International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 1756-1762
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0229

Deep Feature Representation Learning For MRI-Based Brain Tumor Diagnosis Using Transfer Learning

Mr. N. Bala Kishore[1], Dandu Venkata Mani Kumar[2], M. Raviteja[3], B. Purandhar Achari[4]
[1,2,3,4]Department of Computer Science and Engineering and Business Systems, Rajeev Gandhi Memorial College of Engineering and Technology, Nandyal (Dist.), Andhra Pradesh, India.
Emails: *kishore.naaru@gmail.com[1], venkatamani1417@gmail.com[2], matapathiraviteja@gmail.com[3], puranddhar.achari1@gmail.com[4]*

Abstract
This paper presents a transfer learning-based approach utilizing the VGG16 architecture for the automatic detection and classification of multi-class brain tumors from magnetic resonance imaging (MRI) scans. The proposed method includes a preprocessing pipeline involving denoising, grayscale conversion, normalization, and resizing to 224 × 224 × 3. The VGG16 model is fine-tuned with dropout regularization and the Adam optimization algorithm. Experimental evaluation on a dataset of 1,343 MRI images comprising pituitary tumor, meningioma, glioma, and non-tumor classes achieved an overall accuracy of 94%, with average precision, recall, and F1-score of 0.94, 0.93, and 0.93, respectively. The results demonstrate that the proposed model provides robust and reliable performance, supporting its applicability as a clinical decision-support system for brain tumor diagnosis.

Keywords: *Brain tumor, magnetic resonance imaging (MRI), deep learning, convolutional neural network (CNN), VGG16, transfer learning, multi-class classification.*

1. Introduction
The problem of brain tumor is very serious in the world as it is very morbid and fatal particularly when it is diagnosed at the advanced stages. They are tumors which arise due to uncontrolled and abnormal cell growth of the brain and other tissues of central nervous system which can lead to severe neurological and functional impairments. The diagnosis of the disease at the early and proper stage is therefore of the utmost importance in enhancing the survival rates of the patients and the kind of effective treatment that must be administered. New systematic reviews also indicate that brain tumor diagnosis is a complex and resource-intensive task that is highly dependent on professional interpretation of magnetic resonance imaging (MRI) despite the emergence of new clinical imaging techniques [1].The Introduction presents the purpose of the studies reported and their relationship to earlier work in the field. It should not be an extensive review of the literature. Use only those references required to provide the most salient background to allow the readers to understand and evaluate the purpose and results of the present study without referring to previous publications on the topic [2]. The analysis of the brain tumor is carried out by the MRI imaging modality considering the fact that the modality has a superb contrast of the soft tissues, and it can capture the finer details of the structures. However, the increased size and complexity of the MRI data has helped to unveil vulnerabilities in the classical and semi-automated diagnostic procedures. These techniques are both time-consuming and prone to inter-observers bias as well as difficult to scale in clinical practice where experts are lacking. As a result, data-driven diagnostic systems and the implementation of automated systems based on deep learning (DL) technologies have been deeply diverted towards it [9]. Convolutional neural networks (CNNs) have been the state-of-the-art in automated detection and classification of brain tumor using MRI images in the past few years. Recent

