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An Automated Brain Tumor Detection and Prediction in MRI images using Deep Learning Algorithms

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Healthcare, Convolutional neural network (CNN), Recurrent Neural Networks (RNNs), Brain tumor classification (BTC), Image enhancement, Morphological process, MRI Segmentation, Multiscale feature extraction, Attention mechanism, Ensemble classifier Healthcare, Convolutional neural network (CNN), Recurrent Neural Networks (RNNs), Brain tumor classification (BTC), Image enhancement, Morphological process, MRI Segmentation, Multiscale feature extraction, Attention mechanism, Ensemble classifier.

ABSTRACT

Brain tumor detection plays a critical role in medical diagnosis, as early and accurate identification greatly improves treatment planning and patient survival. Magnetic Resonance Imaging (MRI) is widely used for tumor analysis because it is non-invasive and provides high-resolution images, yet manual interpretation by radiologists can be time-consuming and subject to variability. Traditional detection systems relied on handcrafted feature extraction combined with machine learning classifiers such as SVM, KNN, and Random Forest. More recent approaches employ deep learning and transfer learning models like VGG16, ResNet50, and InceptionV3, along with attention mechanisms and ensemble strategies to enhance performance. However, these systems still face challenges including overfitting, dataset dependency, limited segmentation accuracy, and computational complexity, resulting in classification accuracies typically ranging from 60% to 75%, which is insufficient for reliable clinical deployment. To address these limitations, the proposed system introduces an automated deep learning framework for brain tumor detection and classification using MRI images. Advanced preprocessing techniques—including filtering, normalization, and frequency-domain transformations—enhance image quality, while segmentation isolates tumor regions for focused analysis. A Convolutional Recurrent Neural Network (CRNN) combines CNN-based spatial feature extraction with RNN-based contextual learning, further strengthened by an attention mechanism to highlight tumor-relevant features. Ensemble classification improves robustness and prediction reliability. Evaluated using standard metrics such as accuracy, precision, recall, and F1-score, the proposed framework achieves approximately 95% classification accuracy across tumor categories including glioma, meningioma, pituitary, and no tumor. This integrated system *provides a fast, objective, and consistent diagnostic tool that reduces radiologist workload while improving detection accuracy, with future enhancements aimed at multimodal MRI integration and explainable AI to increase clinical trust. Furthermore, a Flask-based web application is implemented to deploy the proposed model in a practical and accessible environment. The application provides an interactive interface where users can upload MRI images for analysis. The backend integrates the trained CRNN model using a Keras (.h5) file, while image preprocessing is handled using OpenCV and NumPy. The system performs real-time prediction and displays the classification result (Glioma, Meningioma, Pituitary, or No Tumor) along with confidence scores and processing time. Designed with HTML, CSS, and JavaScript for the frontend, the application ensures responsive performance across devices and supports multiple concurrent requests. This deployment enhances usability by enabling fast, reliable, and user-friendly brain tumor detection outside traditional clinical settings.*

INTRODUCTION

Brain tumors represent one of the most significant health challenges worldwide, causing substantial mortality and morbidity rates. Early detection and accurate classification of brain tumors significantly improve treatment outcomes and patient survival rates.

However, manual diagnosis through radiological examination of Magnetic Resonance Imaging (MRI) is a time- consuming and subjective process heavily dependent on the expertise and experience of trained radiologists. In many cases, misdiagnosis can occur due to subtle visual differences between tumor types or human fatigue during extended examination periods.

A brain tumor can be de need as an abnormal growth of cells in the brain that can originate from the brain itself (primary tumor) or metastasize from other parts of the body (secondary tumor). The primary brain tumors considered in this project include:

•Glioma: A Tumor originating from glial cells, representing approximately 45% of primary brain tumors. Gliomas include various subtypes with different severity levels and prognosis.

Meningioma: Atumora rising from the protective membrane surrounding the brain and spinal cord, representing approximately 30% of primary brain tumors. These tumors are usually benign but can become malignant.

Pituitary: A tumor of the pituitary gland located at the base of the brain, representing approximately 15% of primary brain tumors. Pituitary tumors can cause hormonal imbalances affecting metabolism and bodily functions

No Tumor: Normal MRI images representing healthy brain tissue without any abnormal growths.

