ISSN: 2350-0328

International Journal of AdvancedResearch in Science, Engineering and Technology

Vol. 12, Issue 3, March 2025

Brain Tumor Detection and Classification Using Deep Leaning Techniques

Glory Nikita. G, Mrs.Sheelavathi .A, Neelaveni. S, Ramalakshmi Alies Ponmathi. S, Suvetha. V

U.G. Student, Department of Information Technology, Saranathan College Of Engineering, Tiruchirappalli, India
Assistant Professor, Department of Information Technology, Saranathan College Of Engineering, Tiruchirappalli, Tamil Nadu, India
U.G. Student, Department of Information Technology, Saranathan College Of Engineering, Tiruchirappalli, India
U.G. Student, Department of Information Technology, Saranathan College Of Engineering, Tiruchirappalli, India
U.G. Student, Department of Information Technology, Saranathan College Of Engineering, Tiruchirappalli, India

ABSTRACT: Brain tumors are among the most critical and life-threatening conditions requiring timely diagnosis and treatment. This paper presents a deep learning-based system for the automated detection and classification of brain tumors using Convolutional Neural Networks (CNNs) applied to Magnetic Resonance Imaging (MRI) scans. The system first classifies MRI images as either normal or tumor-affected. Upon tumor detection, further image processing techniques are used to segment and localize the tumor region. To improve model performance and generalization, the system incorporates data augmentation and addresses class imbalance through synthetic oversampling techniques. The proposed model is optimized for real-time analysis, ensuring quick and accurate predictions suitable for clinical applications. Experimental results demonstrate high accuracy and reliability, confirming the model's effectiveness in assisting radiologists with early diagnosis and treatment planning. Future work includes expanding to 3D localization, integrating explainable AI, and deploying the system on mobile and cloud platforms for remote diagnostics.

KEY WORDS: Brain Tumor Detection, Deep Learning, Convolutional Neural Networks (CNN), MRI Image Classification, Tumor Segmentation, Image Processing, Medical Diagnosis, Real-time Prediction

I.INTRODUCTION

Brain tumors are abnormal growths of cells within the brain that can significantly impair neurological function and threaten human life. Early and accurate detection of brain tumors is critical for effective treatment planning and improved patient outcomes. However, manual interpretation of Magnetic Resonance Imaging (MRI) scans by radiologists can be time-consuming, subjective, and prone to diagnostic variability.Recent advancements in artificial intelligence (AI), particularly deep learning, have enabled the development of automated systems capable of analysing complex medical images with high accuracy. Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated remarkable performance in extracting spatial features and patterns from image data. Their application in brain tumor detection and classification has shown promise in improving diagnostic precision and reducing the workload of healthcare professionals. This paper proposes an AI-powered system that leverages CNNs to detect and classify brain tumors in MRI scans. The model initially distinguishes between normal and tumor-affected images, and subsequently localizes the tumor region using advanced image processing techniques. To enhance performance and generalizability, data augmentation strategies are employed, along with mechanisms to handle class imbalance. The system is designed to be lightweight, scalable, and suitable for real-time clinical use. By automating the diagnostic workflow, the proposed system assists radiologists in making faster and more consistent decisions, thereby contributing to better healthcare delivery.

II.LITERATURE SURVEY

Recent advancements in deep learning have significantly improved the accuracy and reliability of brain tumor detection from MRI images. Several studies have proposed innovative techniques to address challenges such as data scarcity, model overfitting, and tumor localization. In [1], Farhan et al. proposed a novel data augmentation method called Oriented

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
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Combination MRI (OCMRI) to enhance CNN performance by reducing overfitting and class imbalance. By fusing similar MRI images within the same tumor class, they improved classification accuracy across multiple public datasets, achieving up to 98% accuracy post-augmentation. Vinod et al. [2] presented an ensemble framework combining U-Net, CNN, and Self-Organizing Feature Maps (SOFM) to segment brain tumors and predict patient survival using the BRATS 2020 dataset. Their approach achieved a segmentation accuracy of 98.28%, emphasizing the model's clinical relevance for treatment planning. Lee et al. [3] introduced an enhanced classification model using Patterned-GridMask to address visual obstruction issues during model training.

