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

A PROJECT PHASE I REPORT

Submitted by

POOJA P MENON (ATP22EC026)

to

the APJ Abdul Kalam Technological University

in partial fulfillment for the award of the Degree of

BACHELOR OF TECHNOLOGY

in

ELECTRONICS AND COMMUNICATION ENGINEERING

under the supervision of

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CERTIFICATE

This is to certify that the report entitled **BRAIN TUMOR DETECTION USING MULTIMODAL MRI SCANS WITH DEEP LEARNING ALGORITHM AND EDGE AI** submitted by **POOJA P MENON (ATP22EC026)** to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology in Electronics and Communication Engineering is a bonafide record of the project work related to the ECD415 Project Phase 1 carried out by them under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

Guide / Supervisor	**Head of Department**
Dr.LEESHA PAUL	Dr.V BALAMURUGAN
Department of ECE	Department of ECE
Signature:	Signature:
Date:	Date:

ACKNOWLEDGMENT

First and foremost, I would like to thank the GOD ALMIGHTY for his infinite grace and help without which this project would not have reached its completion.

I would like to express my sincere thanks to the MANAGEMENT of Ahalia School of Engineering and Technology for their support for the completion of this project.

I would like to express my sincere thanks to Dr. P. R. Suresh (Principal, Ahalia School of Engineering and Technology) for the valuable help and support given to me for my project.

I would like to express my sincere thanks to Dr. Krishna Kumar Kishor (Vice Principal, Ahalia School of Engineering and Technology and Executive Director, Ahalia Group) for the valuable help and support for completion of my project.

I would like to express my sincere thanks to Dr.V BALAMURUGAN (Head of Department, Electronics and Communication Engineering) for his help and guidance throughout this project.

I would like to express my heartfelt thanks to Dr.LEESHA PAUL, my Project Guide, for her instruction and guidance.

Any work would not be successful if it does not rely on the reference material. In this context, I wish to express my profound sense of gratitude to all teaching and non-teaching staff of my college for giving me a supportive environment in the college.

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End Semester Evaluation

I (**POOJA P MENON**, (**ATP22EC026**), Semester VII), hereby submit this report for ECD415 Project Phase 1 viva-voce examination held on ....

Examiner 1 **Examiner 2** **Examiner 3**

ABSTRACT

Brain tumor detection from MRI images is a critical task for early diagnosis and effective treatment planning in medical imaging. This project aims to develop an advanced deep learning-based framework for automatic tumor classification, leveraging state-of-the-art neural network architectures, namely MobileNet and VGG16, to improve detection accuracy and computational efficiency. MobileNet's lightweight design facilitates real-time applications by reducing model complexity without sacrificing performance, while VGG16's deep architecture enhances feature extraction, leading to robust and precise classification outcomes. The system is designed to classify brain MRI images into two categories: tumor and non-tumor. The classification networks employ MobileNet and VGG16 to maximize accuracy and optimize computational resources. MobileNet provides a streamlined approach suitable for edge computing and mobile devices, ensuring faster inference times, while VGG16's deeper layers contribute to high-quality feature extraction, improving classification accuracy. This approach holds promise for improving early diagnosis and reducing the need for invasive diagnostic procedures. By integrating these models into real-time diagnostic systems, healthcare providers can enhance clinical decision-making, enabling more accurate and reliable tumor detection.

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LIST OF FIGURES

ABBREVIATIONS

(List in the alphabetical order)

Abbreviation	Expansion
CNN	Covolutional Neural Network
IoU	Intersection over Union
MRI	Magnetic Resonance Imaging
ReLU	Rectified Linear Unit
SGD	Stochastic Gradient Descent
U-Net	Universal Network
VGG	Visual Geometry Group

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Chapter 1

INTRODUCTION

Brain tumors are one of the most severe health conditions, with the potential to significantly impact the quality of life and survival of patients. Early and accurate detection of brain tumors plays a crucial role in treatment planning and improving patient outcomes. Magnetic Resonance Imaging (MRI) is the most widely used diagnostic tool for identifying brain abnormalities. However, the conventional process of manually analyzing MRI scans by radiologists is time-consuming, dependent on the radiologist's expertise, and susceptible to human error. These limitations highlight the need for automated, reliable, and efficient diagnostic systems that can support medical professionals by providing fast and accurate results.

