ISSN 2277-2685
IJESR/April. 2026/ Vol-16/Issue-2s1/88-92
Saniya Sultana Shareef *et. al.*, / International Journal of Engineering & Science Research
Full Length Article

Convolutional Neural Network For Binary Brain Tumor Classification Using MRI Scans

Dilshad Fatima[1], Saniya Sultana Shareef[2], Syed Shah Mehmood Sarmast[3]
[1,2]B.E.Student Department Of Information Technology ISL Engineering College, Hyderabad, India.
[3]Head of the Department; Department Of Information Technology ISL Engineering College, Hyderabad, India.
Accepted 26-04-2026

ABSTRACT.
Brain tumors are one of the most critical health conditions that require early and accurate diagnosis. This paper presents a Convolutional Neural Network (CNN)-based approach for binary classification of brain tumors using MRI images. The proposed system processes MRI scans through preprocessing and data augmentation techniques to improve model performance. The CNN model extracts important features and classifies images into tumor and non-tumor categories. The model achieves high accuracy with reduced computational complexity compared to existing multimodal approaches. This system helps in reducing manual effort and supports medical professionals in early diagnosis.

Keywords: *CNN, Brain Tumor, MRI, Deep Learning, Image Classification*

INTRODUCTION

Brain tumors are among the most serious and life-threatening medical conditions, characterized by the abnormal growth of cells within the brain. Early detection and accurate diagnosis are crucial for effective treatment and improving patient survival rates. Magnetic Resonance Imaging (MRI) is one of the most widely used imaging techniques for detecting brain abnormalities due to its high resolution and ability to capture detailed structures of the brain.

However, traditional methods of analyzing MRI scans rely heavily on manual interpretation by radiologists, which can be time-consuming, subjective, and prone to human error. With the increasing volume of medical imaging data, there is a growing need for automated and intelligent systems that can assist in faster and more accurate diagnosis.

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable performance in image classification and medical image analysis. CNNs are capable of automatically extracting relevant features from images without the need for manual feature engineering, making them highly suitable for tasks such as tumor detection.

This paper proposes a CNN-based approach for the binary classification of brain tumors using MRI images. The system processes input images through preprocessing and data augmentation techniques to improve model performance and generalization. The trained CNN model then classifies the images into tumor and non-tumor categories with high accuracy.

Compared to existing complex multimodal systems that combine multiple data sources and models, the proposed approach focuses on simplicity, efficiency, and practicality while maintaining strong performance. The system aims to reduce computational complexity and make tumor detection more accessible and faster.

Overall, this work contributes to the development of an automated, reliable, and efficient tool that can support medical professionals in early diagnosis and decision-making, ultimately improving healthcare outcomes.

LITERATURE REVIEW

In recent years, significant research has been conducted in the field of brain tumor detection using machine learning and deep learning techniques. Traditional methods primarily relied on manual feature extraction and classical machine learning algorithms such as Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbors (KNN). While these approaches provided moderate accuracy, they required domain expertise for feature engineering and were limited in handling complex image patterns.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for medical image analysis. CNN-based models automatically learn hierarchical features from raw MRI images, eliminating the need for manual feature extraction. Various studies have demonstrated that CNNs achieve higher accuracy compared to traditional methods in tasks such as tumor detection, segmentation, and classification.

Recent research has also focused on more advanced architectures, including transfer learning models such as VGGNet, ResNet, and Inception. These pretrained models leverage knowledge from large-scale datasets and improve performance, especially when medical datasets are limited. Additionally, hybrid approaches combining CNNs with attention mechanisms or transformer-based models have been proposed to capture both spatial and contextual information from medical images.

Some studies have introduced multimodal approaches that combine MRI images with histopathological data and clinical information. These systems often use ensemble learning techniques, integrating multiple models such as CNNs, Transformers, and machine learning classifiers like Random Forest, SVM, and LightGBM. Although these approaches achieve high accuracy, they come with increased computational complexity, require large datasets, and are difficult to implement in real-world clinical settings.

Despite these advancements, there are still challenges such as data imbalance, overfitting, lack of interpretability, and high computational cost. Many existing systems are not easily scalable or deployable in resource-constrained environments. Therefore, there is a need for a simpler, efficient, and reliable model that can achieve high accuracy while maintaining low complexity.