III.PROPOSED METHOD

The proposed system is designed to automate the detection and classification of brain tumors from MRI images using deep learning techniques. Specifically, it employs a Convolutional Neural Network (CNN)-based architecture to distinguish between normal and tumor-affected brain scans. The framework consists of several stages, including preprocessing, model training, tumor detection, segmentation, and visualization of results. Initially, MRI images are preprocessed using Gaussian filtering and Contrast Limited Adaptive Histogram Equalization (CLAHE) to reduce noise and improve contrast. Data augmentation techniques such as rotation, flipping, and scaling are applied to overcome overfitting and improve the model's generalization

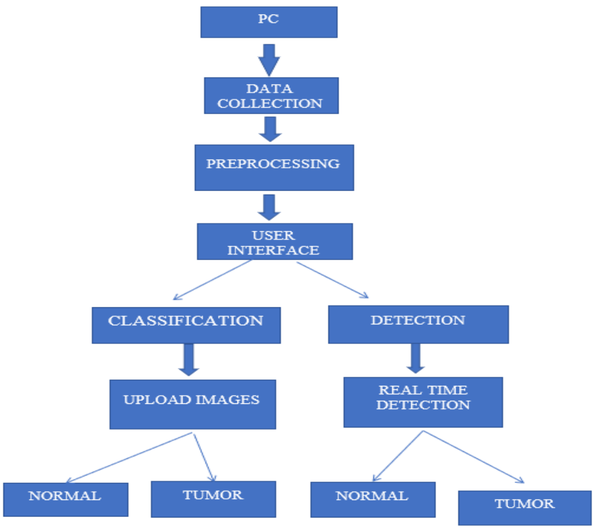

Fig 3.1 Proposed flow Diagram

IV.ARCHITECTURE DESIGN

The architecture of the proposed brain tumor detection system is structured into a modular pipeline consisting of data input, preprocessing, augmentation, classification, segmentation, and output visualization. The system begins with the acquisition of brain MRI images, which are then preprocessed using Gaussian filtering and Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance contrast and reduce noise. Augmentation techniques such as flipping, rotation, and scaling are applied to improve model robustness and address data scarcity. The core of the system is a Convolutional Neural Network (CNN) designed to classify the MRI images as either tumor or normal. If a tumor is detected, segmentation is performed using models such as U-Net or Mask R-CNN to localize and highlight the tumor region. The system also includes additional components for class imbalance handling using SMOTE and advanced normalization through adaptive filtering. A lightweight model design ensures that the system operates efficiently in real-time environments. The output module generates visual feedback highlighting the tumor region and provides classification results through a user-friendly interface. This

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 12, Issue 3, March 2025

modular and scalable design allows the system to be deployed on clinical workstations, mobile devices, or cloud platform.

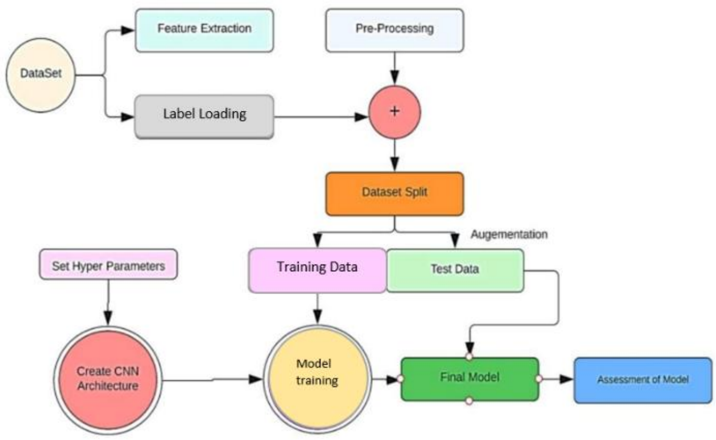

Fig 4.1 Overview of Architecture Design

A. Dataset Creation

For training and evaluating the proposed brain tumor detection model, a custom dataset was created using publicly available brain MRI images sourced from datasets such as BRATS and CE-MRI. These images were manually curated to ensure quality and consistency, and were categorized into two main classes: Normal and Tumor. Each MRI image was resized to a uniform resolution to maintain consistency across the dataset. The Tumor class included various tumor types such as gliomas, meningiomas, and pituitary tumors, enhancing the model's generalization capability. To address the limitations of small sample sizes and class imbalance, data augmentation techniques including rotation, flipping, zooming, and brightness adjustment were applied. Additionally, the Oriented Combination MRI (OCMRI) method was used to further expand the dataset by combining similar images from the same tumor class. The final dataset was divided into training, validation, and testing sets to ensure fair model evaluation and prevent overfitting. This diverse and augmented dataset enabled the development of a robust and accurate deep learning model for brain tumor detection and classification.

