SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V11I4P105

Volume 11 Issue 4, 41-50, April 2024

Original Article

Enhancing Brain Tumor Classification with VGG-19 in Deep Learning Paradigms

Jasmine Paul[1], J. Jerusalin Carol[2], T.S. Sivarani[3]

[1]*Department of Computer Science and Engineering, St. Thomas Institute for Science and Technology, Kerala, India.*
[2]*Computer Science and Engineering, Mar Ephraem College of Engineering & Technology, Tamilnadu, India.*
[3]*Department of Electrical and Electronics Engineering, Arunachala College of Engineering for Women, Tamilnadu, India.*

[1]*Corresponding Author : jasmine.cs@stisttvm.edu.in*

Received: 07 February 2024 Revised: 05 March 2024 Accepted: 04 April 2024 Published: 30 April 2024

Abstract - *The primary and pivotal stage in patient care lies in accurately categorizing brain tumors. This critical process not only identifies potentially life-threatening abnormalities but also lays the groundwork for tailoring effective treatment plans essential for a patient's recovery journey. The proposed methodology entails a structured approach comprising segmentation, classification, feature extraction, and preprocessing. These sequential steps serve as the foundational framework for comprehensively analyzing the data sourced from the Figshare dataset. In the initial phase, photos undergo preprocessing utilizing the Gaussian filter method. Subsequently, the preprocessed images are subjected to segmentation employing the DU-Net method. Following segmentation, feature extraction is performed on the delineated segments. For this task, DesNet-121 is employed to extract feature data. Finally, leveraging the resultant features, data classification is executed. This systematic approach ensures a comprehensive analysis of the data while maintaining consistency and accuracy throughout the process. In the final stage, a VGG-19 deep learning model is employed to classify the MRI pictures into distinct groups. This proposed model is then simulated on a dataset, and its performance metrics, including accuracy, precision, recall, and F1-score, are thoroughly evaluated. The results indicate significant enhancements in brain tumor categorization and detection, affirming the efficacy and reliability of the suggested model for clinical applications. The testing outcomes underscore the capability of the recommended strategy to achieve exceptional accuracy, reaching an impressive 98.15%.*

Keywords - *VGG-19, Convolution Neural Network (CNN), Deep Learning, Image preprocessing, Medical image.*

1. Introduction

Brain tumors constitute a life-threatening condition that tragically claims the lives of thousands of individuals globally [1]. The human body's thin and rigid skull means that, depending on where it grows and how it is positioned, any growth inside the brain could have an impact on how well an organ functions. Additionally, it could migrate to other body parts and impair their operation. Depending on where they are located, brain tumors are typically divided into two classes: primary and secondary [2]. Thirty percent of brain cancers are classified as secondary, while the remaining seventy percent are categorized as primary tumors. Secondary brain tumors originate in another organ before spreading to the brain through the bloodstream.

On the other hand, primary brain tumors consist of growths that initiate within the brain cells themselves. Fine-tuning models in deep learning requires careful decisions, including the selection of an appropriate activation function and adjusting parameters like the number of layers and pooling.

In some cases, the strategy may involve the utilization of pre-trained models for transfer learning, providing an additional dimension to the optimization process [3]. The integration of meta-heuristic algorithms, known for enhancing classification accuracy, proves beneficial for both strategies. This paper explores the identification of brain cancers using MRI data, adopting a comprehensive approach that combines traditional and deep learning techniques. Extensive research has been conducted on employing machine learning approaches to identify brain cancers from MRI scans effectively. Several investigations have been carried out on deep learning, convolutional neural networks and VGG [4].

For more details, the following are the main steps of the suggested strategy-a high-performing Initial and accurate brain tumour detection using an efficient VGG-19 tumour diagnosis system. The pre-processing stage is done through a Gaussian bilateral filter to improve the quality of an image. Then applied, a DU-Net segmentation was applied to segment the brain tumor. The feature will be extracted using DenseNet-121. A VGG-19 model built on the architecture and optimized

for the classification of benign and malignant pictures is proposed. Accuracy, Precision, Recall, and F1-score are used to evaluate how well the suggested strategy performs.

The following describes the way the paper is established: Section 1 illustrates the introduction. The literature review is described in Section 2. Section 3 explains the suggested proposed methodology, and Section 4 displays the experimental results.

2. Literature Review

Magnetic Resonance Imaging (MRI) can more precisely detect and locate brain tumors, according to Zulpe et al. (2012) [5]. Many MRI methods are used to improve the outcome. This study's main objective is to present alternate approaches for estimating the size of a tumor in the brain. When characteristics from an MRI or SPECT image are used as the only input to classifiers, Sai et al. (2019) [6] found that the SVM classifier has an accuracy rating of 95.6 %. This accuracy is higher than that of the SVM, the KNN, and the decision tree classifiers.

