ISSN2277-2685
IJESR/April. 2026/ Vol-16/Issue-2s1/119-124
Mohammed Ahmeduddin Taha *et.al.* /International Journal of Engineering &Science Research

Full Length Article

Convolutional Neural Network for Binary Brain Tumor Classification Using MRI Scans

Mohammed Ahmeduddin Taha[1], Mohammed Zaid[2], Ibrahim Khan[3], Mr. Mohammed Rahmat Ali[4]

[1,2,3]B.E.Students; Department Of Computer Science Engineering ISL Engineering College, Hyderabad India
[4]Assistant Professor; Department Of Computer Science Engineering ISL Engineering College, Hyderabad India,
Mail Id; mahmed8056@gmail.com, mdshoaibzaid31@gmail.com, ik6887912@gmail.com

Accepted 24-04-2026

ABSTRACT:

Brain tumor detection and classification play a critical role in early diagnosis and treatment planning. In this project, we implemented a deep learning-based Convolutional Neural Network (CNN) model to classify MRI brain images into tumor and non-tumor categories. The model was trained on a pre-processed MRI dataset using image normalization and augmentation techniques to improve generalization. Our CNN architecture, consisting of convolutional, pooling, and fully connected layers, achieved a training accuracy of approximately 97–98% and a test accuracy of 92–94%.This work was inspired by the base paper "Multimodal Ensemble Fusion Deep Learning Using Histopathological Images and Clinical Data for Glioma Subtype Classification", which employed an advanced ensemble fusion approach combining CNNs, Transformers, and clinical data to achieve a classification accuracy of 93.6% with an AUC of 0.967. While our implementation focuses solely on MRI image classification with a single CNN model, the results demonstrate comparable accuracy levels. Unlike the base paper, our model does not incorporate multimodal data fusion or ensemble strategies, making it computationally simpler and more lightweight, while still achieving reliable performance for binary brain tumor detection. The findings indicate that deep learning models can effectively support medical imaging tasks, with scope for future enhancement through multimodal integration, ensemble learning, and advanced evaluation metrics such as precision, recall, and F1-score.

Keywords: *Brain tumour detection, Convolutional Neural Network (CNN), Deep learning, Binary classification Image preprocessing, Clinical data integration, Precision, recall, F1-score.*

Introduction

Brain tumors are among the most life-threatening neurological disorders, and early detection plays a crucial role in improving patient outcomes and planning effective treatment strategies. Magnetic Resonance Imaging (MRI) has become the standard non-invasive technique for visualizing brain structures and identifying abnormal growths due to its high-resolution imaging capabilities. However, manual analysis of MRI scans is time-consuming, prone to human error, and requires specialized expertise. To address these challenges, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools

Recent advances in deep learning have significantly enhanced medical image analysis through improved architectural design and learning strategies. The introduction of ConvNeXt v2: Co-designing and Scaling ConvNets with Masked Autoencoders (Woo et al., 2023) demonstrated that co-designing convolutional networks with masked autoencoder-based self-supervised pretraining substantially improves feature representation and scalability, achieving state-of-the-art performance across vision