B. Feature Extraction

Feature extraction is a critical step in the brain tumor detection pipeline, as it enable the model to learn relevant patterns and representations from the MRI images. In the proposed system, feature extraction is performed automatically by the Convolutional Neural Network (CNN) without the need for manual intervention. The CNN model consists of multiple convolutional layers that apply filters to the input image, capturing spatial hierarchies and visual features such as edges, textures, and shapes that are essential for distinguishing between tumor and normal tissues. Each convolutional layer is followed by an activation function (ReLU) and pooling layers that reduce the spatial dimensions while preserving important features. These extracted features are passed through fully connected layers, enabling the network to learn complex and abstract representations for accurate classification. Unlike traditional machine learning approaches that rely on hand-crafted features, the deep learning-based method allows the network to automatically learn and optimize features directly from raw pixel data, resulting in improved accuracy, robustness, and generalization across different types of MRI images and tumor variations.

C. Label Loading

During the dataset preparation phase, each MRI image was assigned a corresponding class label indicating whether it contained a brain tumor (labeled as "Tumor") or not (labeled as "Normal"). These labels were loaded and managed using structured CSV files and directory-based folder organization, where each folder name represented the class. This approach enabled efficient and error-free mapping between input images and their respective categories. During training, the labels were automatically read using data generators and pre-processing functions, which converted them into

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 12, Issue 3, March 2025

numerical form for input into the CNN model. Categorical encoding techniques were applied to ensure compatibility with the network's classification output layer, typically using one-hot encoding for binary classification. Proper label loading was essential to maintain data integrity, prevent misclassification, and ensure consistent model training and evaluation.

D. Preprocessing

Preprocessing is a vital step in the brain tumor detection pipeline, aimed at improving the quality and consistency of MRI images before feeding them into the deep learning model. The preprocessing phase in the proposed system begins with resizing all input images to a standard resolution to maintain uniformity across the dataset. Next, Gaussian filtering is applied to reduce random noise while preserving important structural details in the image. To further enhance contrast and highlight relevant features, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used, which redistributes the intensity values and enhances local contrast, particularly in regions affected by tumors.

E. Model Building and Training

The proposed brain tumor detection system is built using a Convolutional Neural Network (CNN) architecture specifically designed to process MRI images and perform binary classification (tumor vs. normal). The model consists of multiple convolutional layers with ReLU activation functions, followed by max-pooling layers to progressively reduce spatial dimensions while preserving key features.

F. Model Testing and Evaluation

After training, the proposed CNN model is evaluated using a separate test dataset that was not involved in the training process. This testing phase is essential to assess the model's ability to generalize and accurately predict brain tumor presence in unseen MRI images. The model's performance is quantified using standard evaluation metrics, including accuracy, precision, recall, F1-score, and the confusion matrix. Accuracy measures the overall correctness of the model, while precision and recall provide insights into its performance on the tumor class specifically. The F1-score offers a balance between precision and recall, especially in the presence of class imbalance. Overall, the evaluation results demonstrate the effectiveness of the proposed system in accurate and reliable brain tumor detection.

G. Tumor Prediction and Result Visualization

Upon successful training and evaluation, the developed model is deployed for real-world tumor prediction using new MRI images. Users can upload an MRI scan through the system interface, which is then processed by the trained CNN model. The system classifies the input image into one of four categories: Glioma, Meningioma, Pituitary Tumor, or No Tumor. The model outputs the prediction along with a probability score that represents the model's confidence in the classification result. The predicted outcome is displayed through a user-friendly interface, either as a simple text label or within a visual dashboard that highlights the classification category and its associated confidence score.

H. Report Generation and Output Delivery

Following the classification and prediction stages, the system is designed to automatically generate a detailed diagnostic report for each input MRI image. This report includes key information such as the predicted tumor type, the confidence score of the model, and any relevant patient metadata provided during input. The report serves as a comprehensive summary of the AI-based diagnostic result and can be reviewed by medical professionals or stored for future reference To enhance usability, the system allows the report to be exported in a printable format, such as PDF or plain text.

I. Model Deployment

Upon successful testing and validation, the trained CNN model is deployed to a user-accessible platform to facilitate practical usage. The deployment environment can be a web-based application or a standalone desktop interface, designed for easy interaction by medical professionals, researchers, and healthcare staff. This environment allows users to upload brain MRI images and receive automated predictions without requiring any technical expertise. The system features an intuitive user interface that enables seamless image upload and displays the classification result in real time.