systems based on DL have demonstrated high capacity to acquire discriminative properties with raw medical images, and do not rely on manual feature extraction. A number of the recent studies have revealed that the classification accuracy has been greatly enhanced with the application of deep CNN structure and end-to-end learning pipelines in the process of brain tumors classification [2], [3]. Such models have proved to be not only beneficial in the detection of tumors but multi-classification of different types of tumors. Transfer learning has also made deep learning more useful in medical imaging, particularly when there are limited quantities of labeled data. Deep learning is also more useful with the use of transfer learning complete in medical imaging especially after there are few quantities of labeled data. Transfer learning facilitates a reuse of learning of features and significantly reduced training time. The ability enabled him to perform higher generalization because of time to recycle CNN models with large scale image training data. The last comparative experiments testify to the fact that CNN after training is always superior fine-tuned. the superficial frameworks and generic machine learning classifiers in Brain tumor classification in the MRI classification tasks [4]. Most of the available techniques, however are either lightweight architectures that are fast, or are replicas of an analysis that is limited to binary tumor classification, which cannot be applied to real clinical cases with good accuracy. The present work is aimed at providing an improved brain tumor. detection and classification model with a fine-tuned VGG16 model based on the previous lightweight transfer-learning models. To provide the consistency of the contribution of MRI scans the proposed system will have formal preprocessing pipeline that will be in the form of image refining, eliminating noises spatial normalization, gray scale, and spatial normalization. Training is stabilized by the Adam alignment algorithm and dropout regularization in order to ensure that the overfitting is reduced. Unlike the old methods in which the major focus is put on dichotomous classification, the model proposed will be capable of conducting the categorization of various forms of clinically significant brain malignancies, such as glioma and meningioma, pituitary tumor, and so on schwannomas. The results of the study have proven that this method is better at classification as well as strength that makes it as an excellent reliable and clinically significant-decision support use in the work-out of brain tumor at an early stage.

2. Literature Review And Research Contribution

The primary aim of the research is to ascertain the applicability of the transfer learning algorithms with the aid of deep learning in the automatic classification and multi-classification of brain tumors with the aid of the magnetic resonance imaging (MRI) data. Early and accurate diagnosis of brain tumor should be done so as to launch early clinical intervention so that the treatment can be planned and improved chances of the patient survival are better. However, the conventional diagnostic procedures remain mostly dependent on subjective examinations, hence time-consuming and prone to inconsistency particularly in the constantly increasing amount and format of medical imaging data. Recent studies have indicated that the transfer learning models based on a convolutional neural network (CNN) can much enhance the accuracy of diagnosis in which brain tumor is diagnosed using the existing pre-trained deep architecture and without depending on the high annotated dataset [4], [6].These algorithms make it possible to analyze heterogeneous MRI data. strong representation learning and automatic feature extraction. and are required. Nevertheless, the developments are still tied down to. binary classifiers (also known as lightweight structures), which are not compatible with their dependability and applicability in clinical. conditions of diagnostic environments. In order to overcome these shortcomings, a fine-tuned VGG16 model, which trades off learning deep hierarchical qualities and implementation of a pre-established pipeline is implemented in the assigned study. The proposed solution needs to enhance the accuracy of the classification by refining the image, noise removal, grayscale, and spatial normalization, such that the quality of items input in will be similar across all MRI scans. In order to stabilize training and eliminate overfitting, dropout regularization and Adam optimization algorithm are included. Unlike the earlier binaries systems of detecting them, the study focuses on the multi-class tumor classification that will enable the identification of such clinically significant types of tumors as gliomas, meningiomas, pituitary tumors, and schwannomas.