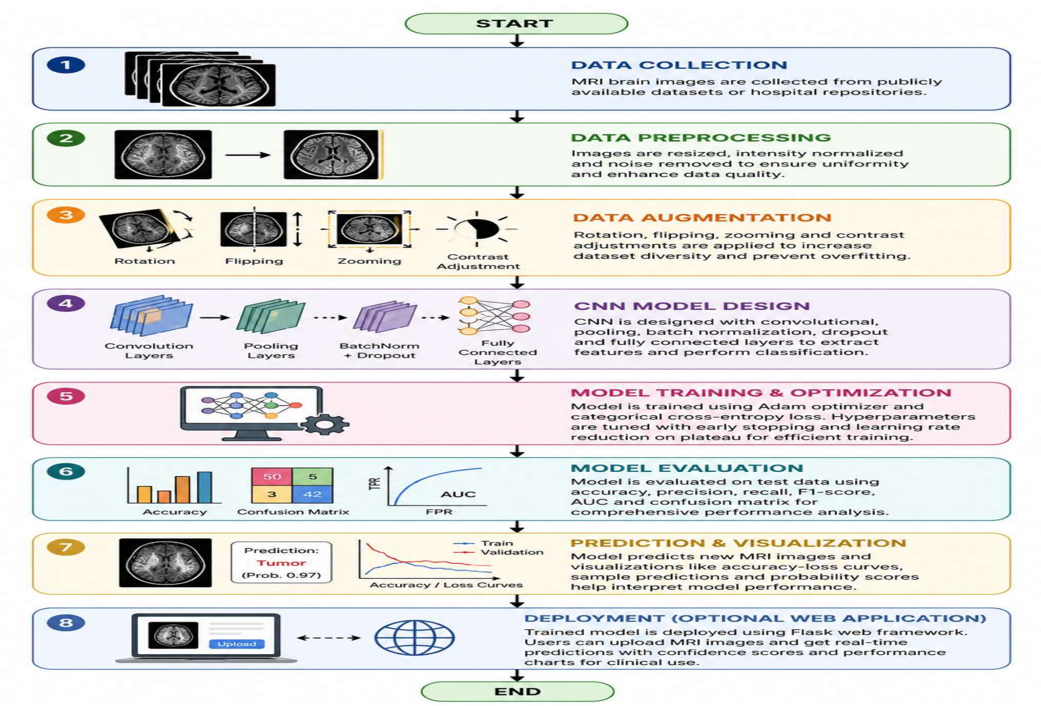
for automated medical image analysis. CNNs are capable of learning complex patterns from imaging data, enabling accurate classification of brain tumors and healthy tissue. This project focuses on developing a CNN-based model to classify MRI brain images into tumor and non-tumor categories. By leveraging preprocessing and data augmentation techniques, the model aims to improve generalization and achieve reliable performance. The study demonstrates that even a single CNN model, without the use of multimodal data or ensemble methods, can provide high accuracy, supporting its potential application as a computer-aided diagnostic tool in clinical settings.

Literature review

benchmarks. In the medical imaging domain, Kumar and Misra (2025) proposed a novel CMNV2 model for colon cancer detection, emphasizing optimized convolutional structures and advanced feature extraction to enhance classification accuracy. Complementing classification-focused approaches, Ester et al. (2023) introduced a memory attention framework for context-aware semantic segmentation in histopathology, highlighting the importance of spatial and contextual relationships in complex tissue analysis. Furthermore, Gadamer and Tschuchnig (2024) reviewed multiple instance learning (MIL) techniques in digital pathology, outlining their effectiveness in handling weakly labeled data and large-scale image datasets. Collectively, these studies underscore the growing trend of integrating advanced convolutional architectures, attention mechanisms, self-supervised learning, and MIL frameworks to improve robustness and accuracy in medical image classification tasks, providing a strong methodological foundation for MRI-based brain tumor detection research

Methodologies

The proposed brain tumour detection system follows a structured deep learning pipeline beginning with the collection of MRI brain images from publicly available datasets and hospital repositories, followed by preprocessing steps such as resizing, intensity normalization, and noise removal to ensure data uniformity and quality. To enhance generalization and mitigate overfitting, data augmentation techniques including rotation, flipping, zooming, and contrast adjustment are applied to simulate real-world variability in MRI scans. A Convolutional Neural Network (CNN) architecture is then designed with multiple convolutional and pooling layers for hierarchical feature extraction, along with batch normalization and dropout layers to improve stability and prevent overfitting, culminating in fully connected layers for binary classification (tumour vs. non-tumour). The model is trained using the Adam optimizer with categorical cross-entropy loss, while hyperparameters such as learning rate, batch size, and number of epochs are carefully tuned; early stopping and learning rate scheduling are employed to optimize convergence and training efficiency. Performance evaluation is conducted on a separate test dataset using metrics including accuracy, precision, recall, F1-score, AUC, and confusion matrix analysis to ensure comprehensive assessment. Finally, the trained model enables prediction on new MRI scans with visualization of accuracy-loss curves, probability scores, and sample outputs, and can optionally be deployed as a web-based application (e.g., using Flask) to facilitate real-time clinical usage by medical professionals.