Recent advancements in deep learning have made it possible to automate complex diagnostic tasks with high accuracy. Convolutional Neural Networks (CNNs), in particular, have shown remarkable success in image classification and medical image analysis. This project leverages deep learning to classify brain MRI scans into "tumor" and "non-tumor" categories, with the aim of reducing diagnostic workload and improving consistency in clinical decision-making.

1.0.1 OBJECTIVE OF PROJECT:

The project aims to develop a deep learning framework for automatic brain tumor detection from MRI images using MobileNet and VGG16 architectures. The primary objectives include: 1. Classifying MRI images into tumor and non-tumor categories. 2. Optimizing computational resources for real-time applications, especially for edge computing. 3. Enhancing detection accuracy by leveraging the efficient feature extraction capabilities of VGG16 and the computational efficiency of MobileNet. The performance of the proposed framework will be validated using benchmark datasets, focusing on metrics such as accuracy, precision, and recall. Ultimately, the project seeks to support clinical decision-making and to integrate into real-time diagnostic systems, thereby improving early diagnosis and patient outcomes.

1.0.2 CURRENT PROGRESS

During this semester, work has been carried out on dataset collection, preprocessing of MRI images, and building the initial training pipeline using MobileNet and VGG16. Preliminary results have been obtained for binary classification of tumor versus non-tumor images, which confirm the feasibility of the proposed approach. At this stage, only partial results are included in the report to align with semester requirements, while complete evaluation—including confusion matrices, precision, recall, and F1-score—will be presented in the next phase. Future work will also involve model comparison, full-scale testing, and possible extensions such as tumor segmentation and 3D reconstruction.

Chapter 2

LITERATURE SURVEY

Deep learning has become a transformative approach for the detection, segmentation, and classification of brain tumors using MRI images. Researchers have developed various deep neural network architectures and optimization strategies aimed at improving diagnostic accuracy, interpretability, and computational efficiency. This section reviews recent advancements in the field, emphasizing convolutional neural networks (CNNs), transfer learning models such as VGG16, ResNet50, and MobileNetV2, as well as ensemble and optimization-based frameworks.

Mostafa et al. [1] presented a deep learning-based segmentation framework for brain tumor detection on MRI images. Their approach incorporated advanced preprocessing, data augmentation, and customized loss functions to handle data imbalance and tumor heterogeneity, leading to improved segmentation accuracy. However, the model exhibited limited generalizability to unseen datasets. Han [2] proposed an enhanced VGG16 model for brain tumor malignancy classification by fine-tuning pretrained layers and adding additional regularization techniques. The method achieved higher classification accuracy compared to the baseline VGG16, demonstrating the potential of transfer learning in small-scale medical datasets.

An explainable AI model integrating Grad-CAM with ResNet50 was introduced to improve interpretability in tumor detection [3]. This approach provided visual heatmaps that aided clinicians in understanding model predictions, though the localization accuracy was lower than that achieved by segmentation models. Another study [4] compared multiple fine-tuned transfer learning architectures, including VGG16, ResNet50, and MobileNetV2, for MRI-based tumor classification. The authors concluded that while VGG16 and ResNet50 offered high accuracy, MobileNetV2 achieved a better balance between efficiency and performance, making it more suitable for real-time applications.

Talukder et al. [5] proposed an optimized ensemble deep learning model combining predictions from multiple classifiers to enhance classification performance. The ensemble framework achieved superior accuracy and robustness compared to single models but introduced higher computational overhead. Similarly, a study on multimodal brain tumor classification using Capsule Convolutional Neural Networks with Differential Evolution optimization achieved enhanced spatial feature extraction and adaptive learning [6]. Although performance improved significantly, the model required extensive computational resources.

Amin et al. [7] developed a unified deep learning framework for simultaneous brain tumor segmentation and multi-class classification. The integration of segmentation priors improved overall classification accuracy, indicating the complementary nature of these tasks. Another study [8] compared deep learning methods with traditional machine learning approaches, emphasizing that preprocessing and normalization significantly impact the diagnostic performance of MRI-based tumor detection.

