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Brain tumor detection using VGG-16 model

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ABSTRACT

Research in medical image analysis, specifically through deep convolutional networks, addresses the challenges of manually analyzing large magnetic resonance imaging (MRI) image volumes for brain tumor detection. The manual analysis is time-consuming, tedious, and prone to inaccuracies due to subtle visual similarities between normal tissue and tumor cells. This research aims to automate tumor detection, increasing accuracy and efficiency in medical treatments. This study aimed to develop a model capable of classifying brain tumors 2D MRI images, and the convolutional neural network (CNN)-based model successfully achieved an accuracy of 99.21% but suffered from noticeable Overfitting. Implementing the independent tests set and early stopping mitigated this issue, making the model more reliable for production deployment and demonstrating its potential in supporting physicians in detecting brain tumors, thereby enhancing treatment efficiency. The use of Python, TensorFlow, and Keras facilitated the development of the proposed solution, focusing on a diverse set of MRI images with varying tumor sizes, locations, shapes, and intensities.

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1. INTRODUCTION

Deep learning significantly impacts the medical field [1], including the development of new drugs, improved clinical decision-making, and innovative medicine [2]. Medical imaging, which involves non-invasive visualization of the body's interior, is critical for diagnosis and treatment, relying on image segmentation to enhance effectiveness [3]. In context of brain tumor classification, medical image processing evaluates 3D datasets from computed tomography (CT) or magnetic resonance imaging (MRI) scanners to diagnose diseases, plan surgeries, and conduct research. Radiologists, physicians, and engineers analyze human anatomy through measures, statistical analysis, and simulation models incorporating real anatomical geometries, enhancing insights. Tumors refer to abnormal cell growth, while cancer is a type of tumor [4].

Deep learning has demonstrated promising results in automated brain tumor classification, enhancing diagnostic accuracy and facilitating timely interventions [5], [6]. Various architectures, such as convolutional neural networks (CNNs), U-Net, and V-Net, have been evaluated on popular datasets like brain tumor segmentation challenge (BraTS), internet brain segmentation repository (IBSR), and medical image computing and computer assisted intervention (MICCAI) [7], [8]. However, challenges remain, including the need for large, annotated datasets to address issues like class imbalance, data scarcity, and inter-scanner variability. Further research is essential to improve diagnostic accuracy and clinical decision-making in neuro-oncology [9]. Key challenges and future directions include creating large-scale, multi-modal, and annotated datasets, standardizing evaluation metrics, and integrating explainable artificial intelligence into clinical environments [10]. Despite the challenges in medical image analysis, deep learning techniques have improved brain tumor classification, benefiting patient outcomes by increasing accuracy and reducing manual labor. These advancements contribute to a better understanding of brain tumors and optimize treatment strategies for researchers, clinicians, and medical imaging professionals.

Glioma segmentation, a crucial aspect of medical image processing, involves detecting tumors in the brain and spinal cord. MRI data derived from clinical scans or artificial databases [11] can be complex due to variations in scanning equipment and techniques, resulting in intensity differences across images. The challenge is further complicated by the necessity of using multiple modalities to distinguish tumor sub-regions.

2. RELATED WORK

Deeksha *et al.* [12] introduce a CNN-based model for classifying prevalent brain tumor types, including meningiomas, gliomas, and pituitary adenomas, using MRI images. The model is constructed using Keras and TensorFlow, incorporating layers of convolution, pooling, and complete connectivity. The proposed model was trained and tested on a dataset of 253 MRI scans, achieving an accuracy of 92.62%. The CNN model's performance was benchmarked against traditional classifiers such as k-nearest neighbors (KNN), decision tree (DT), and random forests (RF), with the CNN model demonstrating superior accuracy. Additionally, the authors developed a web interface for convenient access and utilization of the model.

Febrianto *et al.* [13] conducted a study on detecting brain tumors in MRI images using CNNs. A dataset of 2,065 images was divided into 70% training, 15% testing, and 15% validation. Two CNN models were proposed and compared: model 1 with one convolution layer and model 2 with two convolution layers. Model 2 outperformed model 1, with 96% avg. accuracy on training data, 93% on test data, and an F1-score of 92%. However, model 2 took longer for training. The study confirmed CNN's effectiveness in diagnosing brain tumors (93% accuracy, 0.23264 loss) and emphasized the impact of convolution layers on classification quality. Image augmentation increased diversity and improved classification results. The study suggested that using more images and focusing on specific tumor types could further enhance classification performance.

Gayathri *et al.* [14] provide an overview of various studies that have utilized CNNs, multi-layer perceptrons (MLPs), and multivariable regression and neural network models for detecting and segmenting different types of cancers, including brain tumors, bladder cancer, and lung cancer, through medical imaging. The review addresses the challenges and limitations of these techniques, such as the requirement for domain-specific expert interpretation, significant anatomical variations, and concerns related to image quality. The authors customized and trained visual geometry group 16-layer (VGG-16) model on a dataset consisting of 1,655 brain MRI images with tumors and 1,598 tumor-free images, achieving 94% accuracy after hyperparameter optimization. They also evaluate how well the VGG-16 model performs compared to other techniques for detecting brain tumors, confirming its ability to identify these tumors accurately.

