e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issue:10/October-2025 Impact Factor- 8.187 www.irjmets.com

STUDY OF BRAIN TUMOR DETECTION USING MULTIMODAL MRI SCANS WITH DEEP LEARNING ALGORITHM AND EDGE AI

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DOI: https://www.doi.org/10.56726/IRJMETS83399

ABSTRACT

Early identification of brain tumours through MRI scans is essential for timely treatment and improved patient survival. This work introduces an automated classification framework that integrates two convolutional neural network models—MobileNet and VGG16. MobileNet, due to its lightweight design, enables faster and resource-efficient processing, making it suitable for real-time and mobile applications. On the other hand, VGG16 provides deeper feature extraction, which improves the accuracy of tumour recognition. The proposed system categorizes MRI images into tumour and non-tumour groups, combining the speed of MobileNet with the precision of VGG16. This hybrid approach enhances diagnostic accuracy while reducing computational overhead, supporting its deployment in clinical and edge-AI environments. By assisting radiologists with reliable predictions, the framework has the potential to reduce invasive diagnostic methods and improve medical decision-making.

Keywords: Brain Tumour, MRI, MobileNet, VGG16, Deep Learning, Accuracy, Edge AI.

I. INTRODUCTION

Brain tumours are among the most serious and potentially life-threatening medical conditions, often having a profound impact on both the survival and quality of life of patients. Early and accurate detection is vital for enabling timely treatment and improving clinical outcomes. However, conventional diagnostic techniques—such as the manual interpretation of Magnetic Resonance Imaging (MRI) scans by radiologists—have inherent limitations. These include being time-intensive, heavily dependent on individual expertise, and susceptible to human error. As a result, there is a growing demand for automated, accurate diagnostic systems to support healthcare professionals in making faster and more reliable decisions regarding brain tumour detection. With the emergence of deep learning, the field of medical imaging has experienced significant advancements, offering new avenues for automating complex diagnostic tasks. This project proposes the development of an automated brain tumour classification system based on deep learning techniques, specifically utilizing the MobileNet and VGG16 architectures. The objective is to achieve a balance between high classification accuracy and computational efficiency. The rationale for selecting MobileNet and VGG16 lies in their complementary strengths. MobileNet, known for its lightweight and efficient architecture, is especially suitable for real-time inference and deployment in environments with limited computational resources, such as mobile devices and edge platforms. It maintains solid performance while minimizing the computational load, making it ideal for clinical scenarios requiring quick diagnostics. In contrast, VGG16 is renowned for its powerful feature extraction capabilities, thanks to its deep architecture, which enables the model to capture intricate patterns in imaging data—resulting in improved classification performance. By combining these two architectures, the project aims to create a reliable, efficient, and accurate system for identifying brain tumours from MRI scans. The classification task will focus on distinguishing between tumour and non-tumour cases. The system will be trained, validated, and tested using publicly available MRI datasets that contain annotated images. Ultimately, this framework is intended to support radiologists by enhancing diagnostic accuracy and streamlining clinical workflows.

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The system's performance will be evaluated using widely accepted classification metrics, including accuracy, precision, recall, and F1-score. Incorporating deep learning into the process of brain tumour detection holds promise for improving healthcare outcomes by streamlining the diagnostic workflow, reducing the burden on radiologists, and ensuring more consistent results. This approach is particularly beneficial in underserved or remote regions, where access to specialized medical professionals may be limited. MobileNet's lightweight design is especially suited for deployment on mobile devices and point-of-care systems, enabling quick, on-site screening with immediate diagnostic feedback. VGG16 complements this by offering strong feature extraction capabilities, making it effective in detecting subtle abnormalities in MRI scans that may be overlooked during manual analysis. Together, these models enhance the reliability and speed of tumour detection. Looking ahead, future developments could incorporate more advanced techniques such as image segmentation or 3D reconstruction, allowing for volumetric tumour analysis and more precise pre-surgical planning. Additionally, the system could be extended to interpret other imaging modalities, such as CT scans, or to detect a broader range of neurological disorders, increasing its clinical versatility and impact.