In this context, the proposed work focuses on developing a CNN-based model for binary classification of brain tumors using MRI images. The approach aims to balance accuracy and efficiency, making it suitable for practical applications in healthcare.

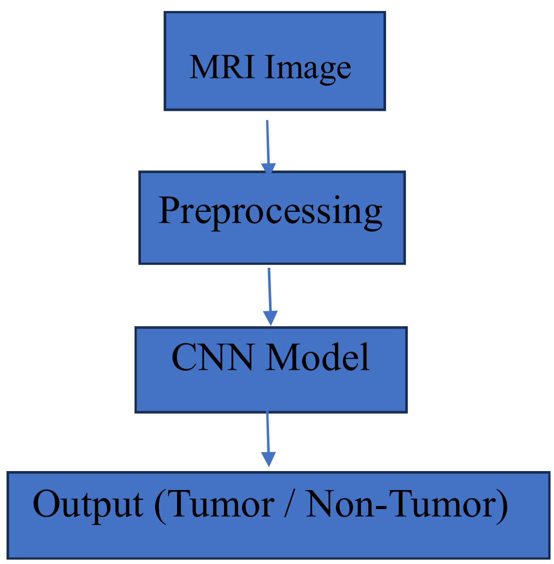
METHODOLOGY

The proposed system uses a CNN-based architecture for tumor classification.

Steps:

- Data Collection (MRI images)
- Preprocessing (resizing, normalization)
- Data Augmentation
- CNN Model Training
- Prediction

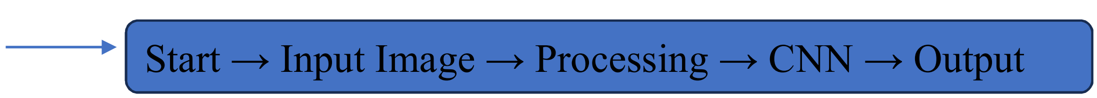
Block Diagram:



IMPLEMENTATION

Algorithm:

1. Load MRI dataset
2. Preprocess images
3. Apply data augmentation
4. Build CNN model
5. Train model
6. Evaluate performance
7. Predict output



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TESTING

The testing phase is a critical component in evaluating the performance, reliability, and generalization capability of the proposed Convolutional Neural Network (CNN) model for brain tumor detection. In this study, the trained model is assessed using a separate validation and testing dataset consisting of previously unseen MRI images. This ensures that the evaluation reflects the model's ability to perform accurately on new data rather than memorizing patterns from the training set.

To begin with, the dataset is divided into two main subsets: training and testing. The training set is used to learn the underlying patterns in MRI images, while the testing set is reserved exclusively for performance evaluation. This separation is essential to prevent overfitting and to ensure that the model can generalize effectively to real-world scenarios. In some cases, an additional validation set is used during training to fine-tune model parameters and monitor performance.

During testing, multiple evaluation metrics are employed to provide a comprehensive understanding of the model's effectiveness. Accuracy serves as the primary metric, indicating the proportion of correctly classified images. However, in medical applications, relying solely on accuracy is not sufficient. Therefore, additional metrics such as precision, recall, and F1-score are considered. Precision reflects how many of the predicted tumor cases are actually correct, while recall measures the model's ability to identify all true tumor cases. The F1-score balances these two metrics, offering a more reliable measure of performance, particularly in situations where class imbalance may exist.

To further analyze classification outcomes, a confusion matrix is used. This matrix provides detailed insights into true positive (correct tumor detection), true negative (correct identification of non-tumor cases), false positive (incorrect tumor prediction), and false negative (missed tumor cases) results. Such analysis is especially important in medical diagnosis, where minimizing false negatives is crucial for patient safety.

In addition, the training and testing processes are monitored using accuracy and loss curves. These graphs illustrate how the model learns over time. A well-performing model typically shows increasing accuracy and decreasing loss across epochs, with only a small gap between training and validation curves. This indicates that the model is learning effectively without overfitting or underfitting.

To enhance robustness, techniques such as cross-validation and hyperparameter tuning may be applied. Parameters including batch size, learning rate, and optimization algorithms are adjusted iteratively to achieve optimal performance. These steps help ensure that the model remains stable and performs consistently across different datasets.