Additionally, the authors highlight the necessity of careful evaluation and use of deep learning tools in medical environments. They emphasize the need to consider ethical concerns and the possible repercussions of false positives and negatives. They also stress the importance of creating clear protocols for the incorporation of these tools into healthcare practice.

Mahmud *et al.* [15] introduce a CNN framework specifically tailored for effective brain tumor identification using MRI. This framework is compared to a number of other models, such as ResNet-50, VGG-16, and Inception-V3. Evaluation is based on criteria including accuracy, recall, loss, and area under the curve (AUC). The findings indicate that the suggested CNN framework outshines the other models in identifying brain tumors from a collection of 3,264 MR images.

Gayathri and Kumar [16] investigate a transfer learning-based VGG-16 model for the segmentation and classification of brain tumors using MRI scans. This analysis employs the BraTS 2018 dataset. The proposed approach achieves an accuracy of 99.6%, 95.35%, and 94% for various tumor locations, exceeding results from earlier methods. It also attains a classification accuracy of 99.6%, better than competing methods like softmax ensemble (99.1%) and support vector machine (SVM)-radial basis function (RBF) (97.70%).

Raghuvanshi and Dhariwal [17] analyze the effectiveness of CNNs, VGG-16, and additional deep learning models in detecting brain tumors through MRI imaging. They also discuss the clinical implications of these technologies, emphasizing their potential to aid radiologists in brain diagnostics and improve patient outcomes. The authors stress the critical role of deep learning in the medical field and its significant influence on brain tumor research.

Ismail *et al.* [18] report on the use of the VGG-16 structure of CNNs for categorizing medical images, specifically targeting datasets related to brain tumors and Alzheimer's disease. They highlight the importance of classifying medical images and how CNNs, particularly VGG-16, can improve precision and dependability in this area. Two datasets were created, with data augmentation techniques such as rotation, scaling, and flipping employed to increase the dataset size and counter class imbalances. The results show that the model is very effective at detecting irregularities in medical images, especially within the brain tumor dataset.

3. METHOD

The methodology consists of several key stages. Initially, we acquired a publicly available dataset of binary-class brain MRI images from the Kaggle platform, which includes a total of 253 images: 155 with tumors and 98 without. Although the original images varied in size, we standardized them to a uniform dimension before feeding them into the model for training. All images are of high quality, and Figure 1 illustrates six examples from the dataset. Following this, we pre-processed the datasets to prepare them for analysis. We employed the VGG-16 model as our deep CNN architecture to train the images. To validate our results, we assessed performance metrics such as accuracy and loss.

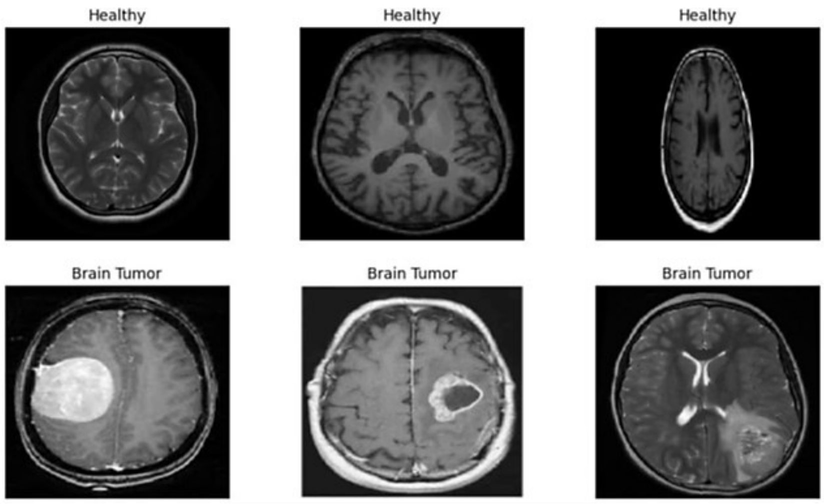


Figure 1. Brain tumor MRI images

3.1. Dataset collection and pre-processing

For this work, the dataset of brain MRI images is utilized for detecting brain tumors. In total, we gathered 253 images, which included 155 with tumors and 98 without, featuring a range of tumor sizes, shapes, locations, and intensities. This dataset aims to distinguish between images containing tumors and those with healthy tissue.