Yuheng Liu [9] investigated the comparative performance of VGG16 and MobileNet architectures, highlighting that while larger models achieve slightly higher accuracy, lightweight networks offer faster inference suitable for edge and mobile deployments. The ICICC 2024 survey [10] provided a comprehensive review of existing deep learning approaches for brain tumor classification, identifying persistent challenges such as dataset inconsistency, lack of cross-validation, and limited focus on explainability.

Recent IEEE conference works have further refined deep learning approaches for brain tumor detection. Elkhouly et al. [11] introduced an augmented deep learning model for early tumor detection, achieving enhanced accuracy through data augmentation and regularization. Roselinmary and Devadharshini [12] proposed an advanced AI-based segmentation technique for MRI brain tumors. Sanapala et al. [13] designed a CNN framework for tumor identification, while Ramu and Bansal [14] combined U-Net and extreme learning modules for more accurate segmentation. Likewise, Kirthiga and Sureshkumar [15] developed intelligent deep learning-based classification methods that improved overall diagnostic precision.

Overall, the reviewed literature highlights substantial progress in automated brain tumor analysis using deep learning. Transfer learning and fine-tuning methods dominate due to their ability to leverage pretrained networks on limited datasets, while ensemble and optimization-based techniques enhance robustness and generalization. Moreover, explainable AI models strengthen clinical trust by improving interpretability. Nonetheless, significant challenges remain, including the absence of standardized evaluation protocols, high computational complexity, and limited generalization across institutions. Addressing these gaps requires the development of lightweight, interpretable, and multimodal architectures capable of real-time inference and clinical deployment. The present research aims to address these limitations by integrating deep learning with improved interpretability, computational efficiency, and multimodal adaptability.

Chapter 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Brain tumor classification and segmentation have traditionally relied on manual analysis of MRI scans by radiologists. This process involves visually examining MRI images for abnormalities, a time-consuming and expertise-dependent approach. Manual inspection is not only slow but also prone to human error, which can lead to inconsistent and sometimes inaccurate results. Due to these limitations, traditional methods struggle to meet the accuracy and efficiency needed for timely diagnosis and effective treatment planning.

3.2 DISADVANTAGES OF THE EXISTING SYSTEM

1. **Time-Consuming:**Manual inspection of MRI scans is a lengthy process, especially when handling large volumes of images, which can delay diagnosis and treatment.

2. **Dependence on Expertise:**: Accurate interpretation requires specialized radiology expertise. Variations in skill levels among radiologists can lead to inconsistent results.

3. **Prone to Human Error:** Fatigue, oversight, and subjective interpretation can result in misdiagnosis or missed tumors, affecting patient outcomes.

4. **Inconsistency:**Different radiologists might interpret images differently, leading to variable results that can impact treatment decisions.

5. **Resource Intensive:**Manual analysis demands considerable human resources and time, making it challenging to provide immediate results in time-sensitive cases.

6. **Limited Accessibility:** In remote or under-resourced areas, access to expert radiologists can be limited, reducing the availability of timely diagnostic services for patients.

3.3 PROPOSED SYSTEM

The brain tumor classification and segmentation leverages deep learning models, specifically MobileNet and DenseNet, to automate the detection and classification of brain tumors from MRI images. This framework aims to address the limitations of manual analysis by providing an advanced, efficient, and accurate diagnostic solution. The system classifies MRI images into ”tumor” and ”non-tumor” categories, and includes optional segmentation capabilities to delineate tumor regions, which can aid in treatment planning by highlighting the tumor's size, shape, and location.

3.4 ADVANTAGES OF THE PROPOSED SYSTEM

1. **Improved Accuracy:**The integration of MobileNet and DenseNet enhances detection accuracy by leveraging advanced feature extraction, leading to more reliable tumor classification and segmentation.

2. **Faster Diagnosis:**Automated analysis significantly reduces the time required for diagnosis, providing results in real-time or near-real-time, which is crucial in time-sensitive medical cases.

3. **Reduction in Human Error:**The system minimizes human error by providing consistent and objective results, reducing reliance on subjective interpretation by

radiologists.