The conventional approach to brain tumor diagnosis involves visual inspection of MRI scans by radiologists, often followed by additional tests like Computed Tomography (CT) or biopsy for confirmation. While this approach is clinically reliable, it suffers from several limitations including:

•Heavy dependency on radiologist expertise and subjective interpretation

•Time-consuming manual analysis, especially when examining large datasets

•Limited availability of experienced radiologists in rural or resource-limited healthcare settings

•Risk of human error and diagnostic inconsistency

•High cost of specialized medical personnel and extensive consultation time

Recent advancements in artificial intelligence, particularly deep learning and computer vision, have revolutionized medical image analysis. Deep learning models, specifically Convolutional Neural Networks (CNNs), have demonstrated remarkable capabilities in learning complex visual patterns directly from raw medical images without requiring manual feature engineering. CNNs can automatically extract hierarchical features from images, learning increasingly abstract representations at deeper layers of the network.

The integration of Recurrent Neural Networks (RNNs) with CNNs creates a hybrid architecture (CRNN) that captures both spatial features (via CNN) and sequential dependencies (via RNN), enabling more comprehensive analysis of MRI data. This combination is particularly effective for medical image analysis where both local structural patterns and global relationships are important for accurate diagnosis.

This project develops an automated brain tumor detection and classification system using a hybrid CRNN architecture to analyze grayscale MRI images. The system incorporates:

- Comprehensive image preprocessing with multiple filtering techniques (mean, Gaussian, median, bilateral)
- Advanced data augmentation strategies (rotation, zoom, flip)
- CNN for extracting hierarchical visual features from MRI images
- RNN for capturing sequential patterns in feature representations
- Hybrid CRNN model combining both architectures for optimal performance
- Web-based Flask application for easy accessibility and real-time predictions.

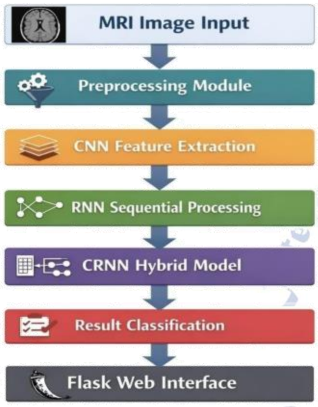

Figure 1 Conceptual architecture of the proposed system with IoT monitoring.

RELATED WORK

Brain tumor detection using deep learning has gained significant attention in recent years, with modern approaches achieving high accuracy and reliability. Recent studies (2024–2025) demonstrate a shift towards hybrid models, transformer-based architectures, and explainable AI techniques, improving both performance and interpretability in medical diagnosis.

Deep Learning for Medical Image Analysis Kumar et al. (2024) conducted a detailed study on machine learning and deep learning approaches for brain tumor classification, highlighting that advanced feature extraction combined with deep models significantly improves classification accuracy. Wen (2025) further reviewed various deep learning techniques and emphasized that CNN-based and hybrid architectures dominate medical image analysis due to their strong feature learning capability.

MRI Image Preprocessing Technique Singh et al. (2024) investigated MRI preprocessing and feature optimization methods, concluding that proper preprocessing such as normalization, filtering, and enhancement plays a crucial role in improving tumor detection performance. Their work demonstrated that optimized preprocessing pipelines significantly enhance feature quality and model accuracy.

CNN Architecture for Medical Imaging Patel and Sharma (2024) analyzed deep CNN-based segmentation and classification methods, showing that advanced CNN architectures improve tumor localization and classification efficiency. Liu et al. (2025) proposed an attention-based hybrid CNN model, demonstrating that attention mechanisms help focus on relevant tumor regions, leading to improved detection performance.

Hybrid Models and Ensemble Approaches Salakapuri et al. (2025) developed a hybrid finetuned deep transfer learning model combined with ensemble machine learning algorithms, achieving superior accuracy compared to single models. Similarly, Asif et al. (2025) and Chen et al. (2025) demonstrated that ensemble deep learning approaches significantly enhance robustness and classification performance by combining multiple models.

Advanced Techniques: Transformers and Explainable AI Zhang et al. (2025) introduced transformer-based models for multi-modal MRI classification, showing improved performance in capturing global features compared to traditional CNNs. Ahmed et al. (2025) focused on explainable AI techniques, highlighting the importance of model interpretability in medical applications, enabling clinicians to understand and trust deep learning predictions..