To mitigate overfitting and enhance the model's effectiveness, we employed data augmentation strategies. Data augmentation involves applying random modifications to the training images, leading to the creation of new data variations. By using these techniques, we enhanced both the diversity and size of the dataset, thereby lowering the chance of overfitting [19]. In this method, the ImageDataGenerator class from Keras was utilized for data augmentation. Various parameters were set to specify the types and levels of transformations to be applied, such as rotation, shifting in width and height, rescaling, shearing, adjusting brightness, and flipping images both horizontally and vertically. By randomly implementing these modifications on the training images, the model becomes more robust and better equipped to manage variations faced in real-life situations.

3.2. Deep learning models

The CNN model is one of the top techniques in medical image analysis is the CNN. This specific kind of artificial neural network is aimed at recognizing and processing images, making it particularly effective for tasks that involve understanding complex visual elements. CNNs can automatically categorize brain tumors through a systematic method that involves both training and validation stages. In this research, the brain imaging dataset was sourced from the publicly available collection on Kaggle. The decision to use a CNN for our model comes from its interconnected parameters and shared features, which improve its effectiveness in image classification tasks. Drawing inspiration from the mental functions of creative animals and sophisticated cognitive abilities, CNNs exemplify an innovative category of deep neural networks (DNNs). The design of a CNN is made up of a layered structure that includes fully connected layers, convolutional layers, pooling layers, flattening layers, and output layers. Each CNN has a distinctive set of images that vary in number, size, and type, along with different activation functions. The settings of the CNN are established through testing and experimental adjustments. Fundamentally, a CNN contains numerous layers, with the main ones being the convolutional layer and the subsampling layer. The convolutional layer detects features in the image, enabling the network to capture critical attributes that remain similar across different parts of the image. This layer boosts the model's capability to identify patterns and characteristics, which are then utilized for classification. Conversely, the subsampling layer decreases the dimensions of the input image, helping to form a vector representation as the information moves through the CNN. This procedure, known as pooling, condenses the data while preserving essential features needed for precise classification [20].

The VGG-16 model is an advanced deep CNN that consists of multiple layers, such as convolutional and fully connected layers, arranged in a sequential manner to process and classify MRI images. This architecture enables the model to identify intricate features from input images, which aids in the accurate identification and classification of brain tumors [21]. VGG-16 contains a total of 16 layers, which include 13 convolutional layers and 3 fully connected layers. The convolutional layers utilize small filters for feature extraction through convolution, effectively capturing spatial arrangements and local characteristics within the images. This allows the model to understand representations at different levels of detail. At the conclusion of the network, the fully connected layers, also known as dense layers, perform classification tasks based on the features obtained from the convolutional layers. They combine the extracted features to make predictions on whether brain tumors are present in the MRI images. By layering several convolutional and fully connected layers, the VGG-16 model skillfully captures subtle details and complex connections in brain tumor imagery, leading to impressive accuracy in tumor detection. The structure of the proposed network model is illustrated in Figure 2.

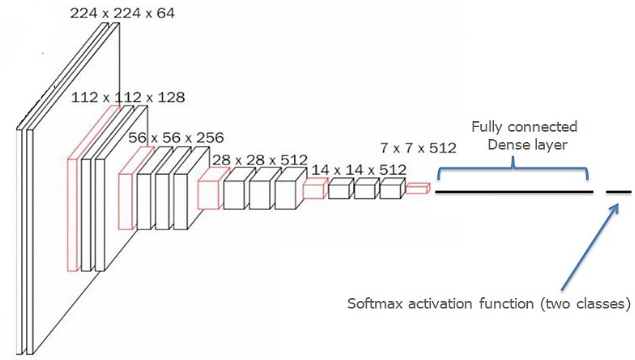


Figure 2. The proposed network model's structure

4. RESULTS AND DISCUSSION

A transfer learning approach using a VGG-16 model pre-trained is employed on the ImageNet database to classify MRI images for brain tumor detection. The methodology involved retrieving the pre-trained VGG-16 model to extract features from MRI images, then replacing the final classification layer with a binary output layer for "tumor present/absent" classification while retaining the other layers to preserve acquired knowledge. The custom architecture added a flatten layer to transform the data into a vector, followed by a dense layer with a softmax activation function for binary classification. Before training, MRI images were preprocessed by resizing to 224×224 pixels and enhanced using data augmentation techniques, including rotation, shifting, flipping, and brightness adjustment, to improve classification performance and prevent overfitting. The model was configured with the Adam optimizer, categorical cross-entropy as the loss function, and accuracy as the primary evaluation metric. Training was conducted over 10 epochs with 26 training steps, achieving an impressive accuracy of 99.21%. This represents a substantial advancement in gradient descent optimization techniques, with the results illustrated in Figure 3.