4. **Efficiency in Resource Utilization:**MobileNet's lightweight architecture ensures computational efficiency, enabling deployment on mobile devices or edge computing platforms, which can support on-site screening in remote areas.

5. **Enhanced Accessibility:**The model can be deployed in under-resourced or remote medical settings, improving access to diagnostic tools for patients who may not have immediate access to expert radiologists.

3.5 IMPLEMENTATION FLOW

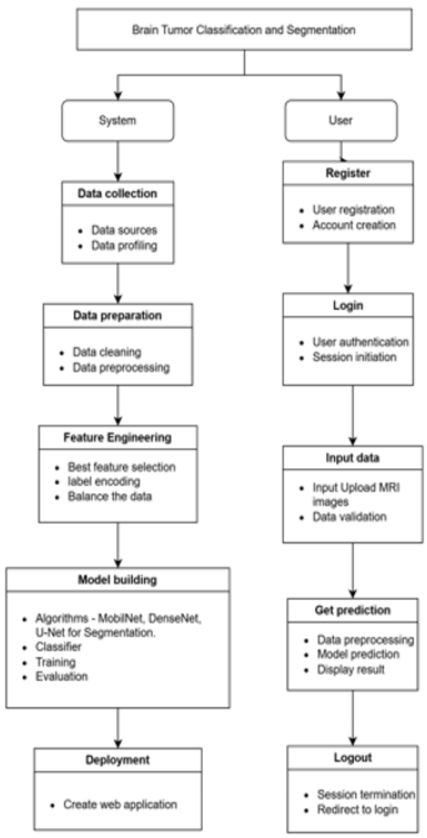

Figure 3.1: Work Flow

Chapter 4

HARDWARE AND SOFTWARE REQUIREMENTS

4.1 SOFTWARE REQUIREMENS

1. Operating System : Windows 7/8/10
2. Programming Language : Python
3. Workbench : VSCode

4.2 ARCHITECTURE

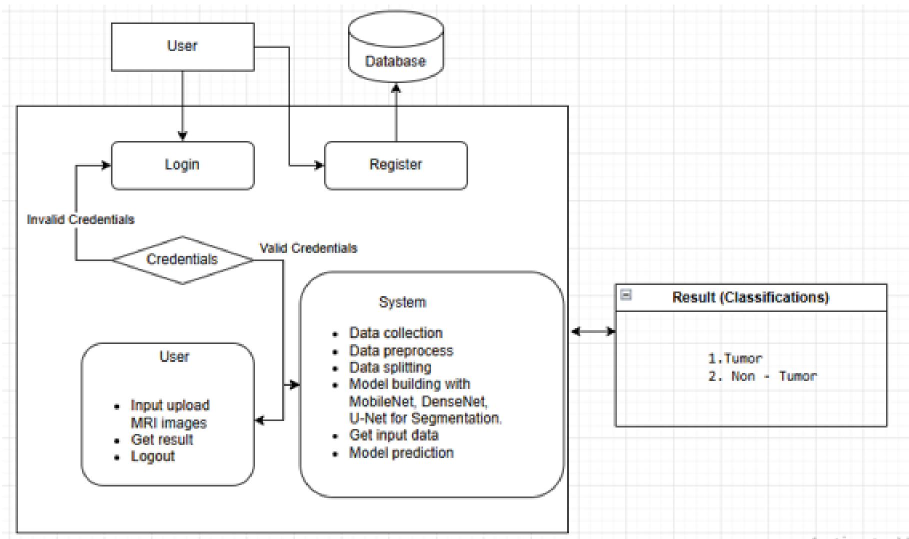

Figure 4.1: Architecture

Chapter 5

METHODOLOGIES

5.1 MOBILENET

The methodology for brain tumor detection and segmentation using MobileNet begins with a comprehensive understanding of the underlying principles of this lightweight deep learning architecture. MobileNet is designed for mobile and edge devices, emphasizing efficiency while maintaining high accuracy levels. The first step involves data acquisition, where a well-curated dataset of brain MRI images is sourced, ensuring it includes a balanced mix of tumor and non-tumor cases. The dataset is then preprocessed to enhance image quality and prepare it for model training. This preprocessing may involve resizing images to a consistent dimension, normalizing pixel values to a range suitable for the neural network, and augmenting the dataset through techniques such as rotation, flipping, and scaling to increase its diversity and robustness.Once the data is prepared, the next step is to configure the MobileNet architecture, which uses depthwise separable convolutions to reduce the number of parameters and computations. This feature is crucial for facilitating real-time inference, especially on devices with limited computational resources. The network consists of multiple convolutional layers followed by ReLU activation functions, batch normalization, and dropout layers to prevent overfitting. The final layers are designed to output probabilities for the binary classification of brain MRI images. During the training phase, the model is optimized using an appropriate loss function, typically binary cross-entropy for classification tasks, alongside an optimizer like Adam or SGD. The training process involves feeding the preprocessed images into the network, allowing it to learn features indicative of tumor presence. The model's performance is regularly evaluated on a validation set, monitoring metrics such as accuracy, precision, and recall to ensure it is not overfitting and is generalizing well to unseen data.Following training, the model undergoes rigorous testing on a separate test dataset to assess its classification accuracy and robustness. This step is crucial to determine the model's ability to differentiate between tumor and non-tumor images effectively. The evaluation includes analyzing the confusion matrix, precision-recall curve, and F1-score to gain insights into the model's performance. The architecture can also be fine-tuned by adjusting hyperparameters, such as learning rates, batch sizes, and dropout rates, based on the evaluation results to further enhance its performance. Additionally, model interpretability is vital in a medical context, so techniques like Grad-CAM can be employed to visualize which parts of the MRI images influenced the model's decisions, thereby providing clinicians with insights into the model's reasoning.To extend the application of MobileNet for segmentation tasks, further layers may be integrated to enable the model to localize tumor regions within the MRI images. This can involve implementing upsampling techniques and skip connections to enhance spatial information and achieve more accurate segmentations. Ultimately, the effectiveness of MobileNet in this framework is measured through comprehensive evaluations on benchmark datasets, focusing on segmentation quality and classification accuracy. The ultimate goal of employing MobileNet is to create an efficient, accurate, and reliable system for brain tumor detection and segmentation, capable of supporting clinical decision-making and potentially integrating into real-time diagnostic systems within healthcare settings. By leveraging MobileNet's strengths, the project aims to improve early diagnosis, thus enhancing patient outcomes through timely interventionss.