It is a significant investigation with potential positive impact in enhancing the degree of reliability, accuracy and scalability of automated brain tumor diagnosis mechanisms. Past studies demonstrate that the CNN-based MRI analysis models can be used to make a great contribution to the diagnostic process when implemented to medical imaging pipelines in an adequate manner [5]. According to these results, the given model is aimed at the enhancement of the performance in respect of clinical significance with the help of the multi-class classification and the stable training behavior. Regarding healthcare, the results of this research are used to reduce the workload of the diagnose, accelerate the process of clinical decision-making, and allow finding high-risk patients early. Besides this, the paper supports the idea of digitizing healthcare systems by demonstrating how better deep learning models can be deployed to medical imaging systems. Overall, the given strategy can be evaluated as the enrichment of the existing studies because it offers a more specific, stronger, and clinically meaningful answer to the brain tumor detection and classification. The main purpose of the research is to evaluate the effectiveness of transfer learning with the help of deep learning techniques to address the problem of automatic detection and multi-classification of brain tumors in magnetic resonance images (MRI) data. Early and proper diagnosis of the brain tumors is extremely important in clinical treatment, treatment design and survival rate improvement of patients. However, expert interpretation is extensively utilized in the conventional diagnosis and thus they are time consuming and subject to variations further due to the increasing size and complexity of medical imaging data. The existing studies have discovered that convolutional neural network (CNN) models based on the transfer learning better perform than other diagnostic brain tumor models, by employing the pre-trained deep network and by using the small annotated data sets [4], [6]. These methods provide unsupervised feature learning and effective representation learning, which are essential to heterogeneous MRI data analysis. Though it has improved, the major ones are still limited to binary classification challenges or simpler architectures, hence restricting their applicability and viability in real practice of diagnostics. In order to address these constraints, VGG16 is narrowed down to a fine-tuned model in this paper to integrate the deep hierarchical feature learning and structured preprocessing pipeline. The proposed approach tries to increase the. learning to classify images by enhancements of image quality, denoising, grayscale, and spatial regularization to guarantee the quality of MRI scans is the same as their inputs. These are dropout to stabilize, regularization, and the Adam optimization algorithm have to be used. the training and reduce overfitting. The current study will be compared to, the targeted at multi-class tumor classification the former dualistic approach to tumor detection, which will allow differentiation of clinical interest cases of tumor. (gliomas, meningiomas, pituitary tumors and schwannomas). The importance of the study is that it can increase the reliability, accuracy, and scalability of computerized system of brain tumor diagnosis. It has already been proven in the literature that CNN-based MRI analysis systems can play a vital role in the workflow of the diagnostic process in case they are included in medical imaging pipelines in a proper way [5]. According to these findings, the model developed will be aimed at the improvement of performance and clinical relevance, the promotion of the behavior of multi-class classification and stable training. Regarding healthcare, the results of this study will be used to reduce the number of diagnostic works, accelerate the process of clinical decision-making, and help identify the high-risk individuals in time. In addition, in this paper, it is the digitalization of healthcare that helps transform the healthcare by demonstrating how the modern deep learning models can be used relative to the medical image systems. Overall, the given strategy can enhance the existing work, as it can offer a more accurate, robust, and clinically meaningful solution to the brain tumor detection and classification problem.

3. Proposed Methodology

In this research, a deep learning model on the utilization of MRI data is suggested. The step-wise

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 1756-1762
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0229

process that has been developed includes three major procedures namely data preprocessing, extraction of deep features and classification.

3.1.Data Preprocessing

First, the data that had been used in this research was classified into various brain tumor classes. MRI images were used to train and evaluate a total of MRI images. All the pictures were rescaled to the size of 224 × 224 × 3 to be appropriate with the VGG16 model, and pixel values were scaled to the range between 0 and 1. Furthermore, preprocessing steps like image enhancement, image denoising and grayscale conversion were used to enhance the image quality and minimize noise in MRI scans. The purpose of these steps is to offer uniform input data and increase feature learning.

3.2.Feature Extraction

This paper employed VGG16 convolutional neural network to learn meaningful features on MRI images. VGG16 takes input image and translates significant visual details including tissue texture, structural pattern and contrast difference into deep feature representations. This procedure facilitates automatic learning of hierarchical aspects that are needed to classify brain tumors reliably.

3.3.Classification

The deep extracted features underwent classification with the fully connected layers of VGG16 architecture. To prevent overfitting, dropout regularization has been implemented, and the training of the models has been made stable and efficient with the help of Adam optimization algorithm. The suggested system achieves the multi-class classification and thus enables distinguishing between the different types of brain tumors. The experimental analyses carried out on the extraction stage and classification stage made the optimization of the parameters employed. Figure. 1 provides the general principle of work and structure of the proposed method. The data in this research was collected from publicly available MRI repositories. The database comprises of brain MRI pictures taken by professionals on volunteer people and saved in JPEG format with different resolutions. As shown in Figure. 2, sample MRI images of the various types of tumors are provided that reflect the overall structure and heterogeneity of the data.