The model was trained for 10 epochs, each comprising 26 steps and taking 71 to 93 seconds to complete. Training loss decreased significantly from 0.9787 in the first epoch to 0.1276 by the tenth epoch, while training accuracy improved from 69.17% to 94.07%. Validation metrics also showed positive trends, with validation loss dropping from 0.7683 to 0.0496 and validation accuracy rising from 66.80% to 99.2%. Notably, validation accuracy consistently surpassed training accuracy, suggesting effective data augmentation, potential overfitting, or issues with dataset splitting. Despite a minor fluctuation in epoch 9, the model stabilized by epoch 10, achieving high performance metrics overall. However, the unusually high validation accuracy raises concerns about possible overfitting or data leakage.

```
Epoch 1/10
26/26 [==============================] - 71s 3s/step - loss: 0.9787 - accuracy: 0.6917 -
 val_loss: 0.7683 - val_accuracy: 0.6680
Epoch 2/10
26/26 [==============================] - 72s 3s/step - loss: 0.6203 - accuracy: 0.7668 -
 val_loss: 0.3960 - val_accuracy: 0.8340
Epoch 3/10
26/26 [==============================] - 72s 3s/step - loss: 0.3204 - accuracy: 0.8656 -
 val_loss: 0.1865 - val_accuracy: 0.9328
Epoch 4/10
26/26 [==============================] - 72s 3s/step - loss: 0.2303 - accuracy: 0.9051 -
 val_loss: 0.1365 - val_accuracy: 0.9526
Epoch 5/10
26/26 [==============================] - 72s 3s/step - loss: 0.2164 - accuracy: 0.9091 -
 val_loss: 0.1115 - val_accuracy: 0.9644
Epoch 6/10
26/26 [==============================] - 72s 3s/step - loss: 0.2124 - accuracy: 0.9130 -
 val_loss: 0.0852 - val_accuracy: 0.9802
Epoch 7/10
26/26 [==============================] - 72s 3s/step - loss: 0.1780 - accuracy: 0.9289 -
 val_loss: 0.1527 - val_accuracy: 0.9328
Epoch 8/10
26/26 [==============================] - 74s 3s/step - loss: 0.1419 - accuracy: 0.9407 -
 val_loss: 0.1265 - val_accuracy: 0.9368
Epoch 9/10
26/26 [==============================] - 93s 4s/step - loss: 0.4443 - accuracy: 0.8538 -
 val_loss: 0.0911 - val_accuracy: 0.9605
Epoch 10/10
26/26 [==============================] - 72s 3s/step - loss: 0.1276 - accuracy: 0.9407 -
 val_loss: 0.0496 - val_accuracy: 0.992
```

Figure 3. Outcome generated by our suggested approach

In Figures 4 and 5, the analysis of the training and validation losses reveals a positive learning trend, with both metrics decreasing over time, particularly steeply in the initial epochs before leveling off. Initially, training loss was higher than validation loss, but they converged around epoch 6, with validation loss becoming slightly lower thereafter. However, a notable spike in training loss around epoch 8 suggests some instability, possibly due to a challenging batch of training data. In terms of accuracy, both training, and validation metrics increased as expected, but validation accuracy consistently exceeded training accuracy, which is unusual and may indicate peculiarities in the dataset or the data augmentation process. By the end of the training, both accuracies were impressively high, with validation accuracy approaching 100%. This indicates clear learning progress and good generalization, as evidenced by the close alignment of training and validation metrics. However, the consistently higher validation accuracy raises concerns about potential overfitting or data leakage, warranting further investigation. The spike in training loss also highlights a need to assess model stability. To mitigate the risks of overfitting, which arise from the model memorizing features of the training set rather than learning them, and from an imbalance or insufficient size in the validation set, we first performed a set of independent tests and then applied early stopping.

