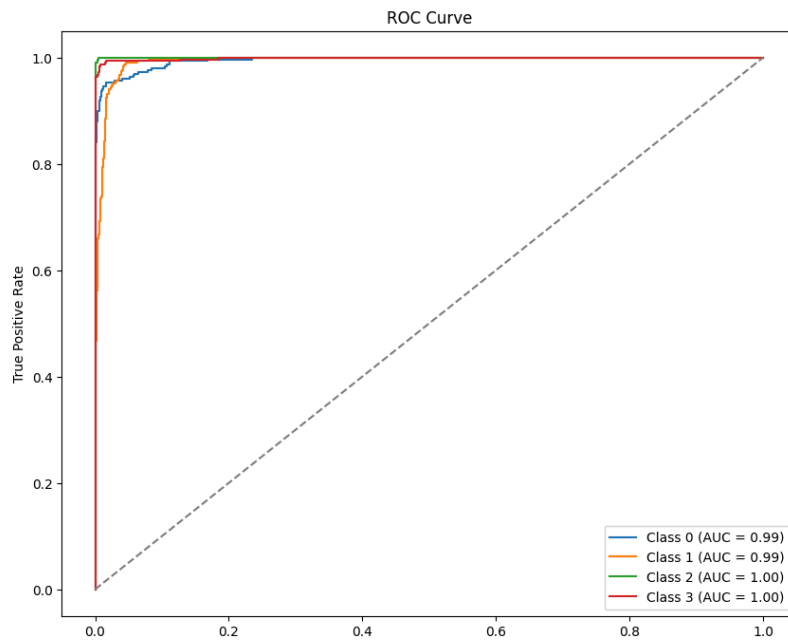
**Fig no.5.1 Data Labelling**

```
plt.figure(figsize=(8,4))
plt.grid(True)
plt.plot(history.history['sparse_categorical_accuracy'], '.g-', linewidth=2)
plt.plot(history.history['loss'], '.r-', linewidth=2)
plt.title('Model Training History')
plt.xlabel('epoch')
plt.xticks([x for x in range(epochs)])
plt.legend(['Accuracy', 'Loss'], loc='upper left', bbox_to_anchor=(1, 1))
plt.show()
```



**Fig no.5.2 Training Model History**

```
plt.plot([0, 1], [0, 1], linestyle='--', color='gray') # Diagonal Line
plt.title("ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc="lower right")
plt.show()
```

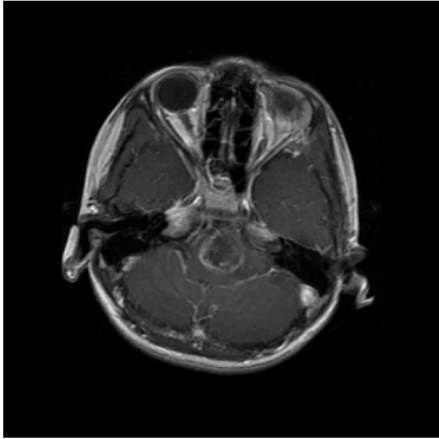


**Fig no.5.3 ROC Curve**

```
image_path = r'C:\Users\moham\FOML Projects/datasets/Testing/glioma/Te-gl_0091.jpg'  
detect_and_display(image_path, model)
```

1/1 ————— 0s 283ms/step

Tumor: pituitary (Confidence: 99.90%)

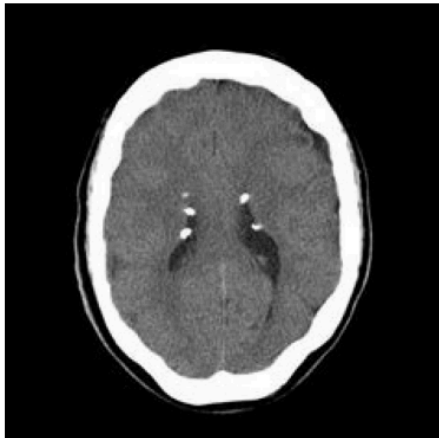


**Fig no.5.4 Output Prediction(1)**

```
image_path = r'C:\Users\moham\FOML Projects/datasets/Testing/notumor/Te-no_0056.jpg'  
detect_and_display(image_path, model)
```

1/1 ————— 0s 269ms/step

No Tumor (Confidence: 99.99%)



**Fig no.5.5 Output Prediction(2)**

## **CHAPTER 6**

### **CONCLUSION**

The brain tumor classification system developed in this project demonstrates the successful application of deep learning techniques, particularly Convolutional Neural Networks (CNNs), for medical image analysis. The model, which utilizes the VGG16 architecture fine-tuned for this specific task, has shown promising results in classifying brain MRI images into distinct tumor categories: pituitary, glioma, notumor, and meningioma. Through the use of data augmentation, the model has become more robust, effectively handling variations in the images and enhancing its generalization capabilities. The model's performance, as evaluated using key metrics such as accuracy, precision, recall, F1-score, and ROC AUC, demonstrates its ability to classify brain tumors with a high degree of accuracy. The confusion matrix and ROC curve provided valuable insights into the model's strengths and areas for improvement, particularly in terms of differentiating between similar tumor types. The use of transfer learning with the VGG16 model allowed for efficient training, leveraging pre-existing knowledge from large-scale image datasets.

In conclusion, the implementation of this brain tumor classification system highlights the potential of deep learning in the medical field, particularly for assisting radiologists and healthcare professionals in diagnosing and treating brain tumors. While the model performs well in the test set, future work could focus on further refining the model's performance, expanding the dataset, and exploring advanced techniques such as ensemble learning or fine-tuning more layers of the base model. The ultimate goal is to develop a reliable, scalable tool that can aid in early detection and diagnosis, improving patient outcomes and streamlining medical workflows.

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