II. METHODOLOGY

1. System Module

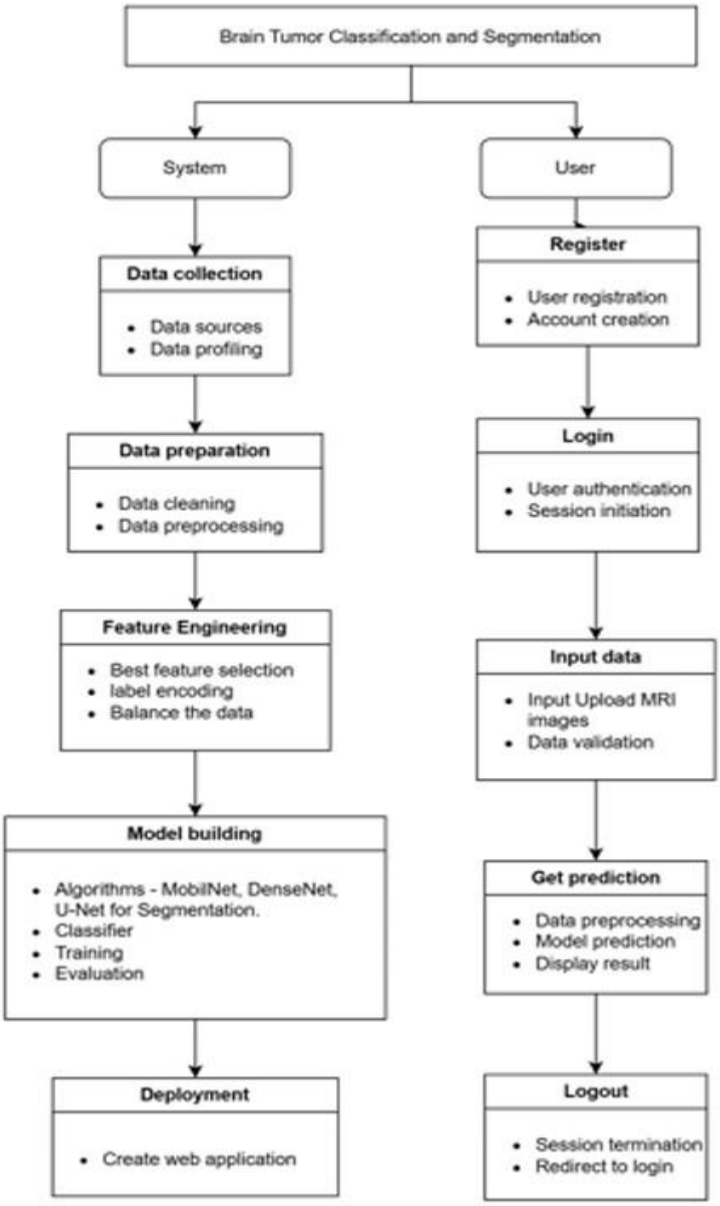

Fig. 1. Flow Chart

1.1 Data Collection: This module involves sourcing MRI brain scan data for tumour detection from publicly available datasets, such as those found on Kaggle. The data is collected and prepared for further processing.
1.2 Data Preprocessing: The collected dataset undergoes preprocessing steps, including data cleaning, handling missing values, feature engineering, and normalization. This step ensures the data is clean, consistent, and ready for training the deep learning models.
1.3 Data Splitting: The pre-processed dataset is divided into subsets for training and testing: Model Training: 80% of the data is used to train the models. During this phase, the models learn to distinguish between tumour and non-tumour images based on patterns in the dataset. Model Testing: The remaining 20% is set aside to test and evaluate the models' performance. Metrics like accuracy, precision, recall, and F1-score are calculated to measure performance.
1.4 Model Training: The deep learning models, including MobileNet and VGG16, are trained on the training subset. Iterative optimization techniques like gradient descent are used to adjust the model parameters and minimize classification errors.
1.5 Model Evaluation: Each trained model is evaluated using the testing subset. Key performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC are used to assess the effectiveness of each model in classifying MRI images as tumour or non-tumour.
1.6 Model Saving: The best-performing models are saved in a serialized format, such as .pkl, to retain learned.
1.7 Model Prediction: The saved models can be used to classify new MRI images as tumour or non-tumour in real time, supporting healthcare providers with quick and accurate diagnostic information.

2. User Module

2.1 Register: Users, such as doctors or hospital administrators, can register on the system by providing necessary details and setting up secure login credentials.
2.2 Login: Registered users log in with their credentials to access the system's features. Secure authentication ensures only authorized access.
2.3 Input Data: Users can upload new MRI images to the system. The uploaded data is then processed and fed into the trained models for tumour classification.
2.4 Viewing Results: After analysing the input data, the system displays the classification results, indicating whether the MRI image is classified as "tumour" or "non-tumour."
2.5 Logout: Users can log out to secure their session, ensuring personal data protection and preventing unauthorized access.

III. WORKING PRINCIPLE

The working principle of this project is based on the application of artificial intelligence and deep learning models to automatically classify brain MRI scans into tumour and non-tumour categories.:

A. Input (Multimodal MRI Scans): MRI brain images are collected from benchmark datasets. These images may come from different modalities (T1, T2, FLAIR, etc.) that provide complementary information about brain tissues.

B. Preprocessing: Images are resized, normalized, and augmented to remove noise and improve quality. This ensures uniformity in input data and improves the model's generalization capability.

C. Feature Extraction using Deep Learning Models: MobileNet: A lightweight convolutional neural network that extracts essential features quickly with low computational cost, making the system efficient. VGG16: A deeper convolutional neural network that extracts rich hierarchical features for more accurate classification.

D. Classification Layer: The extracted features are passed to fully connected layers. The network outputs a probability score indicating whether the MRI belongs to the tumour or non-tumour category.

E. Prediction & Output: Based on the probability score, the system classifies the MRI scan. The output is displayed to the user/doctor as either "Tumour Detected" or "No Tumour Detected."