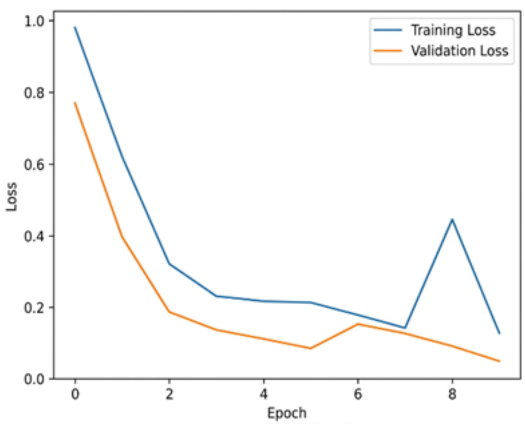


Figure 4. Training and validation losses

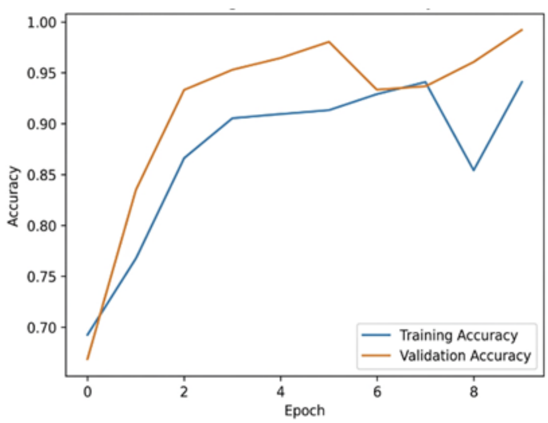
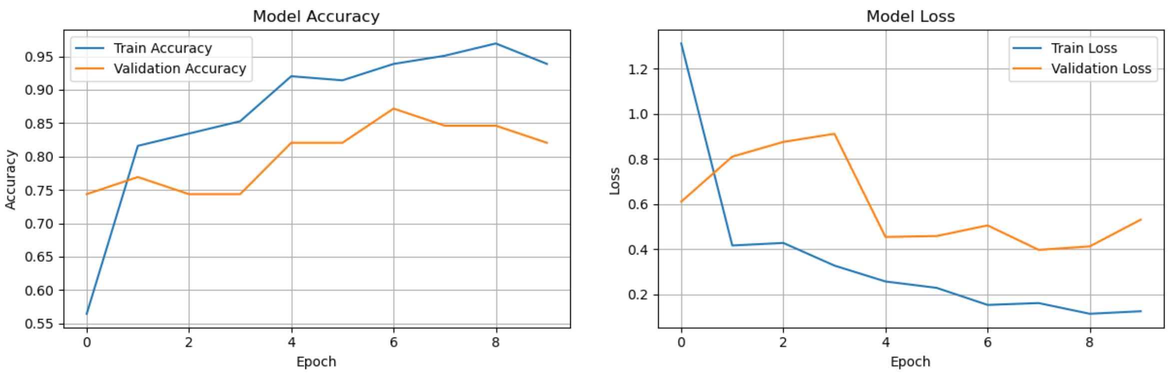


Figure 5. Training and validation accuracy

The dataset is divided into a training set, a test set, and a validation set. Then performed a set of independent tests. The new results, as illustrated in Figures 6 and 7, demonstrate a significant improvement in model performance following these modifications, where Figure 7(a) shows training and validation accuracy and Figure 7(b) shows training and validation losses. With a final test accuracy of 86.27% and a test loss reduced to 0.2610, the model now exhibits better generalization capabilities. The tripartite division of the dataset (training/validation/test) significantly mitigated the previously observed overfitting problem. However, a slight tendency towards overfitting is still observed after epoch 6, suggesting that an early stopping strategy could further optimize the results. Implementing independence tests and a separate set of tests ensures a more rigorous and reliable evaluation of the model's true predictive power.

```
Epoch 1/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 29s 2s/step - accuracy: 0.4639 - loss: 1.7156 - val_accuracy: 0.7436 - val_loss: 0.6104
Epoch 2/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 31s 2s/step - accuracy: 0.8070 - loss: 0.4180 - val_accuracy: 0.7692 - val_loss: 0.8104
Epoch 3/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 25s 1s/step - accuracy: 0.7967 - loss: 0.4867 - val_accuracy: 0.7436 - val_loss: 0.8757
Epoch 4/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 26s 1s/step - accuracy: 0.8505 - loss: 0.3050 - val_accuracy: 0.7436 - val_loss: 0.9118
Epoch 5/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 25s 1s/step - accuracy: 0.9106 - loss: 0.2821 - val_accuracy: 0.8205 - val_loss: 0.4538
Epoch 6/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 27s 2s/step - accuracy: 0.8667 - loss: 0.3309 - val_accuracy: 0.8205 - val_loss: 0.4578
Epoch 7/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 27s 2s/step - accuracy: 0.9500 - loss: 0.1531 - val_accuracy: 0.8718 - val_loss: 0.5051
Epoch 8/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 26s 1s/step - accuracy: 0.9583 - loss: 0.1507 - val_accuracy: 0.8462 - val_loss: 0.3966
Epoch 9/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 25s 1s/step - accuracy: 0.9879 - loss: 0.0916 - val_accuracy: 0.8462 - val_loss: 0.4119
Epoch 10/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 36s 2s/step - accuracy: 0.9456 - loss: 0.1218 - val_accuracy: 0.8205 - val_loss: 0.5307
```

Figure 6. Outcome generated by our suggested approach after implementing independent tests set