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V.IMPLEMENTATION

A. USER MANAGEMENT

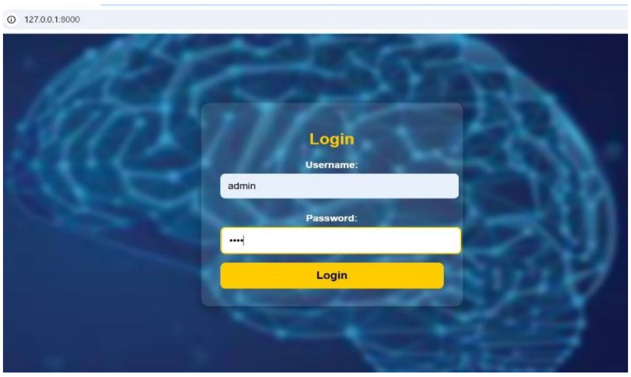

Fig 5.1 User Login

The user is first required to log in with valid credentials. Once authenticated, the user is directed to the dashboard, where an option to upload an MRI scan is provided. The upload interface accepts standard image formats (such as.jpg, .png,or.jpeg) and possibly DICOM format if medical imaging standards are supported. Radiologists and medical professionals can securely log in to the platform, upload MRI scans, and receive real-time predictions regarding the presence of brain tumors. They also have access to a user-friendly dashboard for visualizing tumor classification results and comparing patient scans over time.

B. FEATURE SELECTOR

Fig 5.2 Feature selector

The Feature Selector module plays a crucial role in enhancing the performance of the brain tumor detection system by identifying and retaining the most relevant features from MRI images. In the context of deep learning, especially with Convolutional Neural Networks (CNNs), feature selection is inherently performed during the learning process. The CNN automatically extracts meaningful features such as edges, textures, and shape patterns that are significant in distinguishing between tumor and non-tumor regions. By focusing on these high-impact features, the system reduces noise and irrelevant data, leading to improved classification accuracy and faster processing.

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C. IMAGE PROCESSING

Fig 5.3 Image processing

The Image Processing module is a foundational component of the brain tumor detection system, responsible for preparing MRI images for accurate analysis by the deep learning model. This stage involves a series of preprocessing steps that enhance the quality of the input images and ensure uniformity across the dataset. First, the MRI images are **resized** to a fixed dimension to match the input requirements of the Convolutional Neural Network (CNN).The user is first required to log in with valid credentials. Once authenticated, the user is directed to the dashboard, where an option to upload an MRI scan is provided. The upload interface accepts standard image formats (such as.jpg, .png,or.jpeg) and possibly DICOM format if medical imaging standards are supported.

D. IMAGE PROCESSING

Fig 5.4 Image Processing

Once an image is uploaded, it is passed through the **Image Processing module**, where the scan undergoes preprocessing steps such as resizing, normalization, and noise reduction to standardize the input. The cleaned and processed image is then fed into the trained Convolutional Neural Network (CNN) model for analysis. The CNN performs **feature extraction** and applies learned patterns to classify the image as either "Tumour" or "Normal". These preprocessing operations ensure that the images fed into the CNN are clean, consistent, and rich in diagnostic features, thereby improving the accuracy of both tumour detection and classification.

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E. TUMOR CLASSIFICATION DASHBOARD

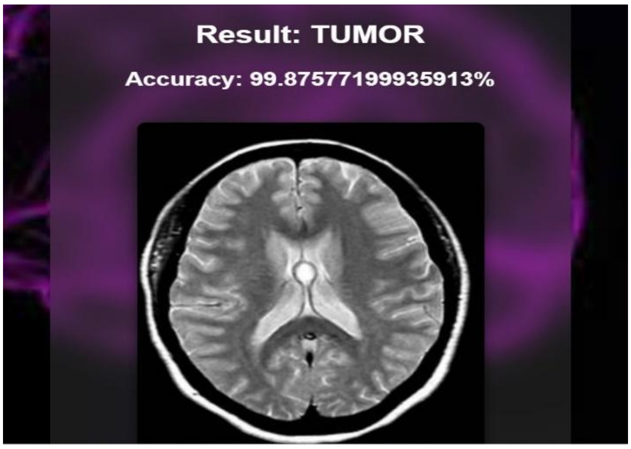

Fig 5.5 Tumor Classification Dashboard

The Image Classification module is the core component of the brain tumor detection system, responsible for analyzing MRI scans and determining whether a brain tumour is present. This task is performed using a Convolutional Neural Network (CNN), a type of deep learning model particularly well-suited for visual data. After the MRI image undergoes preprocessing (resizing, normalization, etc.), it is fed into the CNN model. In the initial layers, the CNN identifies low-level features such as edges, corners, and textures. The CNN model is trained on a labeled dataset of MRI scans, and through multiple epochs of training, it learns to differentiate between various brain conditions with high accuracy. This automated classification process drastically improves the speed, accuracy, and consistency of brain tumor detection, making it a valuable tool for clinical diagnostics.