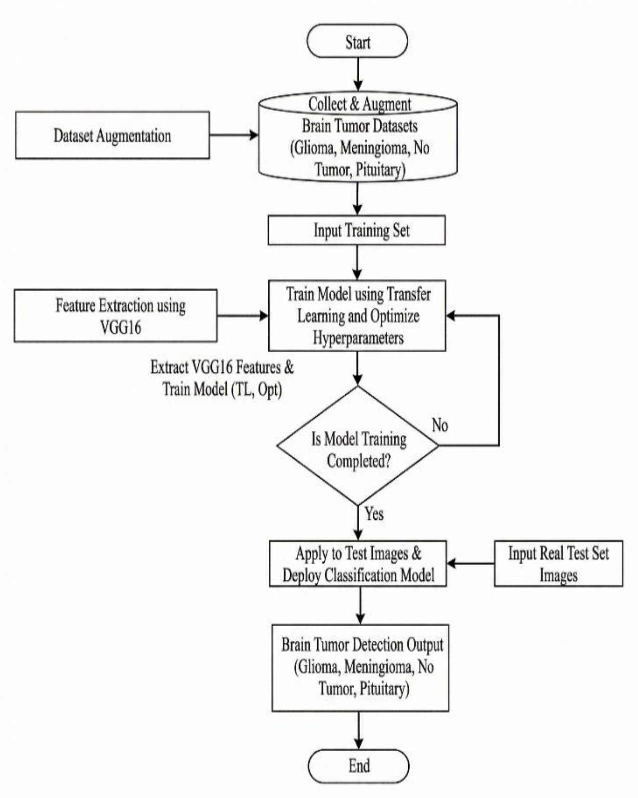

Figure 1 Flowchart Of The Processes Of The Proposed Method.

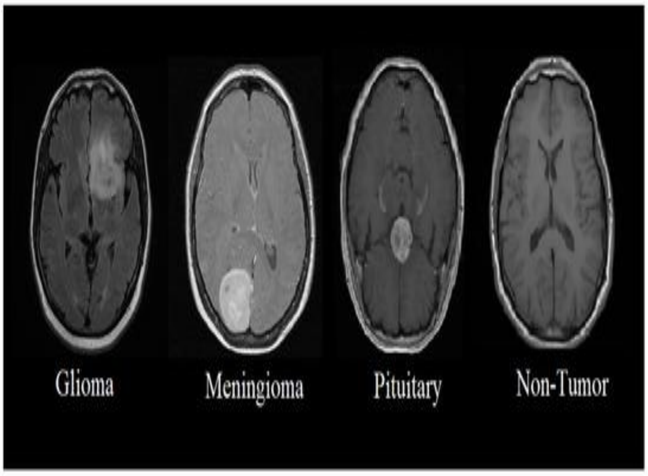

Figure 2. Sample MRI Images Of Various Tumor Types.

3.4.Convolutional Neural Network

Convolutional neural network CNN is a deep learning framework which allows learning features effectively by combining multiple layers. CNN architectures have been extensively applied in

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 1756-1762
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0229

medical image analysis because they have strong ability to acquire spatial and hierarchical characteristics. MRI-based analysis has been using CNN models due to their strength and good classification. A CNN normally consists of pooling and convolutional. layers which produce deep features, and finally connected. layers that does classification:

- Convolutional Layer: This entails the application of learnable. filters to remove the spatial features of the input image with a movement of the filters over the picture.
- Pooling Layer: Enhancing The Downsizing Of Feature Maps. Calculating Speed And Overtraining.
- Fully Connected Layer: The feature map is taken out. and it is denominated connected. narrowed down to a classification final vector.