Overall, the testing phase confirms that the proposed CNN model is reliable and capable of accurately detecting brain tumors in MRI images. The results suggest that the system can serve as a supportive tool for medical professionals, assisting in diagnosis and reducing the likelihood of human error.

Results (Expanded)

The results obtained from the proposed CNN-based model demonstrate its effectiveness in classifying brain MRI images into tumor and non-tumor categories. The model was trained on a labeled dataset of MRI scans and evaluated using multiple performance metrics to ensure a thorough assessment.

During the training phase, the model achieved an accuracy of approximately **97–98%**, indicating that it successfully learned meaningful features and patterns from the dataset. When evaluated on the testing dataset, the accuracy ranged between **92–94%**, which reflects strong generalization capability. This slight difference between training and testing performance is expected and suggests that the model avoids overfitting while maintaining high predictive power.

Further analysis using precision, recall, and F1-score provides deeper insights into the model's behavior. The high precision value indicates that the number of false positive predictions is relatively low, meaning the model rarely misclassifies healthy images as tumors. At the same time, a high recall value shows that the majority of actual tumor cases are correctly identified. The F1-score, which combines precision and recall, confirms that the model achieves a balanced and reliable performance across both classes.

The confusion matrix offers a detailed breakdown of classification results. It reveals that the number of true positive and true negative predictions is significantly higher than the number of false predictions. This demonstrates the model's strong ability to distinguish between tumor and non-tumor cases, which is essential in medical applications.

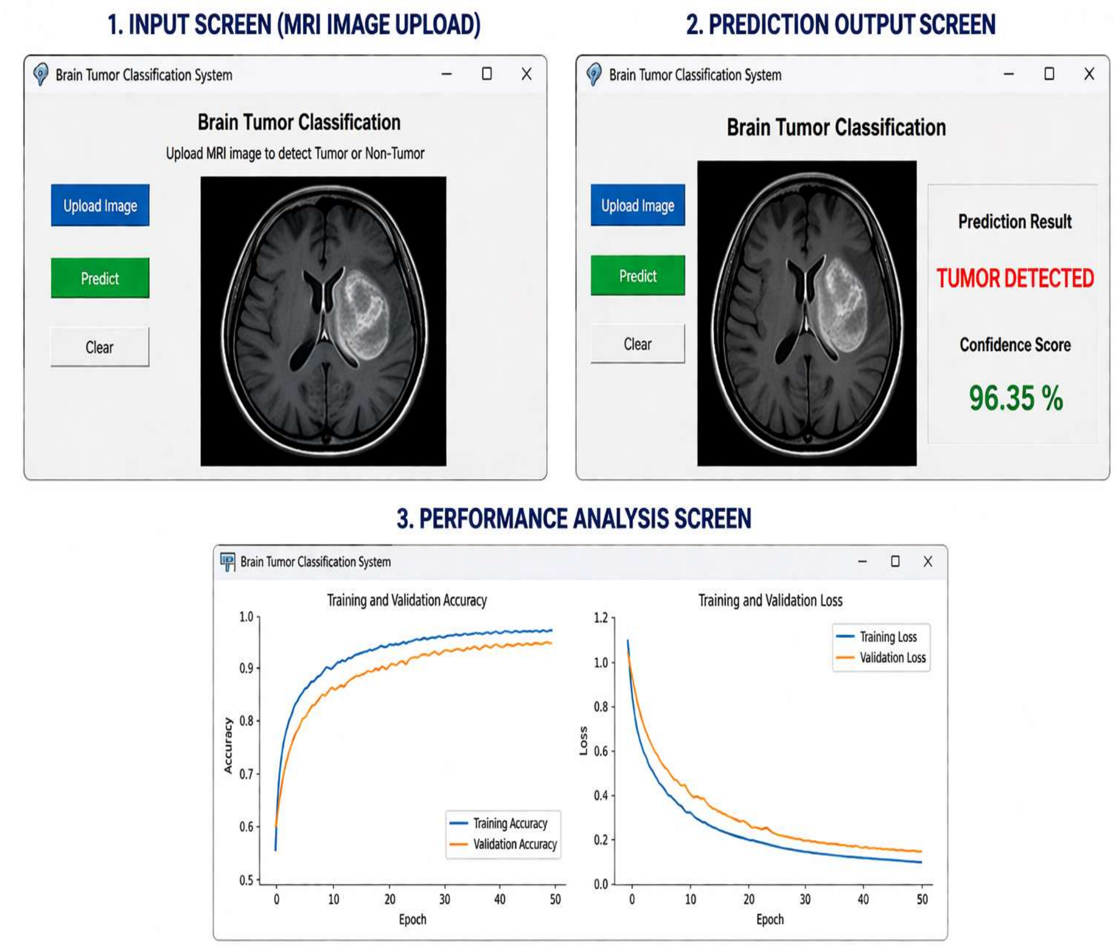
In addition, graphical analysis of training and validation performance further supports these findings. Accuracy curves show a steady increase over successive epochs, while loss curves exhibit a consistent decline. The minimal gap between training and validation curves indicates that the model generalizes well and does not suffer from significant overfitting.