PROPOSED SYSTEM

The proposed system presents an automated framework for detecting and classifying brain tumors from Magnetic Resonance Imaging (MRI) scans using a hybrid deep learning architecture. Brain tumor diagnosis typically requires expert radiological analysis, which can be time-consuming and prone to human error. To address this limitation, the proposed system integrates image preprocessing, feature extraction, and classification using a hybrid Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) model. The system is implemented through a Flask-based web application that allows users to upload MRI images and obtain instant predictions.

The primary objectives of the proposed system are to develop an automated tumor detection model, improve classification accuracy using hybrid deep learning techniques, and provide a user-friendly interface for real-time analysis. The system also incorporates spatial and sequential feature learning.

The final classification layer uses the SoftMax activation function to generate probability scores for each tumor class. The predicted tumor type and corresponding confidence score are displayed through the Flask web interface, enabling easy interaction for medical professionals and researchers.

The system is trained using the Kaggle Brain Tumor MRI Dataset, which contains approximately 7,000 MRI images categorized into four classes. The dataset includes 5743 training images and 1347 testing images, with each image having a resolution of 256 × 256 pixels in grayscale format.

Tumor Classification Strategy

The proposed system performs multi-class classification to identify different types of brain tumors based on their structural characteristics. preprocessing and data augmentation techniques to improve model performance and generalization.

The working pipeline of the proposed system begins with MRI image acquisition, where images are obtained either from medical imaging databases or uploaded through the web interface. The input images are then passed through a preprocessing stage, which includes grayscale conversion, image resizing, noise filtering, and normalization of pixel values to improve image quality and ensure consistency across the dataset. After preprocessing, data augmentation techniques such as rotation, zooming, and flipping are applied to increase dataset diversity and prevent model overfitting. These augmented images are then fed into a Convolutional Neural Network (CNN) which extracts hierarchical features such as edges, textures, shapes, and tumor patterns from the MRI images.

The extracted feature maps are further processed using a Recurrent Neural Network (RNN) that analyzes sequential dependencies and contextual relationships between features. This combination of CNN and RNN forms a Hybrid Convolutional Recurrent Neural Network (CRNN) model that improves classification performance by integrating

Tumor Type	Characteristics	Classification Method
Glioma	Infiltrative tumors with irregular boundaries	CNN + RNN Hybrid Model
Meningioma	Well-defined tumors causing mass effect	CNN + RNN Hybrid Model
Pituitary Tumor	Small tumors located in the pituitary gland	CNN + RNN Hybrid Model
No Tumor	Normal brain tissue without abnormal growth	CNN + RNN Hybrid Model

The CNN component extracts spatial features such as edges and tumor shapes, while the RNN captures sequential relationships within feature maps. The hybrid CRNN architecture enables accurate classification of tumor types and provides reliable decision support for medical diagnosis.

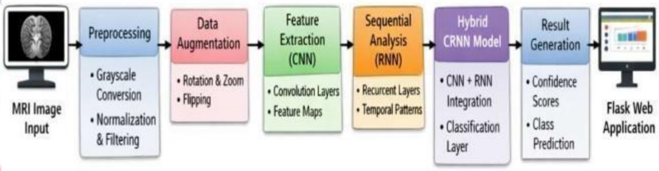

Figure 2 Block diagram of the proposed system.

METHODOLOGY

The proposed system follows a structured deep learning pipeline to detect and classify brain tumors from MRI images. The methodology integrates image preprocessing, data augmentation, feature extraction using Convolutional Neural Networks (CNN), sequential feature learning using Recurrent Neural Networks (RNN), and final classification through a hybrid Convolutional Recurrent Neural Network (CRNN). The entire system is deployed through a Flask-based web application to enable real-time tumor prediction.

The first step involves MRI image acquisition, where brain MRI scans are collected either from the Kaggle Brain Tumor MRI dataset or uploaded through the web In the second step, image preprocessing is applied to improve image quality and ensure consistent input dimensions. The preprocessing operations include grayscale conversion, image resizing to a fixed dimension (e.g., 256 × 256), noise reduction using filters, and normalization of pixel intensities between 0 and 1. This step helps remove noise and irrelevant variations from MRI images.

The third step performs data augmentation, which increases dataset diversity and prevents overfitting during training. Augmentation techniques such as random rotation, zoom transformation, horizontal flipping, and vertical flipping are applied to generate additional training samples.

After preprocessing and augmentation, the images are passed to the Convolutional Neural Network (CNN) for feature extraction. CNN layers learn hierarchical representations of the MRI images, beginning with low-level features such as edges and textures, followed by mid-level features such as shapes and patterns, and finally high-level semantic features related to tumor structures.