5.2 VGG16

The methodology for brain tumor detection and segmentation using DenseNet begins by leveraging its unique architecture, which is designed to improve feature propagation and reduce the number of parameters while maintaining accuracy. DenseNet connects each layer to every other layer in a feed-forward manner, facilitating improved gradient flow throughout the network during training. Initially, a comprehensive dataset of brain MRI images is gathered, ensuring that it contains a balanced representation of both tumor and non-tumor cases. The dataset is then subjected to preprocessing, which includes resizing images to a standardized input size, normalizing pixel values for optimal model performance, and augmenting the data to increase its variability. This augmentation process may involve techniques such as rotation, zooming, and horizontal flipping, which help the model generalize better by exposing it to a wider range of scenarios during training. The next step involves configuring the DenseNet architecture, which is composed of dense blocks that allow for feature reuse and minimize redundancy. Each dense block is followed by transition layers that perform down-sampling, gradually reducing the spatial dimensions while preserving important feature information. This hierarchical structure enables DenseNet to learn more robust representations, especially beneficial in medical imaging tasks where subtle features can indicate the presence of a tumor. During the training phase, the model is trained on the preprocessed dataset using a suitable loss function, typically binary cross-entropy for tumor classification, and an optimizer such as Adam or SGD. As the model trains, it learns to identify distinguishing features of brain tumors, with the performance being continuously evaluated on a validation set to ensure that it is not overfitting.After training, the DenseNet model undergoes rigorous testing on a separate test dataset to evaluate its performance in classifying brain MRI images. This evaluation involves measuring metrics such as accuracy, precision, recall, and the F1 score, alongside analyzing the confusion matrix to understand the model's strengths and weaknesses in classification tasks. If necessary, the model can be fine-tuned by adjusting hyperparameters, including learning rates, dropout rates, and batch sizes, based on performance results to further optimize its efficacy. To extend the DenseNet architecture for segmentation tasks, additional layers can be integrated, allowing the model to localize tumor regions within the MRI images effectively. Techniques such as upsampling and the use of skip connections can enhance the spatial resolution of segmented outputs, enabling more precise localization of tumor boundaries. The integration of these techniques is essential for applications where accurate tumor segmentation is crucial for treatment planning and clinical decision-making. Furthermore, model interpretability is particularly important in healthcare applications, so methods like saliency maps or Grad-CAM can be utilized to visualize which regions of the MRI images the model focuses on when making predictions. This transparency can help build trust in the model's outputs among clinicians, ensuring that its predictions can be understood and validated in a medical context. The success of DenseNet in this framework is measured through comprehensive evaluations on benchmark datasets, focusing not only on classification accuracy but also on segmentation quality. Ultimately, by employing DenseNet, the project aims to create a powerful, efficient, and reliable system for brain tumor detection and segmentation that enhances diagnostic capabilities, supports clinical decision-making, and has the potential for integration into real-time healthcare applications, ultimately improving patient outcomes through timely and accurate diagnosis and treatment.