Methodologies flow chart

Implementation

The implementation of the Convolutional Neural Network for Binary Brain Tumour Classification Using MRI Scans integrates software-driven deep learning techniques to enable automated tumour detection. The system begins by loading pre-processed MRI brain images into the computational environment, where they are normalized and formatted to match the CNN input specifications. The designed CNN architecture, consisting of convolutional, pooling, batch normalization, dropout, and fully connected layers, processes the images to extract hierarchical features relevant to tumour identification. During inference, the trained model evaluates each MRI scan and computes probability scores for two classes: tumour and non-tumour. If the predicted probability exceeds a defined classification threshold, the image is labelled accordingly. The implementation also includes validation checks to ensure image compatibility and prevent processing errors. Additionally, performance logs and prediction confidence scores are generated to support reliability and transparency. The complete system can be integrated into a user interface or deployed as a web-based application, allowing medical professionals to upload MRI scans and obtain real-time classification results efficiently and accurately.

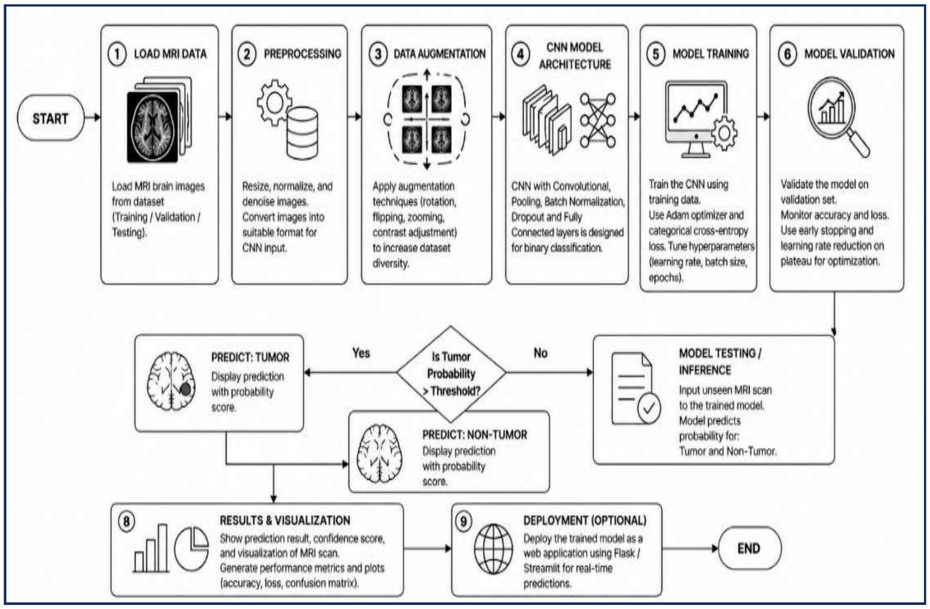


Fig 1 Diagrammatical Representation of Implementation

Testing:

