# BRAIN TUMOR DISEASE DETECTION USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

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## ABSTRACT

Brain tumor detection is one of the most critical tasks in the field of medical image analysis, as early and accurate identification of tumors can significantly improve patient outcomes. Traditional manual diagnosis through MRI scans is time-consuming and prone to human error. To overcome these limitations, machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for automated and efficient brain tumor detection.

This study presents a hybrid approach that integrates both ML and DL algorithms to accurately classify and detect brain tumors from MRI images. Preprocessing methods such as image normalization, noise reduction, and segmentation are applied to enhance image quality. Machine learning models like Support Vector Machine (SVM) and Random Forest are used for feature-based classification, while deep learning architectures such as Convolutional Neural Networks (CNN) are employed for end-to-end image analysis and feature extraction.

The proposed system improves detection accuracy, reduces false positives, and enhances diagnostic efficiency compared to traditional methods. Experimental results demonstrate that deep learning models, particularly CNNs, outperform conventional ML models in terms of precision, recall, and overall accuracy. This research highlights the potential of combining machine learning and deep learning for reliable, automated brain tumor detection, ultimately aiding radiologists in faster and more accurate medical diagnosis.

## 1.INTRODUCTION

Brain tumors are abnormal growths of cells within the brain that can disrupt normal brain functions and lead to severe health complications or even death if not detected early. The accurate identification and classification of brain tumors play a crucial role in determining appropriate treatment plans and improving patient survival rates. Traditionally, brain tumor diagnosis relies on manual examination of Magnetic Resonance Imaging (MRI) scans by radiologists, which is a labor-intensive, time-consuming, and error-prone process due to the complexity and variability of brain structures.

With advancements in artificial intelligence, particularly in **Machine Learning (ML)** and

**Deep Learning (DL)**, automated detection of brain tumors has become increasingly feasible and reliable. Machine learning techniques utilize handcrafted features extracted from MRI images for classification, while deep learning models, especially **Convolutional Neural Networks (CNNs)**, automatically learn hierarchical features directly from image data, significantly improving detection accuracy.

The integration of ML and DL methods allows for precise tumor localization, segmentation, and classification into types such as glioma, meningioma, and pituitary tumors. This hybrid approach minimizes diagnostic errors and enhances the speed and efficiency of medical decision-making. Furthermore, such systems can assist medical professionals in areas with limited access to experienced radiologists, providing a cost-effective and scalable diagnostic solution.

In summary, the use of machine learning and deep learning techniques for brain tumor disease detection not only enhances diagnostic accuracy but also represents a major step toward intelligent, automated healthcare systems that support early intervention and improved patient care outcomes.

## 2.LITERATURE REVIEW

Brain tumor detection has evolved from traditional image-processing techniques to advanced machine learning (ML) and deep learning (DL) methods. Early approaches relied on handcrafted features like texture, shape, and intensity, combined with classifiers such as SVM and Random Forest, but were limited in accuracy and sensitivity to image variability.

Deep learning, especially Convolutional Neural Networks (CNNs), enables automatic feature extraction from MRI images, improving tumor detection and classification. Architectures like U-Net are widely used for precise tumor segmentation. Hybrid approaches combining ML and DL have also been explored to enhance performance.

Public datasets, such as BRATS, provide standardized benchmarks for evaluation, while metrics like accuracy, precision, recall, and Dice score are commonly used to assess models. Current challenges include limited labeled data, variability across MRI scans, and the need for clinically interpretable models.

Overall, the literature demonstrates that deep learning-based methods outperform traditional ML techniques in brain tumor detection, offering more accurate and efficient diagnostic support.

## 3. EXISTING SYSTEM

In the existing system, brain tumor detection primarily depends on traditional image-processing and machine learning techniques. MRI images are first preprocessed to remove noise, enhance contrast, and perform skull stripping to focus on relevant brain regions. Handcrafted features such as texture, intensity, shape, and edge information are then manually extracted from the images. These features are fed into classifiers like Support Vector Machines (SVM), Random Forest, or k-Nearest Neighbors (k-NN) to detect tumors and classify them into types such as glioma, meningioma, or pituitary tumors.