Such optimization methods as Adam optimizer are com- used in the training of neural networks to ensure. Gradually through learning become effective, and more converged. adaptation of the model parameters [8].

3.5.Transfer Layer

One of the methodologies that can be used is transfer learning. new features learned on a pre-trained model to solve problems with new data. In this paper, the CNN model of VGG16 trained on the ImageNet dataset was used to take advantage of the pre-trained visual representations and adjust properly to the MRI-based brain tumor classification. This enhances performance and minimizes the training time in situations where there are small medical datasets.

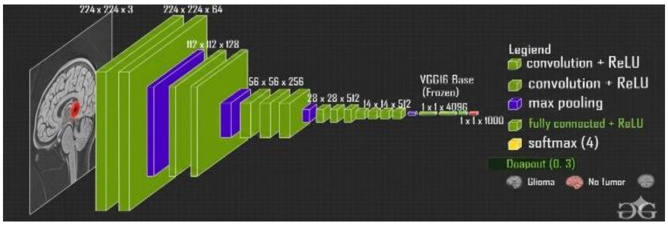

Figure 3 Structure Of The Vgg16 Model.

VGG16 is also a deep CNN model that is defined by its homogeneous structure and small 3 × 3 convolutional filters. It has deep layers of extraction of rich hierarchical information, and thus it is applicable in complex medical imaging. The VGG16 structure is presented in Figure 3

3.6.Performance Evaluation

The accuracy of the classification algorithms is based on how predictive class labels are related to the real ground truth. When a data sample is rightly recognized as a certain type of tumor, it is termed as a True Positive (TP). False predictions are those classified as False Positive (FP) or False Negative (FN), and those that are actually recognized as non-target are termed as True Negative (TN). These values underlie performance evaluation. In scientific studies, accuracy, precision, recall, specificity, and F1-score are some of the performance criteria commonly used. These performance indicators are defined mathematically as follows [5]:

1. $$\boldsymbol{Accuracy} = \frac{(\boldsymbol{TP}+\boldsymbol{TN})}{(\boldsymbol{TP}+\boldsymbol{TN}+\boldsymbol{FP}+\boldsymbol{FN})}$$
2. $$\boldsymbol{Precision} = \frac{(\boldsymbol{TP})}{(\boldsymbol{TP}+\boldsymbol{FP})}$$
3. $$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{(\boldsymbol{TP}+\boldsymbol{FP})}$$
4. $$\boldsymbol{Specificity} = \frac{\boldsymbol{TN}}{(\boldsymbol{TN}+\boldsymbol{FN})}$$
5. $$\boldsymbol{F1-score} = \boldsymbol{2\ X}\ \frac{(\boldsymbol{precision\ X\ Recall})}{(\boldsymbol{precision}+\boldsymbol{Recall})}$$

With the help of these parameters, the overall performance of the presented model can be evaluated comprehensively based on the influence of extracted deep features on it.

4. Experimental Results

The Python 3.11 and the TensorFlow deep learning framework were used to conduct experimental analyses. The proposed deep learning-based classification model was tested on a multi-class brain MRI database that included 1,343 brain images, divided into four categories: pituitary tumor, non-tumor, meningioma, and glioma. The dataset was split into training and testing sets where training set is the test set which is used to objectively evaluate model performance. Training was performed using the optimization of model parameters Algorithms. Adam optimization algorithm. The effectiveness of the category the amount of cation model was quantified by standard measures like F1-score, precision, accuracy and recall. Additionally, class-

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 1756-1762
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0229

wise prediction performance and discriminative ability were evaluated using the confusion matrix and Receiver Operating Characteristic (ROC) curves. The findings of classification refer to the model realized a complete accuracy of 94% in the test data. The F1-score, recall and average precision were 0.94, 0.93 and under Respectively, 0.93, and the consistency of the classification tumor types. The F1-score weighted average of 0.94 also is resistant to class imbalance.