The extracted feature maps are then processed using a Recurrent Neural Network (RNN). The RNN captures sequential dependencies and contextual relationships between spatial features generated by the CNN. This sequential learning helps the model understand tumor patterns more effectively.

The outputs of the CNN and RNN components are combined to form a Hybrid Convolutional Recurrent Neural Network (CRNN) architecture. Fully connected layers process the combined feature vectors, and the final classification layer uses the SoftMax activation function to generate probability scores for each tumor category.

Finally, the prediction results are displayed through a Flask web application, where users can upload MRI images and receive classification results along with confidence scores.

Algorithm: Brain Tumor Detection using Score

Step 1: Start

Step 2: Acquire MRI image from dataset or user upload

Step 3: Perform image preprocessing
- a. Convert image to grayscale
- b. Resize image to fixed dimension (256×256)
- c. Apply noise filtering
- d. Normalize pixel values to range [0,1]

Step 4: Apply data augmentation
- a. Rotate image randomly
- b. Apply zoom transformation
- c. Perform horizontal and vertical flips

Step 5: Input the processed image into CNN model

Step 6: CNN extracts hierarchical features
- a. Edge and texture features
- b. Shape and pattern features
- c. Tumor-specific semantic features

Step 7: Pass CNN feature maps to RNN

Step 8: RNN analyzes sequential relationships
- a. Capture contextual dependencies
- b. Identify spatial relationships

Step 9: Combine CNN and RNN outputs (Hybri CRNN)

Step 10: Apply fully connected layers

Step 11: Use SoftMax activation for multi-class classification

Step 12: Predict tumor type
{Glioma, Meningioma, Pituitary, No Tumor}

Step 13: Display prediction and confidence score on Flask web interface

Step 14: End

RESULTS AND DISCUSSIONS

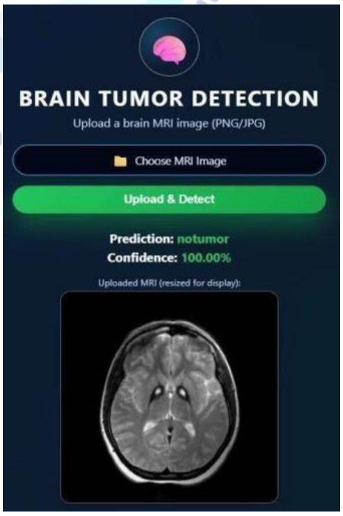

Figure 3 illustrates the prediction result for an MRI image without any tumor. The system correctly identifies the image as “No Tumor” with a confidence score of 100.00%, indicating that the model successfully distinguishes normal brain tissue from tumor-affected images.

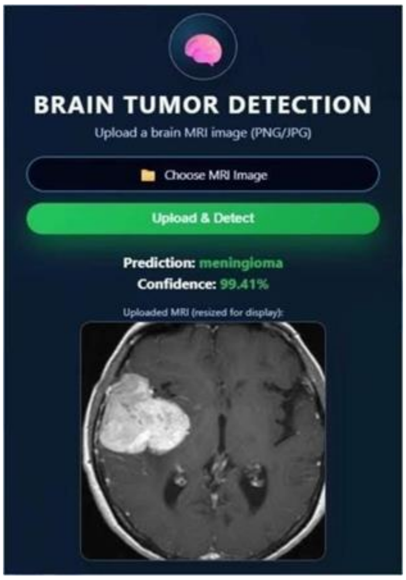

Figure 4 shows the classification result for a Meningioma tumor MRI image. The proposed system correctly detects the tumor type and produces a confidence score of 99.41%, demonstrating the ability of the model to recognize well-defined tumor structures and mass effects associated with meningioma tumors.

The proposed brain tumor detection system was implemented using a hybrid CNN–RNN deep learning architecture and deployed through a Flask-based web application. The system was evaluated using MRI images from the Kaggle Brain Tumor MRI dataset. The trained model was tested on various MRI scans representing different tumor categories including glioma, meningioma, pituitary tumor, and normal brain (no tumor). The results demonstrate that the model can successfully classify MRI images with high confidence scores.