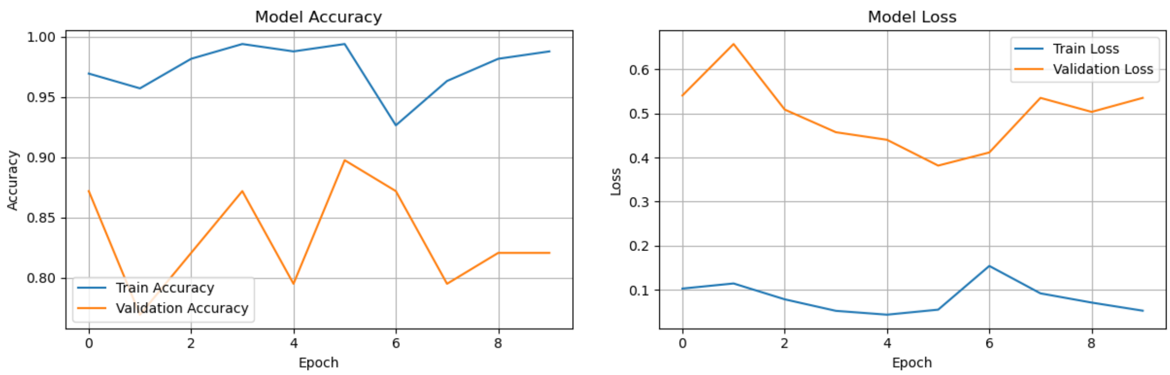
(a) (b)

Figure 7. Training and validation results after implementing an independent testing set on (a) model accuracy and (b) model loss

The results obtained after implementing early stopping, illustrated in Figures 8 and 9, reveal a remarkable improvement in the model's performance, where Figure 9(a) shows training and validation accuracy and Figure 9(b) shows training and validation losses. Test accuracy now reaches 84.31% with a loss of 0.2846, demonstrating excellent generalization capabilities. Training stopped automatically after 10 epochs, allowing the model to converge to an optimal point without excessive overfitting. Compared to the previous results (86.27%), the slight decrease in test accuracy to 84.31% is actually a positive indicator: it suggests that the model prioritizes robustness and generalization over excessive memorization. The accuracy graph shows more stable and predictable curves, with less volatility than before. Early stopping prevented prolonged training beyond the optimal point, thus ensuring a better-balanced model, more reliable for production, and capable of maintaining consistent performance on new data. Table 1 shows a detailed comparison of the results obtained at the three stages of model improvement.

```
Epoch 1/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 23s 1s/step - accuracy: 0.9728 - loss: 0.0928 - val_accuracy: 0.8718 - val_loss: 0.5405
Epoch 2/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 36s 2s/step - accuracy: 0.9571 - loss: 0.1347 - val_accuracy: 0.7692 - val_loss: 0.6570
Epoch 3/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 31s 2s/step - accuracy: 0.9629 - loss: 0.1029 - val_accuracy: 0.8205 - val_loss: 0.5085
Epoch 4/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 29s 2s/step - accuracy: 0.9990 - loss: 0.0408 - val_accuracy: 0.8718 - val_loss: 0.4572
Epoch 5/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 42s 2s/step - accuracy: 0.9858 - loss: 0.0480 - val_accuracy: 0.7949 - val_loss: 0.4400
Epoch 6/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 28s 2s/step - accuracy: 0.9805 - loss: 0.0844 - val_accuracy: 0.8974 - val_loss: 0.3816
Epoch 7/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 38s 2s/step - accuracy: 0.9626 - loss: 0.0934 - val_accuracy: 0.8718 - val_loss: 0.4114
Epoch 8/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 27s 2s/step - accuracy: 0.9477 - loss: 0.1189 - val_accuracy: 0.7949 - val_loss: 0.5350
Epoch 9/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 28s 2s/step - accuracy: 0.9851 - loss: 0.0530 - val_accuracy: 0.8205 - val_loss: 0.5032
Epoch 10/10
17/17 ━━━━━━━━━━━━━━━━━━━━ 29s 2s/step - accuracy: 0.9930 - loss: 0.0469 - val_accuracy: 0.8205 - val_loss: 0.5350
```

Figure 8. Outcome generated by our suggested approach after implementing an early stopping strategy



(a) (b)

Figure 9. Training and validation results after implementing an implementing an early stopping strategy on (a) model accuracy and (b) model loss

Table 1. Comparative table of model performances

Criteria	Initial Model	Independent tests set	Early stopping strategy
Test accuracy		86.27%	84.31%
Test loss		0.2610	0.2846
Training accuracy	~93% (époque 8)	~96% (époque 8)	~99.30% (époque 10)
Validation accuracy	99.2% (époque 10)	~82% (époque 10)	~82.05% (époque 10)
Training loss	~0.05	~0.12	~0.05
Validation loss	0.992	~0.53	~0.54
Number of epochs	10	10	10(with early stopping)
Overfitting	Severe (from period 6-7)	Moderate (slight after epoch 5-6)	Minimal (control effectively)
Curve stability	Low (strong divergence)	Average (reduced divergence)	Excellent (harmonious convergence)
Data division	Train/validation only	Train/validation/test	Train/validation/test
Generalization capacity	Very low	Good	Excellent

4.1. Comparative analysis with existing techniques

Several recent studies have investigated CNN-based methods for brain tumor detection in MRI images, with varying success levels as shown in Table 2. Research by Irsheidat and Duwairi [22] used a two-stage CNN approach that first employed bounding boxes for tumor localization, and then conducted classification. The study in [23] showed the use of MobileNet v2, InceptionV3, and ResNet50 architectures, reporting 98.3%, 98.6%, and 98.6% at 5, 10, and 20-fold cross-validation. Meanwhile, Sowrirajan *et al.* [24] examined VGG-16, achieving 97.9% accuracy in their tests. Another important work in [25] combined

VGG-16 with gray-level co-occurrence matrix (GLCM) features for brain MRI analysis, reaching 96% accuracy. The proposed VGG-16 transfer learning framework greatly surpasses these methods, delivering higher classification accuracy at 99.21%. The notable increase in accuracy highlights the effectiveness and reliability of our approach for automated brain tumor detection and classification.