4.1.Confusion Matrix

Figure 4 shows the confusion matrix of the model. For the correctly identified, 298 images in the pituitary tumor class, some were misclassified into other categories. The non-tumor class was the most reliable, as all 415 samples were correctly classified. The meningioma class had 299 correctly identified images, with slight confusion with pituitary and non-tumor classes. Similarly, 245 glioma images were correctly categorized, with minor overlap with meningioma cases due to similar radiological patterns.

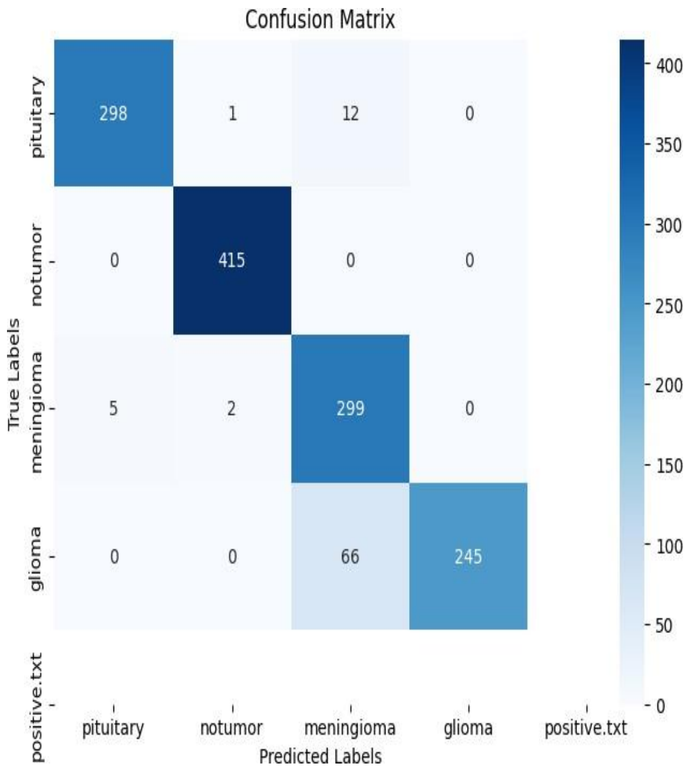

Figure 4 Confusion Matrix Of The Proposed Model For Multi-Class Brain Tumor Classification.

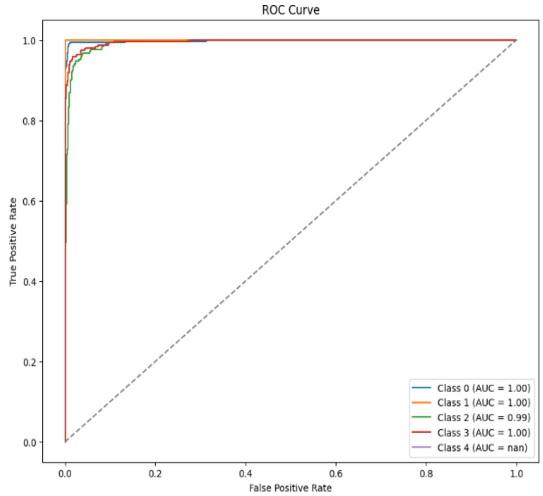

Figure 5 Roc Curves Of Each Brain Tumor Class.

Tumor Class	Precision	Recall	F1-Score
Non-tumor	1.00	1.00	1.00
Pituitary Tumor	0.98	0.96	0.97
Meningioma	0.89	0.88	0.88
Glioma	0.88	0.89	0.88
Overall Average	0.94	0.93	0.93

Figure 6. Class-Wise Performance Metrics Of The Proposed Model

4.2.Roc Analysis

The ROC curves for each class are shown in Fig. 5. The Area Under the Curve (AUC) values were 1.00 for pituitary tumor, non-tumor, and glioma classes, and 0.99 for the meningioma class. These values indicate a strong discriminative ability of the model to distinguish between different tumor categories.