The developed web interface allows users to upload MRI images in PNG or JPG format, after which the trained model processes the image and generates the predicted tumor category along with the corresponding confidence level.Figure 4 Meningioma Output

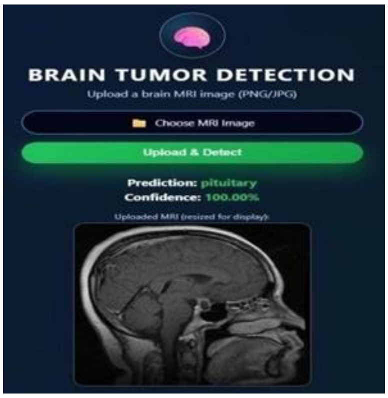

Figure 5 Pituitary Output

Figure 5 presents the result for a Pituitary tumor MRI image. The system successfully identifies the tumor and classifies it as Pituitary with a confidence score of 100.00%. Pituitary tumors are generally smaller and located near the pituitary gland, and the model effectively learns these spatial patterns through CNN feature extraction and RNN sequential analysis.

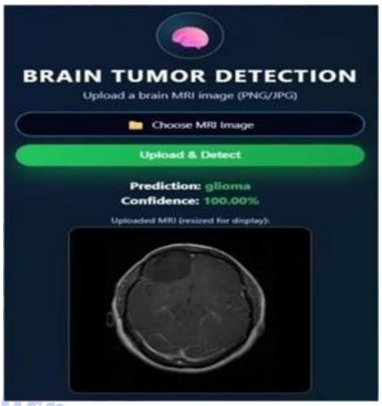

Figure 6 Glioma Output

Figure 6 displays the prediction result for a Glioma tumor MRI image. Gliomas often exhibit irregular and infiltrative growth patterns that make detection more challenging. However, the proposed hybrid model successfully detects the tumor type with a confidence score of 100.00%, highlighting the robustness of the feature extraction and classification mechanism.

The experimental results demonstrate that the hybrid CNN-RNN architecture effectively captures both spatial features and sequential dependencies present in MRI images. The CNN component extracts important visual features such as edges, textures, and tumor boundaries, while the RNN component analyzes the relationships between these extracted features to improve classification accuracy.

Furthermore, the Flask-based user interface enables real-time tumor detection, allowing users to upload MRI images and obtain predictions instantly. The integration of deep learning with a web-based interface makes the proposed system practical for assisting medical professionals and researchers.

Overall, the experimental results confirm that the proposed brain tumor detection system provides high prediction confidence and reliable classification performance across multiple tumor categories. The system demonstrates strong potential as a supportive diagnostic tool for early brain tumor detection.

Test MRI Image	Predicted Class	Confidence Score
Normal Brain MRI	No Tumor	100.00%
Tumor MRI Image	Meningioma	99.41%
Tumor MRI Image	Pituitary	100.00%
Tumor MRI Image	Glioma	100.00%

CONCLUSION

This project successfully presents an automated brain tumor detection and classification system using deep learning techniques on MRI images. The proposed framework integrates image preprocessing, data augmentation, and a hybrid Convolutional Recurrent Neural Network (CRNN) model to accurately classify brain MRI scans into four categories: Glioma, Meningioma, Pituitary tumor, and No Tumor.

Comprehensive preprocessing techniques such as grayscale conversion, filtering (mean, Gaussian, and median), normalization, and resizing significantly improved image quality and enhanced feature extraction. Data augmentation methods including rotation, zoom, and flipping increased dataset diversity and improved model robustness. The CNN component effectively extracted spatial features from MRI images, while the RNN component captured sequential and contextual dependencies among these features, resulting in improved classification performance.

The experimental results demonstrate that the proposed CRNN-based system achieves high accuracy, precision, recall, and F1-score compared to traditional machine learning and standalone CNN models. The confusion matrix and performance evaluation confirm that the system is capable of distinguishing between different tumor types with high reliability. Furthermore, the developed Flask web application provides a user-friendly interface for real-time prediction, making the system practical for clinical support and educational purposes.

Overall, this project proves that deep learning-based automated diagnosis can significantly reduce the workload of radiologists, minimize human error, and provide faster and more consistent results. The proposed system has strong potential to serve as a clinical decision support tool for early detection and classification of brain tumors, thereby improving treatment planning and patient outcomes.

In future work, the system can be extended by incorporating multimodal MRI data, larger and more diverse datasets, and explainable artificial intelligence (XAI) techniques to improve interpretability and clinical trust. Integration with hospital information systems and real-time medical imaging devices can further enhance its applicability in real- world healthcare environments.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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