Table 2. Comparison with existing techniques

Reference	Algorithm	Accuracy (%)
[22]	CNN	96.7
[23]	MobileNetV2, InceptionV3, and ResNet50	98.3, 98.6, and 98.6 at five, ten, and 20-fold cross-validation
[24]	VGG-16	97.9
[25]	VGG-16 with GLCM	96
Proposed method	VGG-16	99.21

5. CONCLUSION

Tumors pose a major danger to people because malignant cells can invade nearby tissues and spread to different parts of the body. Timely identification of brain tumors is essential for delivering the best treatment. This research utilizes CNNs to create a model that classifies MRI scans of brain tumors. A notable benefit of this method is its capacity to automatically detect intricate features in multi-modal MRI scans, allowing it to differentiate between brain regions with tumors and those that are healthy. The model shows remarkable results, reaching an accuracy of 99% when evaluated on a small selection of brain tumor datasets that have uneven classifications. However, despite these encouraging findings, the model encounters several issues that could affect its success in practical medical settings. To tackle these challenges, future initiatives should aim to increase and diversify the dataset, use 3D CNN for thorough spatial analysis, and add more data types like patient medical history and genetic details. Improving the model's transparency and dependability can be accomplished by using explainable AI strategies, quantifying uncertainty, and conducting comprehensive testing. Moreover, investigating federated learning, continuous learning systems, and ensemble techniques can enhance the model's effectiveness and adaptability. Lastly, thorough clinical validation and adherence to ethical and regulatory guidelines are crucial for the effective incorporation of the model into healthcare practices, making sure that it not only operates well but also complies with all necessary legal and ethical standards.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Abderrahmane Ez-Zahout	✓			✓						✓		✓	✓	
Soumia Ziti	✓			✓						✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares that there are no known conflicts of interest associated with this publication. There are no financial or personal relationships that could inappropriately influence or bias the content of this work.

INFORMED CONSENT

We haven't used a predefined person; we have acquired a publicly available dataset of binary-class brain MRI images from the Kaggle platform.

ETHICAL APPROVAL

This section not applicable. This research did not involve human subjects, human biological materials, or experimental procedures on animals. The work was conducted solely on computational models, publicly available datasets, or non-sensitive data that did not require intervention with living organisms. Therefore, ethical approval from an institutional review board or animal ethics committee was not necessary for this study.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

REFERENCES

[1] A. Oussous, A. Ez-Zahout, S. Ziti, and A. Oussous, "An overview of the most efficient methods for predicting healthcare disorders," in *AIP Conference Proceedings*, 2023, vol. 2814, no. 1, doi: 10.1063/5.0150025.

[2] A. Oussous, A. Ez-Zahout, and S. Ziti, "Reviewing chronic ailments: predicting diseases with a multi-symptom approach," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 35, no. 1, pp. 418–427, 2024, doi: 10.11591/ijeecs.v35.i1.pp418-427.

[3] D. S. Prabha and J. S. Kumar, "Performance evaluation of image segmentation using objective methods," *Indian Journal of Science and Technology*, vol. 9, no. 8, 2016, doi: 10.17485/ijst/2016/v9i8/87907.

[4] A. Mustaqeem, A. Javed, and T. Fatima, "An efficient brain tumor detection algorithm using watershed and thresholding based segmentation," *International Journal of Image, Graphics and Signal Processing*, vol. 4, no. 10, pp. 34–39, 2012, doi: 10.5815/ijigsp.2012.10.05.

[5] M. I. Sharif, J. P. Li, J. Amin, and A. Sharif, "An improved framework for brain tumor analysis using MRI based on YOLOv2 and convolutional neural network," *Complex & Intelligent Systems*, vol. 7, pp. 2023–2036, 2021, doi: 10.1007/s40747-021-00310-3.

[6] A. Raza *et al.,* "A hybrid deep learning-based approach for brain tumor classification," *Electronics*, vol. 11, no. 7, 2022, doi: 10.3390/electronics11071146.

[7] P. Agrawal, N. Katal, and N. Hooda, "Segmentation and classification of brain tumor using 3D-UNet deep networks," *International Journal of Cognitive Computing in Engineering*, vol. 3, pp. 199–210, 2022, doi: 10.1016/j.ijcce.2022.11.001.