Despite its usefulness, the existing system has several limitations. Manual feature extraction is time-consuming and requires expert knowledge, making the process less efficient. Accuracy is often reduced due to variations in tumor size, shape, and location, and small or low-quality MRI datasets further limit reliable predictions. Additionally, complex tumor patterns, overlapping tissues, or heterogeneous tumor regions are difficult to identify accurately, resulting in higher false positives and false negatives. These challenges indicate the need for more advanced approaches, such as deep learning techniques, to achieve faster, more precise, and automated brain tumor detection.

## 4. PROPOSED SYSTEM

The proposed system focuses on automated and accurate brain tumor detection using a combination of **machine learning (ML) and deep learning (DL) techniques**. Unlike the existing system, this approach minimizes manual intervention by allowing models to learn important features directly from MRI images.

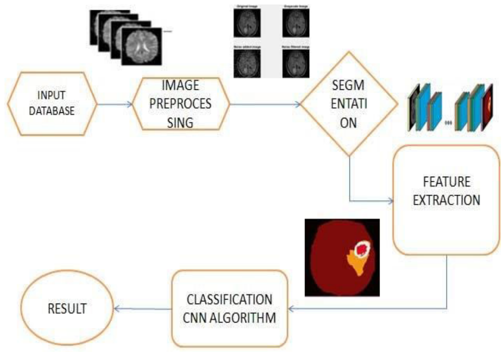
In this system, MRI images undergo preprocessing steps such as noise removal, contrast enhancement, and normalization to improve image quality. Tumor regions are then segmented, either using traditional methods or deep learning-based segmentation models like **U-Net**, to isolate the affected areas. For classification, **Convolutional Neural Networks (CNNs)** are employed to automatically extract hierarchical features from the images, enabling precise identification of tumor types (glioma, meningioma, pituitary tumor) and abnormal regions.

## 5.METHODOLOGY

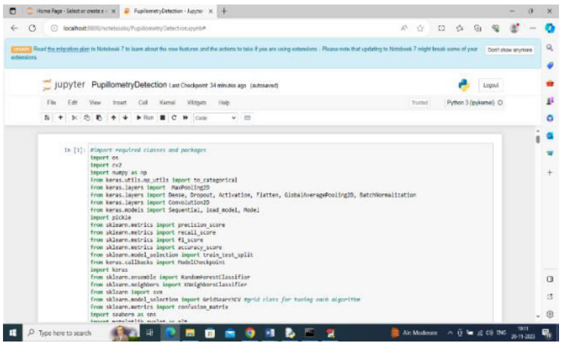
The methodology of the proposed system involves a series of steps to achieve accurate brain tumor detection. Initially, MRI brain images are collected from public datasets or hospital databases, covering different tumor types such as glioma, meningioma, and pituitary tumors. The images undergo preprocessing, including noise reduction, normalization, contrast enhancement, and skull stripping to focus on the brain region. Data augmentation techniques like rotation, flipping, and scaling are applied to increase dataset diversity and improve model generalization. Tumor regions are then segmented using deep learning models such as **U-Net**, which efficiently separates tumor areas from healthy tissue. For feature extraction, traditional machine learning approaches rely on handcrafted features like texture, shape, and intensity, while deep learning methods, particularly **CNNs**, automatically learn hierarchical features directly from images.