The Random Forest and K Nearest Neighbors were explained by Wei et al. (2021) [7] to have a cross-entropy of 0.097 and a validation accuracy of 71%, making it one of the efficient approaches for carrying out different phases of brain tumor categorization. The average rate of classification for brain cancers using the Convolutional Neural Network classifier is 98%.

According to research by Sharma et al. (2013) [8], the accuracy using a cell-graph representation for cancer diagnosis is 95.45%; the proportions of test sample categories that correctly identify healthy, malignant, and inflamed tissues are 98.15, 95.14 and 92.50 percent, respectively. Using the GLCM (Grey Level co-occurrence matrix), attributes in the proposed study. For the purpose of classifying malignancies in MRI scans, Ghassemi et al. (2020) [9] have developed a unique deep learning technique. Instead, a discriminator using a deep neural network for Generative Adversarial Networks (GAN) would be built.

Majib et al. (2021) [15] have demonstrated that to classify brain tumor images without requiring human input, hybrid machine learning models were built and thoroughly examined. Furthermore, a study including sixteen different transfer learning models was carried out to ascertain which model would work best for neural network-based brain cancer classification. Ultimately, a stacked classifier that surpasses all other current models was proposed using numerous cutting-edge technologies. As per Srinivas et al. (2022), [16] the Convolution Neural Network (CNN) is the most comprehensive and extensively utilized deep learning technology for the analysis and classification of brain tumors. This study is a comparative performance analysis of transfer learning-based automatic brain tumor cell prediction using CNN-pretrained VGG-16, ResNet-50, and Inception-v3 models. The trained models are presented on 233 photos taken from the MRI brain tumor images collection.

In order to detect brain tumors, Ahmad et al. (2022) [17] investigate a number of deep learning methods that use a range of traditional classifiers and are based on transfer learning. The study's findings are predicated on a labeled dataset that includes pictures of both normal and aberrant brain tissue. Seven methods-VGG-16, VGG-19, ResNet50, InceptionResNetV2, InceptionV3, Xception, and DenseNet201 are employed for transfer learning. Every possible combination of a classifier and deep learning-based feature extractor is examined in order to assess the relevant performance in terms of recall, accuracy, precision, F1-score, Cohen's kappa, AUC, Jaccard, and specificity.

In order to obtain high accuracy in brain tumor identification, a novel model was created by Sener et al. (2023) [18] utilizing the widely recognized VGG-19 architecture convolutional neural network model. The study employed many metrics, including precision, F1 score, accuracy, specificity, Matthew's correlation coefficient, and recall, to assess the efficacy of the constructed model. Using MRI pictures of gliomas, meningiomas, pituitary tumors, and healthy brains, a deep learning model for the detection of brain malignancies was constructed. The study's findings show how the established model may be used in clinical settings to detect brain tumors with great promise.

A deep learning method for classifying brain tumors is presented by Rastogi et al. (2023) [19] in an effort to automate difficult medical operations and aid in the diagnosis of medical professionals. Brain image analysis is carried out on publically available datasets such as Kaggle and Brats. Three pre-trained Deep Convolution Neural Network architectures (DCNN)-AlexNet, VGG16, and ResNet50-are used to create the suggested model. The Support Vector Machine (SVM) classifier is used to classify the features that were taken out of the pretrained DCNN architecture through the use of these transfer learning architectures.

Techniques for enhancing Magnetic Resonance Imaging (MRI) data are employed to keep the network from overfitting. Kuraparthi et al. (2021) [20] CNNs and other deep learning methods should be improved for increased efficiency. One of the most popular techniques for enhancing model performance is data augmentation. The implementation of several VGG-19 architectures as a base layer for particular models is described in detail in this article. The suggested method includes pre-processing, cropping, augmentation, VGG-19 as a foundation layer with transfer learning-based binary classification of brain tumors, and further layers of normalization, dense, and activation layers. The proposed method produced the Cohen Kappa Score, f1-score, recall, accuracy, precision, and ROC AUC score on brain cancer kaggle MRI datasets.