[8] M. F. Ahamed *et al*., "A review on brain tumor segmentation based on deep learning methods with federated learning techniques," *Computerized Medical Imaging and Graphics*, vol. 110, 2023, doi: 10.1016/j.compmedimag.2023.102313.

[9] T. Magadza and S. Viriri, "Deep learning for brain tumor segmentation: a survey of state-of-the-art," *Journal of Imaging*, vol. 7, no. 2, 2021, doi: 10.3390/jimaging7020019.

[10] E. S. Biratu, F. Schwenker, Y. M. Ayano, and T. G. Debelee, "A survey of brain tumor segmentation and classification algorithms," *Journal of Imaging*, vol. 7, no. 9, 2021, doi: 10.3390/jimaging7090179.

[11] M. Prastawa, E. Bullitt, and G. Gerig, "Simulation of brain tumors in MR images for evaluation of segmentation efficacy," *Medical Image Analysis*, vol. 13, no. 2, pp. 297–311, 2009, doi: 10.1016/j.media.2008.11.002.

[12] K. N. Deeksha, D. M, A. V Girish, A. S. Bhat, and L. H, "Classification of brain tumor and its types using convolutional neural network," in *2020 IEEE International Conference for Innovation in Technology (INOCON)*, 2020, pp. 1–6, doi: 10.1109/INOCON50539.2020.9298306.

[13] D. C. Febrianto, I. Soesanti, and H. A. Nugroho, "Convolutional neural network for brain tumor detection," in *IOP Conference Series: Materials Science and Engineering*, 2020, vol. 771, doi: 10.1088/1757-899X/771/1/012031.

[14] P. Gayathri, A. Dhavileswarapu, S. Ibrahim, R. Paul, and R. Gupta, "Exploring the potential of VGG-16 architecture for accurate brain tumor detection using deep learning," *Journal of Computers, Mechanical and Management*, vol. 2, no. 2, 2023, doi: 10.57159/gadl.jcmm.2.2.23056.

[15] M. I. Mahmud, M. Mamun, and A. Abdelgawad, "A deep analysis of brain tumor detection from MR images using deep learning networks," *Algorithms*, vol. 16, no. 4, 2023, doi: 10.3390/a16040176.

[16] T. Gayathri and S. K. Kumar, "Brain tumor segmentation and classification using CNN pre-trained VGG-16 model in MRI images," *IIUM Engineering Journal*, vol. 25, no. 2, pp. 196–211, 2024, doi: 10.31436/iiumej.v25i2.2963.

[17] S. Raghuvanshi and S. Dhariwal, "The VGG16 method is a powerful tool for detecting brain tumors using deep learning techniques," in *RAiSE-2023, MDPI Engineering Proceedings*, 2023, doi: 10.3390/engproc2023059046.

[18] A. R. Ismail, S. Q. Nisa, S. A. Shaharuddin, S. I. Masni, and S. A. S. Amin, "Utilising VGG-16 of convolutional neural network for medical image classification," *International Journal of Pervasive Computing and Communications*, vol. 10, no. 1, pp. 113–118, 2024, doi: 10.31436/ijpcc.v10i1.460.

[19] D. Santos, "Brain tumor detection using the VGG-16 model: a deep learning approach," *Preprints*, 2023, doi: 10.20944/preprints202308.0983.v1.

[20] Z. Rasheed *et al.*, "Brain tumor classification from MRI using image enhancement and convolutional neural network techniques," *Brain Sciences*, vol. 13, no. 9, 2023, doi: 10.3390/brainsci13091320.

[21] M. Humayun, R. Sujatha, S. N. Almuayqil, and N. Z. Jhanjhi, "A transfer learning approach with a convolutional neural network for the classification of lung carcinoma," *Healthcare*, vol. 10, no. 6, 2022, doi: 10.3390/healthcare10061058.

[22] S. Irsheidat and R. Duwairi, "Brain tumor detection using artificial convolutional neural networks," in *Proceedings of the 11th International Conference on Information and Communication Systems (ICICS)*, Apr. 2020, pp. 197–203.

[23] S. Jain and V. Jain "Novel approach to classify brain tumor based on transfer learning and deep learning," *International Journal of Information Technology*, vol. 15, no. 4, 2031–2038, Apr. 2023, doi: 10.1007/s41870-023-01259-x.

[24] S. R. Sowrirajan, S. Balasubramanian, and R. S. P. Raj, "MRI brain tumor classification using a hybrid VGG16-NADE model," *Brazilian Archives of Biology and Technology*, vol. 66, 2023, doi: 10.1590/1678-4324-2023220071.

[25] H. Kibriya, R. Amin, J. Kim, M. Nawaz, and R. Gantassi, "A novel approach for brain tumor classification using an ensemble of deep and hand-crafted features," *Sensors*, vol. 23, no. 10, 2023, doi: 10.3390/s23104693.

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