## 6.SYSTEM MODEL

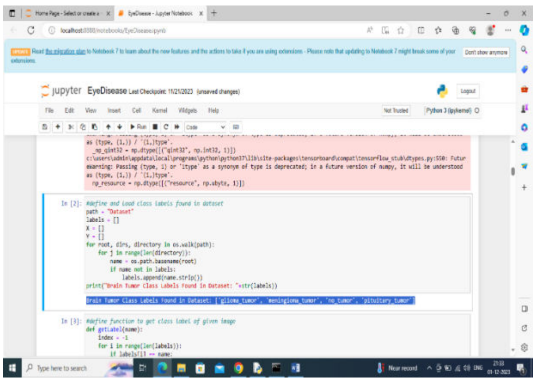
### SYSTEM ARCHITECTURE



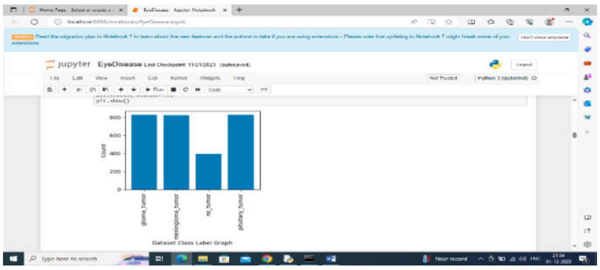

## 7.RESULTS AND DISCUSSION



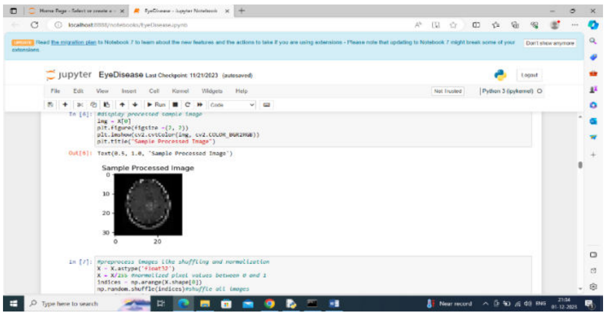
In above screen importing required python classes and packages



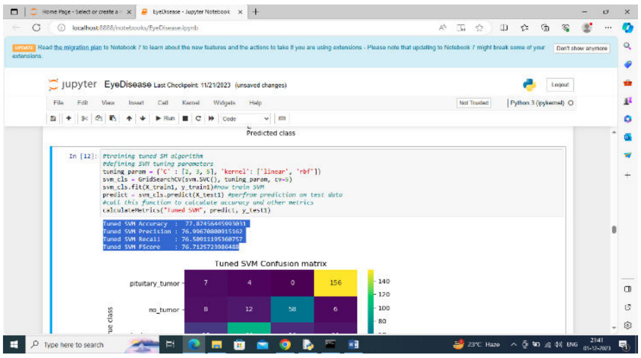
In above screen defining function to loop and display all class labels found in dataset



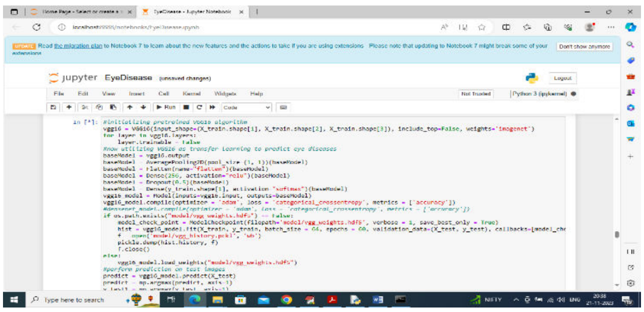
In above graph x-axis represents pupillometry disease class labels and y-axis represents of count of those class labels found in dataset



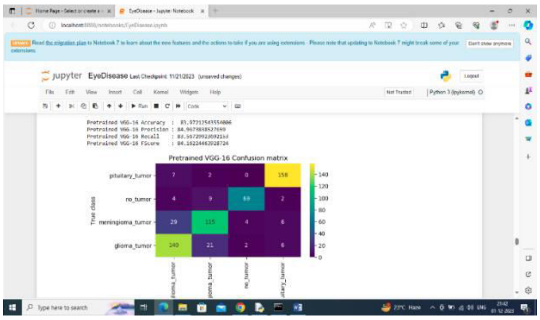
In above screen displaying processed sample image