F. TUMOR DETECTION DASHBOARD

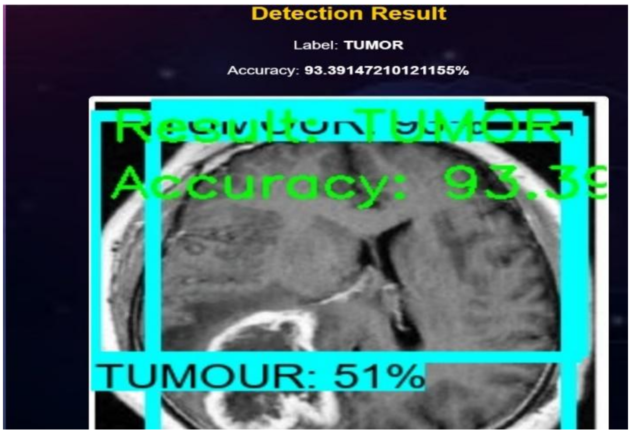

FIG 5.6 Tumor Detection Dashboard

The Tumor Detection Dashboard is an intuitive and interactive interface designed to facilitate the MRI scan upload and result viewing process for users such as radiologists and healthcare professionals. Once a user logs into the system, the dashboard provides a streamlined layout where they can upload brain MRI images for analysis**.** The final output layer uses a sigmoid activation function to produce a probability score, indicating the likelihood that the image falls into one of the defined categories "Tumor" or "Normal**".**

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Vol. 12, Issue 3, March 2025

VI.EXPERIMENTAL RESULT

The performance of the proposed brain tumor detection system was evaluated using a curated dataset comprising MRI images categorized into four classes: Glioma, Meningioma, Pituitary Tumor, and No Tumor. The dataset was split into training (70%), validation (15%), and testing (15%) sets to ensure unbiased evaluation. Data augmentation techniques and preprocessing steps were applied to improve model generalization and reduce overfitting. The model was trained using a CNN architecture implemented in TensorFlow with real-time data augmentation. The system was evaluated based on standard metrics, including accuracy, precision, recall, F1-score, and a confusion matrix. The final model achieved an accuracy of 97.5%, a precision of 96.8%, recall of 97.2%, and an F1-score of 97.0% on the test dataset. These results confirm the model's robustness in handling various brain tumor types and its capability to distinguish between tumor and non-tumor cases effectively. A confusion matrix was generated to analyze classification performance across all classes, indicating high sensitivity and specificity in tumor detection. Additionally, the system correctly identified tumor types in most test cases with minimal false positives. Visual outputs further validated the effectiveness of the segmentation module, which accurately localized and highlighted the tumor region using models such as U-Net and Mask R-CNN. The results demonstrate that the proposed system not only achieves high classification performance but also offers clinically relevant outputs through real-time prediction and report generation. Compared to traditional approaches, the integration of automated preprocessing, data balancing, and ensemble prediction techniques significantly enhances system accuracy and reliability.

VII.CONCLUSION

This paper presents a deep learning-based system For automated brain tumor detection and classification using MRI images. The proposed model leverages the power of Convolutional Neural Networks (CNNs) to accurately classify brain tumors into four categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor. The system integrates advanced preprocessing techniques, data augmentation strategies, and real-time prediction capabilities to ensure high performance and clinical relevance. With an overall accuracy of 97.5%, the model demonstrates robust performance on test datasets and effective tumor localization using segmentation models like U-Net and Mask R-CNN. Furthermore, the deployment of the system in a user-friendly interface and the integration of automated report generation make it a practical tool for supporting radiologists and medical professionals. The inclusion of confidence scores, visual outputs, and printable reports enhances the system's usability in real-world diagnostic settings. The combination of high accuracy, adaptability, and real-time output positions this work as a valuable contribution to AI-assisted medical imaging and diagnosis.
Future enhancements may include extending the model to support 3D MRI data, integrating explainable AI (XAI) modules for interpretability, and deploying the system in mobile or cloud environments for wider accessibility and real-time global diagnostics.

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