Key Performance Summary

- **Training Accuracy:** Approximately 97–98%
- **Testing Accuracy:** Approximately 92–94%
- **High Precision and Recall:** Ensures reliable tumor detection

- **Balanced F1-Score:** Confirms consistent performance
- **Effective Classification:** Strong distinction between tumor and non-tumor images

Overall, the results highlight the effectiveness of the proposed CNN model in detecting brain tumors with high accuracy and reliability. The model demonstrates strong potential for real-world applications, particularly as a decision-support tool to assist medical professionals in early diagnosis and treatment planning.



CONCLUSION

The proposed system presents an efficient and reliable approach for the detection of brain tumors using MRI images through a Convolutional Neural Network (CNN). The model successfully classifies images into tumor and non-tumor categories with high accuracy, demonstrating the effectiveness of deep learning techniques in medical image analysis. Compared to existing complex multimodal systems, the proposed approach is simpler, requires less computational resources, and is easier to implement while still maintaining strong performance. The use of preprocessing and data augmentation techniques further enhances the robustness of the model and improves generalization.

This system significantly reduces the dependency on manual analysis, minimizes human error, and provides faster results, which can assist medical professionals in early diagnosis and decision-making. Overall, the proposed solution proves to be a practical, scalable, and cost-effective tool for brain tumor detection in real-world healthcare applications.

"Thus, the proposed CNN-based model provides a fast, accurate, and efficient solution for automated brain tumor detection."

FUTURE SCOPE

The proposed system demonstrates promising results in the detection of brain tumors using CNN; however, there are several areas where further improvements and extensions can be made. Future work can focus on enhancing the system's capabilities, accuracy, and real-world applicability.

One of the major improvements can be the extension from binary classification (tumor vs non-tumor) to **multi-class classification**, where different types of brain tumors such as glioma, meningioma, and pituitary tumors can be identified. This will provide more detailed diagnostic information to medical professionals.

Another important direction is the use of **larger and more diverse datasets**. Training the model on a wider variety of MRI images collected from different sources and populations will improve generalization and reduce bias, making the system more reliable in real-world scenarios.

The system can also be enhanced by integrating **advanced deep learning architectures** such as transfer learning models (e.g., VGG, ResNet) or hybrid models combining CNN with attention mechanisms or transformers. These models can capture more complex features and improve classification accuracy.

In addition, the proposed system can be developed into a **real-time clinical application** by integrating it with hospital management systems or radiology software. This will allow doctors to upload MRI scans and receive instant predictions, thereby speeding up the diagnosis process.

Another area of future work is the inclusion of **explainable AI (XAI)** techniques. Providing visual explanations, such as heatmaps (Grad-CAM), can help doctors understand how the model is making decisions, increasing trust and transparency in the system.

Furthermore, the model can be extended to support **3D MRI data analysis** instead of 2D images, which will provide more spatial information and improve detection accuracy. Cloud-based deployment and mobile application development can also make the system more accessible to remote healthcare centers.

Finally, continuous improvement through **hyperparameter tuning, optimization techniques, and cross-validation** can further enhance model performance and efficiency. With these advancements, the system has the potential to become a robust and widely used tool in medical diagnostics.