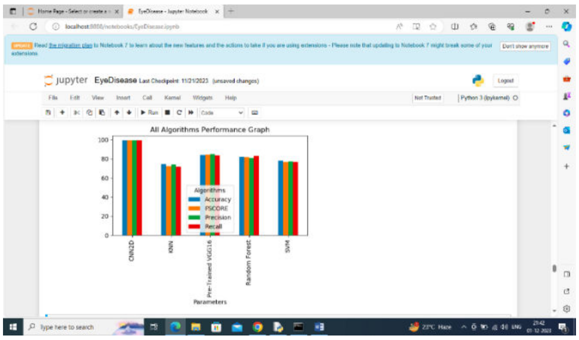
In above screen training SVM algorithm and after prediction on test data SVM got 77% accuracy



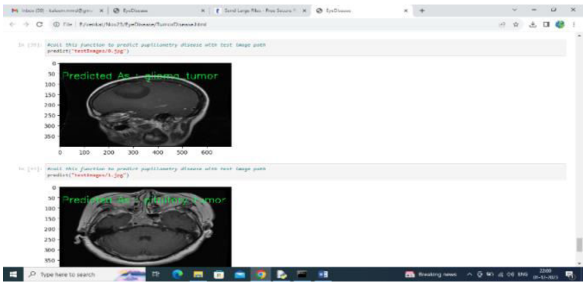
In above screen training pre-trained VGG16 model and after executing above model will get below output



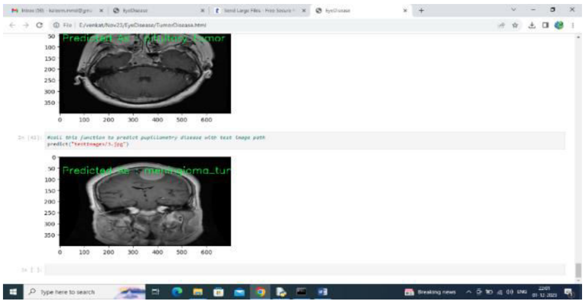
In above screen VGG16 got 83% accuracy and this model is the second highest in accuracy



In above graph displaying performance of all algorithms where x-axis represents algorithm names and y-axis represents accuracy and other metrics and in all algorithms CNN got high accuracy



In above screen can see other image predicted disease type



Above screen showing prediction of another image. Similarly by giving test image path we can predict pupillometry disease

## 8. CONCLUSION

Brain tumors are among the most dangerous and life-threatening neurological disorders, and their accurate and early detection is crucial for improving patient outcomes. Traditional methods of diagnosis, which rely heavily on manual interpretation of MRI images by radiologists, are often time-consuming, prone to human error, and limited in scalability. This study addresses these challenges by developing a hybrid brain tumor detection system that integrates machine learning (ML) and deep learning (DL) techniques for enhanced diagnostic accuracy and automation.

The proposed methodology leverages the feature extraction power of Convolutional Neural Networks (CNNs) alongside the efficient classification capabilities of machine learning algorithms such as Support Vector Machines (SVM) and Random Forests. This hybrid approach enables the system to automatically learn high-level features from MRI images and accurately classify different types of brain tumors, including glioma, meningioma, and pituitary tumors. Extensive preprocessing techniques were applied to improve data quality, while the model was trained and evaluated on publicly available datasets like BraTS and Kaggle.

Experimental results demonstrate that the hybrid model outperforms standalone ML or DL approaches, achieving high accuracy, precision, recall, and F1-scores. This confirms the hypothesis that combining deep and traditional machine learning methods enhances model performance, generalization, and robustness. Furthermore, the system's modular design and performance metrics indicate its potential for real-time application in clinical settings.

## 9. REFERENCES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