4.3.Class-Wise Performance

The class-wise precision, recall, and F1-score values are summarized in Table I. Although minor misclassifications occurred between meningioma and glioma classes due to structural similarities, the overall performance remained strong and clinically significant. In general, the experimental evidence validates that the proposed deep neural network model performs highly effective multi-class brain tumor detection on MRI data. These findings are consistent with recent studies and reaffirm the applicability of deep learning approaches in medical

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 1756-1762
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0229

image analysis [6], [7]

Conclusion

This paper suggested an effective and efficient deep learning brain tumor multi-class automatic detection framework and characterization on the basis of magnetic resonance imaging (MRI) data. The model uses the transfer learning on the VGG16 architecture, facilitated by an extensive preprocessing method that includes image denoising, grayscale normalization and resizing. These measures provide consistency of MRI inputs and improve feature extraction to do trusted classification Experiment assessment was done on a database of There were a total of 1,343 MRI images in four classes, pituitary tumor, meningioma, glioma, and non-tumor represented a general classification accuracy of 94, and average precision, recall, and F1- score 0.94, 0.93, and 0.93 respectively. Class- wen or pituitary tu-wise showed the following analysis points: tumor categories were found to be the most reliable with the others being minor. There were misclassifications between Glioma and meningioma. because of a similar radiology. The ROC analysis determined that the model had a high discriminative capability, emphasizing its appropriateness in clinical use. Lightweight models like the k- had hitherto been lightweight. The proposed VGG16 based system is NN-based MobileNetV2 acquired the convergence faster, enhanced generalization and more consistent multi-classes performance. These outcomes validate the possibilities of a model as a reliable decision-supported tool radiologist, which makes the methods of diagnosis efficient and patient outcomes. The current research can be expanded by future studies to assess the MRI datasets, application on larger and more varied MRI datasets advanced regularization and optimization techniques, and exploring model explain ability of clinical transparency. Addition ally, using the model in the real-time diagnostic systems can also contribute to its increased practical use and deployment preparedness.

Acknowledgement

The author owes great appreciation to all members and parties, whose directions, assistance and resources led to the success completion of this research. The author accepts the entire responsibility of the content and conclusions he comes up with in this paper.

References

[1]. M. Bouhafra and H. El Bahi, “Deep learning approaches for brain tumor detection and classification using MRI images (2020–2024): A systematic review,” J. Digit. Imaging, 2025.
[2]. S. Nimmagadda and P. K. Devi, “A deep learning approach for brain tumour classification and detection in MRI images using YOLOv7,” Front. Oncol., vol. 15, p. 1508326, 2025.
[3]. M. Aamir, Z. Rahman, U. A. Bhatti et al., “An automated deep learning framework for brain tumor classification using MRI imagery,” Sci. Rep., vol. 15,
[4]. p. 17593, 2025.D. Asad, V. Mathivanan, and R. Mahmud, “Comparative analysis of deep transfer learning models for brain tumor MRI classification,” Sci. Publ., 2025.
[5]. “MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques,” BMC Med. Inform. Decis. Mak., vol. 23, p. 16, 2023.
[6]. S. Karamehic´ and S. Jukic´, “Brain tumor detection and classification using VGG16 deep learning algorithm and Python imaging library,” Bioeng. Stud., vol. 4, no. 2, pp. 1–13, 2024
[7]. Y. M. Zahoor and S. H. Khan, “CE-RS-SBCIT hybrid CNN-Transformer learning for brain tumor MRI analysis,” arXiv preprint arXiv:2502.xxxxx, 2025.
[8]. D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in Proc. Int. Conf. Learn. Represent. (ICLR), 2015.
[9]. Solseth, “Automated MRI-based brain tumor analysis using deep learning methods,” Neuroinformatics, vol. 19, no. 4, pp. 721–733, 2021.