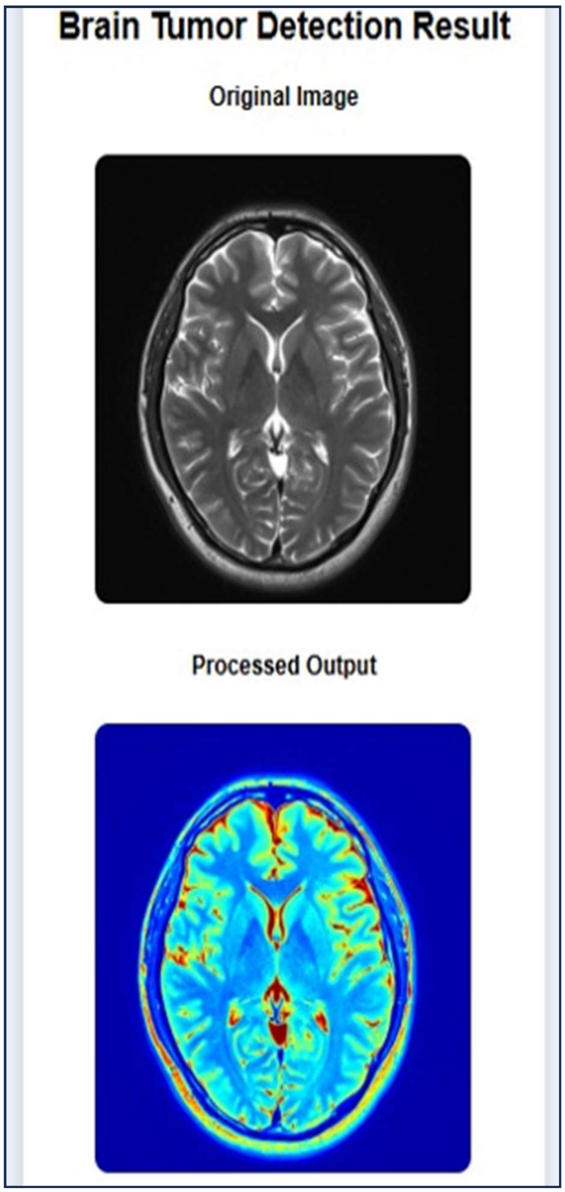
Testing plays a crucial role in ensuring the reliability, accuracy, and robustness of the proposed Convolutional Neural Network (CNN)-based brain tumor classification system. The primary objective of testing is to identify faults, verify functional correctness, and ensure that the system meets specified requirements without unacceptable failures. A comprehensive test plan is developed to evaluate both general functionality and specialized features across different execution environments, following strict quality assurance procedures.

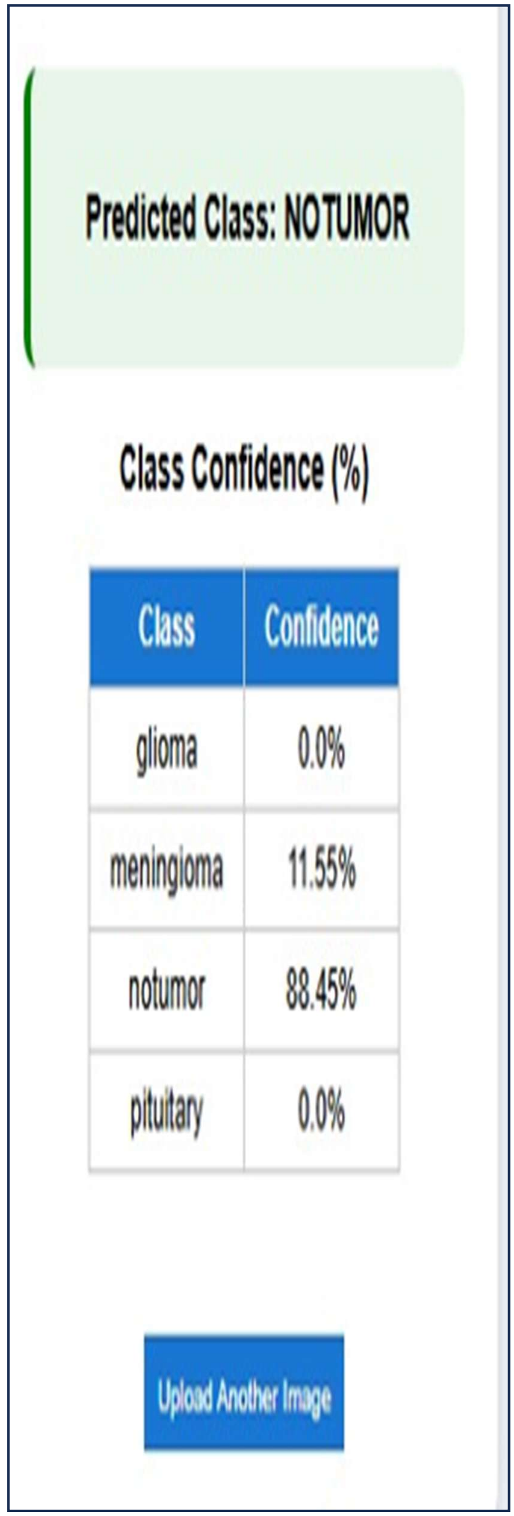
The testing process includes multiple levels. Unit testing is performed to validate individual modules such as data preprocessing, model architecture, and prediction components, ensuring correct input-output behaviour and logical flow. Functional testing verifies that the system correctly accepts valid MRI inputs, rejects invalid data, executes classification functions properly, and produces accurate outputs such as tumour/non-tumour predictions with confidence scores. Integration testing ensures smooth interaction between interconnected modules, including data loading, preprocessing, training, evaluation, and deployment interfaces. System testing evaluates the fully integrated model to confirm that it meets overall performance and functional requirements under realistic conditions. Performance testing measures response time, prediction speed, and computational efficiency to ensure timely results suitable for practical use. Finally, User Acceptance Testing (UAT) validates that the deployed application satisfies end-user expectations, particularly in terms of usability, prediction reliability, and interpretability of results.