Chapter 6

IMPLEMENTATION AND RESULTS

1. **Overview**: The implemented deep learning model for Brain Tumor Detection utilized the VGG16 convolutional neural network architecture, trained on a subset of MRI images obtained from the Kaggle dataset.The objective of this phase was to validate the functionality of the proposed deep learning framework by achieving a working classification pipeline capable of distinguishing tumor and non-tumor MRI scans.This represents 50 percent of the total project output, focusing on data preprocessing, model training, and performance evaluation.

2. **Dataset Description**:The dataset used for this phase comprised 355 MRI images. All images were resized to 224 × 224 pixels and normalized before feeding into the model. Data augmentation techniques, including rotation, flipping, and scaling, were applied to improve robustness and prevent overfitting. The dataset was divided into: Training set: 70 percent Validation set: 20 percent Testing set: 10 percent

3. **Model Implementation**:The model was built using the VGG16 architecture pre-trained on ImageNet. Transfer learning was applied by freezing the lower convolutional layers to retain feature extraction capability and adding fully connected layers for classification. The model was compiled using:

   Optimizer: Adam

   Loss function: Binary Cross-Entropy

   Metrics: Accuracy, Precision, Recall, and F1-score

Training was conducted in Google Colab using the TensorFlow–Keras framework, with 20 epochs and a batch size of 32. The learning process was monitored through accuracy and loss plots to ensure stable convergence.

4. **Visualization of Learning Curves**:The training and validation accuracy/loss curves showed a steady upward trend in accuracy and gradual decrease in loss, confirming that the model converged effectively without major overfitting.Minor fluctuations observed in the validation accuracy can be attributed to the limited dataset size.