F. Decision Support: The AI model reduces human error, speeds up diagnosis, and assists radiologists by providing quick, reliable classification results.

IV. RESULTS AND DISCUSSION

MobileNet Model

The classification report displays performance metrics for a binary classification task distinguishing between 'no-tumor' and 'tumor' categories. Precision, recall, and F1-score are provided for each class, with overall accuracy at 0.94. The model shows high precision and recall, indicating effective detection and classification of brain tumors in MRI images. The confusion matrix for the MobileNet model demonstrates exceptional performance, accurately predicting 209 instances as 'no-tumor' and 217 as 'tumor.' It only misclassified 1 'no-tumor' case as 'tumor' and 2 'tumor' cases as 'no-tumor,' reflecting a highly effective classification capability.

VGG16 Performance

The classification report shows a precision of 1.00 and a recall of 0.98 for the 'no_tumor' category, along with a precision of 0.98 and a recall of 1.00 for the 'tumor' category. The overall accuracy is reported at 0.99, indicating that the model effectively detects and classifies brain tumors with a high level of reliability, making it a valuable tool for medical imaging applications. The macro average and weighted average metrics also reflect strong model performance, with precision, recall, and F1-score values all at 0.99. The confusion matrix demonstrates strong model performance, correctly classifying 116 'no_tumor' instances and 97 'tumor' instances. There were only 2 misclassifications of 'no_tumor' as 'tumor,' while no misclassifications of 'tumor' as 'no_tumor' occurred. This performance shows that the model is particularly effective at detecting brain tumors with minimal false negatives, making it well-suited for aiding in accurate diagnosis.

V. CONCLUSION

This study presents the development of an AI-based framework for classifying brain tumours using multimodal MRI data, leveraging deep learning models such as MobileNet and VGG16. The initial phase involved assembling the dataset, applying preprocessing techniques, and conducting preliminary training of both models. Early experiments showed that both architectures successfully differentiated between tumour and non-tumour MRI images. VGG16 delivered slightly superior accuracy, while MobileNet offered faster inference times due to its lightweight design. These initial findings confirm the practicality of the proposed method and underscore the potential of AI to support radiologists in making earlier and more accurate diagnoses. Future stages of the project will focus on extensive model training, fine-tuning of hyperparameters, performance optimization, and the development of an intuitive diagnostic interface to ensure usability in real-world clinical environments.

VI. REFERENCES

[1] Mostafa, A. M., Zakariah, M., & Aldakheel, E. A. (2023). Brain Tumor Segmentation Using Deep Learning on MRI Images. Diagnostics, 13(9), 1562.

[2] Han, J. (2024). Brain tumor malignancy classification using improved VGG16 based on MRI images. Applied and Computational Engineering, 35, 221-228.

[3] Enhancing brain tumor detection in MRI images through explainable AI using Grad-CAM with ResNet50. BMC Medical Imaging, 2024.

[4] Brain tumor classification using fine-tuned transfer learning models on MRI images. (2023) uses VGG16, ResNet50, MobileNetV2 etc.

[5] Talukder, M. A., Islam, M. M., Uddin, M. A. (2023). An Optimized Ensemble Deep Learning Model For Brain Tumor Classification. arXiv preprint.

[6] Multimodal Brain Tumor Classification Using Capsule Convolution Neural Network with Differential Evolution Optimization Process. Measurement Science Review, Volume 24 (2024).

[7] Brain tumor multi classification and segmentation in MRI images using deep learning. Amin, B., et al. (2023). arXiv preprint.

[8] MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Medical Informatics & Decision Making, 2023.

[9] Brain tumor diagnoses based on VGG-16 and MobileNet. Yuheng Liu (2023). Applied and Computational Engineering

[10] Brain Tumor Classification Based on Deep Learning Techniques: An Extensive Study. ICICC 2024.

[11] Abeer Elkhouly, Mahmoud Kakouri, Mohamed Safwan, and Obada Al Khatib, "Augmented Deep Learning for Enhanced Early Brain Tumor Detection," in 2024 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET). [Publisher: IEEE]

[12] Roselinmary S. and Devadharshini Y., "Image Segmentation for MRI Brain Tumor Detection Using Advanced AI Algorithm," in 2024 2nd International Conference on Networking, Embedded and Wireless Systems (ICNEWS). [Publisher: IEEE]

[13] Swapna Sanapala, M. R. Rashmi, and Tolga Özer, "Brain Tumor Identification Using Convolutional Neural Network," in 2024 5th International Conference on Smart Electronics and Communication (ICOSEC). [Publisher: IEEE]

[14] B. Ramu and Sandeep Bansal, "Accurate Detection and Classification of Brain Tumors Using U-Net and Extreme Learning Module," in 2024 5th International Conference on Smart Electronics and Communication (ICOSEC). [Publisher: IEEE]

[15] N. Kirthiga and N. Sureshkumar, "Intelligent Techniques for the Identification and Classification of Brain Tumors," in 2024 5th International Conference on Smart Electronics and Communication (ICOSEC). [Publisher: IEEE]