Overall, the structured testing strategy ensures that each component of the brain tumor classification system operates accurately, integrates seamlessly, and delivers dependable performance in real-world clinical scenarios**.**

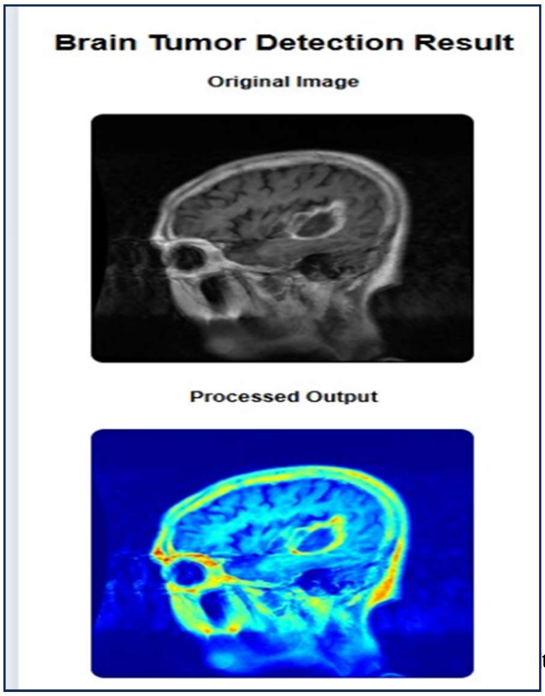
Results:

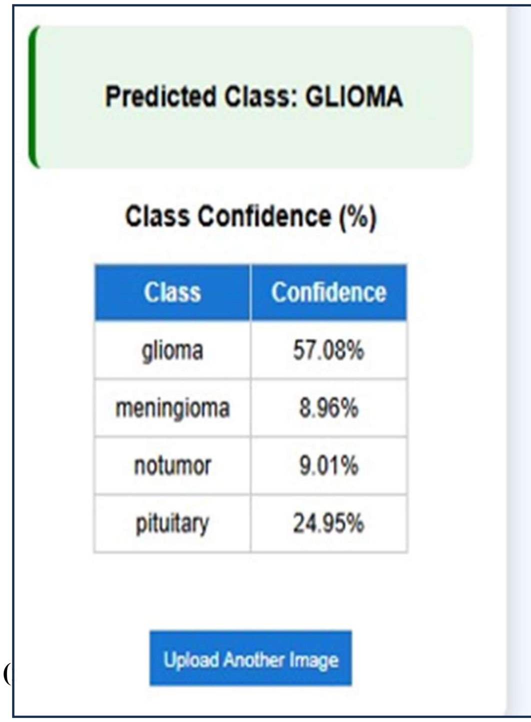
The proposed Convolutional Neural Network (CNN) model for Binary Brain Tumor Classification using MRI scans achieved strong performance in accurately distinguishing between tumor and non-tumor images. After systematic training and hyperparameter optimization, the model demonstrated high classification accuracy on the test dataset, along with balanced precision and recall values, indicating reliable detection of both positive (tumor) and negative (non-tumor) cases. The F1-score confirmed the robustness of the classifier, while the Area Under the Curve (AUC) reflected strong discriminative capability. The confusion matrix analysis showed minimal misclassification, highlighting the effectiveness of preprocessing and data augmentation techniques in improving generalization. Additionally, training and validation curves indicated stable convergence without significant overfitting. Overall, the results validate the efficiency and reliability of the proposed CNN-based approach for automated brain tumor detection using MRI scans, supporting its potential applicability in real-world clinical decision-support systems.