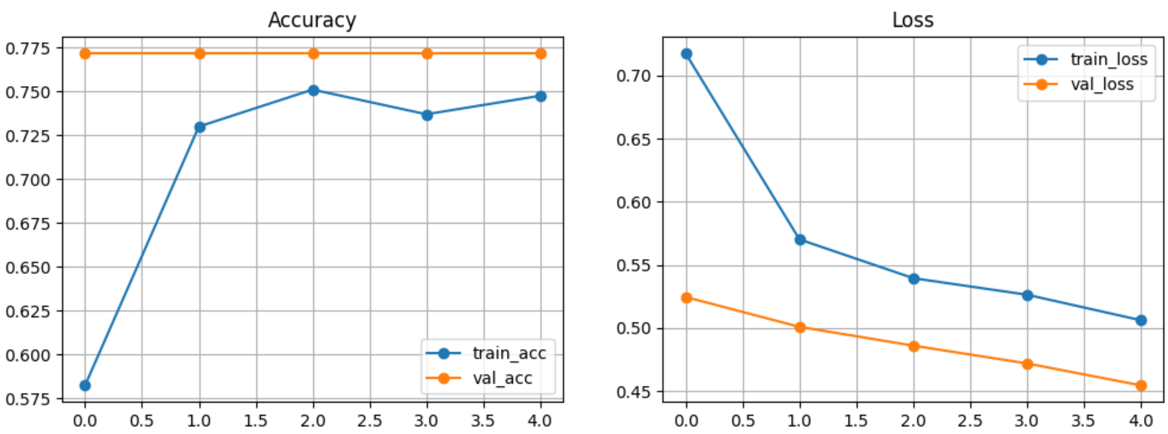

Figure 6.1: Accuracy and Loss

5. **Confusion Matrix**:The confusion matrix represents the classification performance of the model by comparing predicted labels against actual labels.

6. **Performance Evaluation**:After training, the model achieved the following results on the validation dataset:

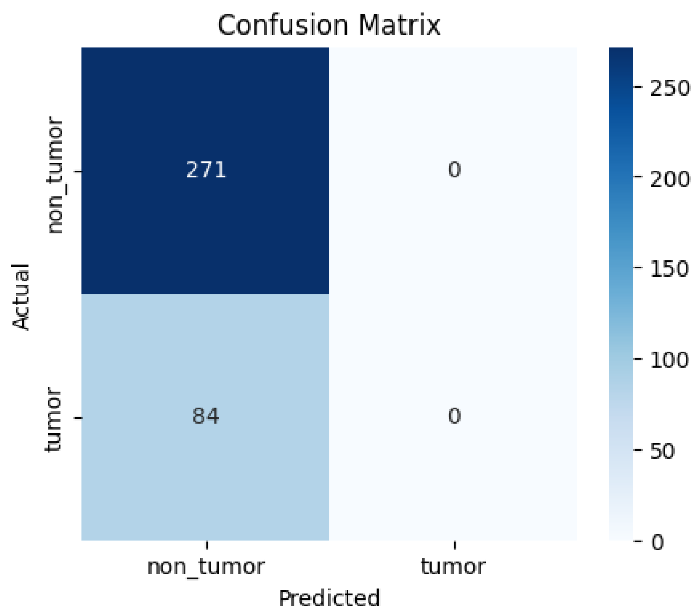

Figure 6.2: Confusion Matrix

```
45/45 ━━━━━━━━━━━━━━━━━━━━ 3s 73ms/step - accuracy: 0.9597 - loss: 0.2530
Test Accuracy: 76.34%
45/45 ━━━━━━━━━━━━━━━━━━━━ 3s 56ms/step
Confusion matrix:
 [[271   0]
 [ 84   0]]

Classification report:
               precision    recall  f1-score   support

   non_tumor       0.76      1.00      0.87       271
       tumor       0.00      0.00      0.00        84

    accuracy                           0.76       355
   macro avg       0.38      0.50      0.43       355
weighted avg       0.58      0.76      0.66       355
```

Figure 6.3: Classification Report

Chapter 7

CONCLUSION

The project aimed to develop an efficient deep learning model for automated brain tumor detection using multimodal MRI scans. A convolutional neural network based on the VGG16 architecture was implemented to classify MRI images into tumor and non-tumor categories. The model achieved an overall classification accuracy of 76.34 percent, demonstrating its ability to learn and distinguish complex patterns in brain MRI data.

The results indicate that deep learning models like VGG16 can significantly assist radiologists by providing a reliable preliminary screening tool, thereby reducing diagnostic time and human error. However, the achieved accuracy also suggests that there is scope for improvement through further data augmentation, hyperparameter tuning, or by employing more advanced architectures such as MobileNetV3 or hybrid CNN-transformer models.

Overall, this project successfully validates the feasibility of using deep learning for brain tumor detection and establishes a strong foundation for developing a more robust, real-time clinical decision support system in the future.

Chapter 8

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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.