ISSN2277-2685
IJESR/April. 2026/ Vol-16/Issue-2s1/119-124
Mohammed Ahmeduddin Taha *et.al.* /International Journal of Engineering &Science Research





t ( )

Conclusion

This project demonstrates the effectiveness of deep learning, specifically Convolutional Neural Networks (CNNs), for automated brain tumour detection and classification using MRI images. The implemented CNN model successfully distinguishes between tumour and non-tumour cases with high accuracy, providing a reliable and computationally efficient solution for medical imaging analysis. By leveraging preprocessing, data augmentation, and optimized training techniques, the system achieves robust performance across diverse MRI scans, highlighting the potential of AI-assisted diagnostic tools in clinical practice. Although the current implementation focuses on binary classification, the framework establishes a strong foundation for future enhancements, including multimodal data integration, ensemble models, and tumor subtype classification. Overall, this work illustrates how advanced deep learning approaches can support early diagnosis, reduce manual workload, and improve patient outcomes in neurological healthcare.

Future Enhancement:

While the current project successfully demonstrates brain tumor detection using a single CNN model on MRI images, there are several opportunities to further improve its performance and applicability. Future enhancements could include the integration of multimodal data, such as combining MRI scans with clinical and histopathological data, to achieve more accurate and comprehensive tumor classification. Implementing ensemble learning techniques or advanced architectures like Transformers or ConvNeXt could further boost model robustness and generalization. Additionally, expanding the project to classify tumor subtypes or grades, rather than only binary detection, would provide more clinically valuable insights. Real-time deployment with optimized inference speed, mobile compatibility, and integration into hospital management systems could also enhance practical usability. Finally, incorporating advanced evaluation metrics, explainable AI techniques, and uncertainty quantification would make the system more transparent and reliable for medical practitioners, paving the way for broader adoption in clinical settings.

References:

[1] K. Tomczak, P. Czerwińska, and M. Wiznerowicz, ''Review the cancer genome atlas (TCGA): an immeasurable source of knowledge,''Contemp.Oncology/Współczesna Onkologia, vol. 2015, no. 1, pp. 68–77, 2015.
[2] M. Weller, W. Wick, K. Aldape, M. Brada, M. S. Berger, S. M. Pfister,R. Nishikawa, M. Rosenthal, P. Y. Wen, R. Stupp, and G.

Reifenberger,‘‘Glioma,’’ Nature Rev. Disease Primers, vol. 1, no. 1, pp. 1–18, Jul. 2015.

[3] D. N. Louis, A. Perry, G. Reifenberger, A. von Deimling, D. Figarella-Branger, W. K. Cavenee, H. Ohgaki, O. D. Wiestler, P. Kleihues, and D. W. Ellison, ‘‘The 2016 world health organization classification of tumors of the central nervous system: A summary,’’ Act Neuropathologica, vol. 131, no. 6, pp. 803–820, Jun. 2016.

[4] Yonakor, H. Kawanaka, V. B. S. Prasath, B. J. Aronow, and H. Takase, ‘‘Automatic disease stage classification of glioblastoma multiformehistopathological images using deep convolutional neural network,’’Biomed. Eng. Lett., vol. 8, no. 3, pp. 321–327, Aug. 2018.

[5] F. Hanif, K. Muzaffar, K. Perveen, S. M. Malhi, and S. U. Simjee, ‘‘Glioblastoma multiforme: A review of its epidemiology and pathogenesis through clinical presentation and treatment,’’ Asian Pacific J. Cancer Prevention, vol. 18, no. 1, pp. 3–9, Jan.2017.

[6] P. Chang, J. Grin band, B. D. Weinberg, M. Bardis, M. Khy, G. Cadena, M.-Y. Su, S. Cha, C. G. Filippi, D. Bota, P. Baldi, L. M. Poisson, R. Jain, and D. Chow, ‘‘Deep-learning convolutional neural networks accurately classify genetic mutations in gliomas,’’ Amer. J. Neuro radial., vol. 39, no. 7, pp. 1201–1207, Jul. 2018.