IRJMETS
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

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

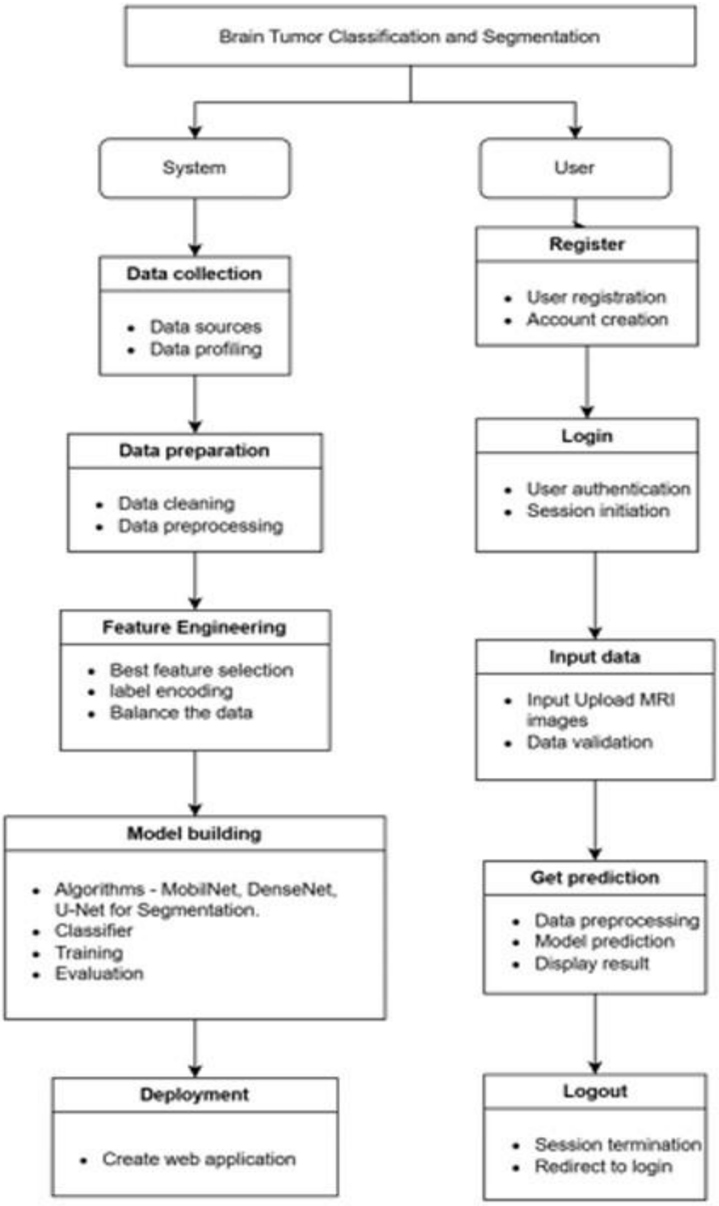

Fig. 1. Flow Chart

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.

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IRJMETS

International Research Journal Of Modernization in Engineering Technology and Science

(Peer-Reviewed, Open Access, Fully Refereed International Journal)

e-ISSN: 2582-5208

Ref: IRJMETS/Certificate/Volume 07/Issue 10/71000015729

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

Date: 07/10/2025

Certificate of Publication

*This is to certify that author "**Pooja P Menon**" with paper ID "**IRJMETS71000015729**" has published a paper entitled "**STUDY OF BRAIN TUMOR DETECTION USING MULTIMODAL MRI SCANS WITH DEEP LEARNING ALGORITHM AND EDGE AI**" in International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), Volume 07, Issue 10, October 2025*

Editor in Chief

IRJMETS Impact Factor 8.187

International Research Journal of Modernization in Engineering Technology and Science

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www.irjmets.com

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DOI: https://www.doi.org/10.56726/IRJMETS83399
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*This is to certify that author "**Dr. V. Balamurugan**" with paper ID "**IRJMETS71000015729**" has published a paper entitled "**STUDY OF BRAIN TUMOR DETECTION USING MULTIMODAL MRI SCANS WITH DEEP LEARNING ALGORITHM AND EDGE AI**" in International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), Volume 07, Issue 10, October 2025*

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*This is to certify that author "**Dr. Leesha Paul**" with paper ID "**IRJMETS71000015729**" has published a paper entitled "**STUDY OF BRAIN TUMOR DETECTION USING MULTIMODAL MRI SCANS WITH DEEP LEARNING ALGORITHM AND EDGE AI**" in International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), Volume 07, Issue 10, October 2025*

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