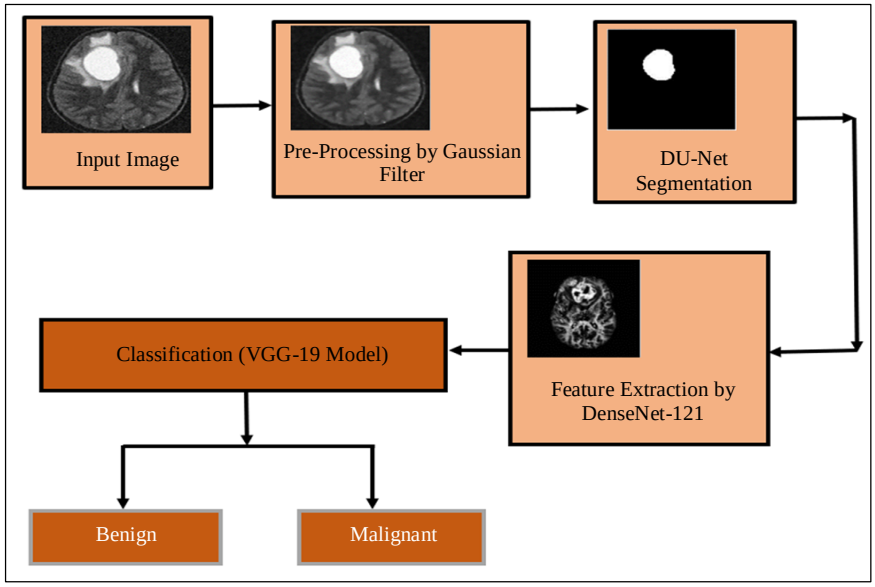

Fig. 1 Flowchart for proposed methodology

3. Proposed Methodology

The initial part of the discussion provides a comprehensive overview of the deep learning models employed for classifying diverse subtypes of brain tumors. Following this, it takes a closer look into the procedural aspects of obtaining the dataset. An overview of the deep learning technique based on VGG-19 is shown in Figure 1.

The pre-processing phase incorporates Gaussian filters, enhancing the overall system performance. The application of a segmentation technique based on DU-Net further contributes to the suggested system's improved efficiency. Feature extraction is accomplished through the utilization of DenseNet-121 [10-12]. The distinction between benign and malignant brain tumor subtypes is achieved by the suggested VGG-19 model [13, 14].

3.1. Dataset

The brain tumor dataset from (https://figshare.com/articles/dataset/brain_tumor_dataset/1512427) was utilized in this study to analyze brain tumor photos. Each category is represented by an image from this dataset. The total number of MRI scan pictures in the collection is 3064. The collection provided a diverse range of brain tumor photos from various users, guaranteeing a broad representation of tumor types and attributes. The data set contains about 400 photos, of which 253 are used for testing and the remaining 147 for training.

3.2. Image Preprocessing

The Gaussian filter is one method for filtering the image before categorization. Based on the Gaussian function's shape, this approach chooses a linear filter with a weighted value for each component. This approach was selected due to its capacity to adjust images while accounting for the kernel center of the filter. This filter is useful for effectively eliminating noise that is regularly distributed. The values of every element in the Gaussian smoothing filter that will be built can be determined or calculated with the use of the subsequent equation.

$$h(x,y) = \frac{1}{c} e^{x^2+y^2/2\sigma} \quad (1)$$

Where c is the normalization constant, and σ is the Gaussian Kernel standard deviation. Small organized details are present in the residual image when the noisy image is processed via multiple layers for noise prediction, which goes against the presumption of independent, identically distributed noise.

Gaussian convolution is applied to the residual image to effectively capture the structure that was left out in order to solve the aforementioned issue. The following represents the image after Gaussian convolution filtering:

$$G(I_p) = \sum_{q \in p} G_\sigma (p - q I_q) \quad (2)$$

$$G(x) = \frac{1}{2\pi\sigma^2} \exp(-\frac{x^2}{2\sigma}) \quad (3)$$

I stand for the image, p for a pixel's position, s for the picture's spatial location, p-q for the Euclidian distance between p and q, which indicates the neighborhood's size, and G_σ (x) for the Gaussian kernel.

3.3. Segmentation

After pre-processing, the pictures were ready for processing for segmentation and classification. The segmentation and classification phases were included in the DU-Net architecture. Segmenting an image can be compared

to a pixel-by-pixel classification. By first building a path of dense blocks that contracts with spatial lowering to extract the features and then building a path of dense blocks that expands with the same spatial lowering to generate an output picture the same size as the input data, we extend the traditional U-Net model to create the DU-Net Model. The DU-Net model is shown in Figure 2.

3.4. Feature Extraction

DenseNet121 uses a fixed size input of an RGB picture with dimensions of 224 × 224. DenseNet121 comprises around 8 million parameters and 121 layers. It is separated into Dense Blocks, each of which has a different number of filters but the same feature map size. The layers that lie between the blocks are called transition layers, and they are in charge of down sampling and batch normalization. The feature extraction of DenseNet-121 is shown in Figure 3.

Consider an input image (x_0) that is processed by the proposed convolutional network. Every NN layer in the network performs the nonlinear transformation F(n). Assume that all feature maps from previous convolutional layers comprise layer n. Layers 0 through $n-1$ input feature maps are combined. This model has N(N+1)/2N(N+1)/2 connections, making it a NN-layer network. The output of the nth layer is given by

$$x_n = F_n([x_o, x_1 \ldots\ldots, x_n - 1]) \quad (4)$$

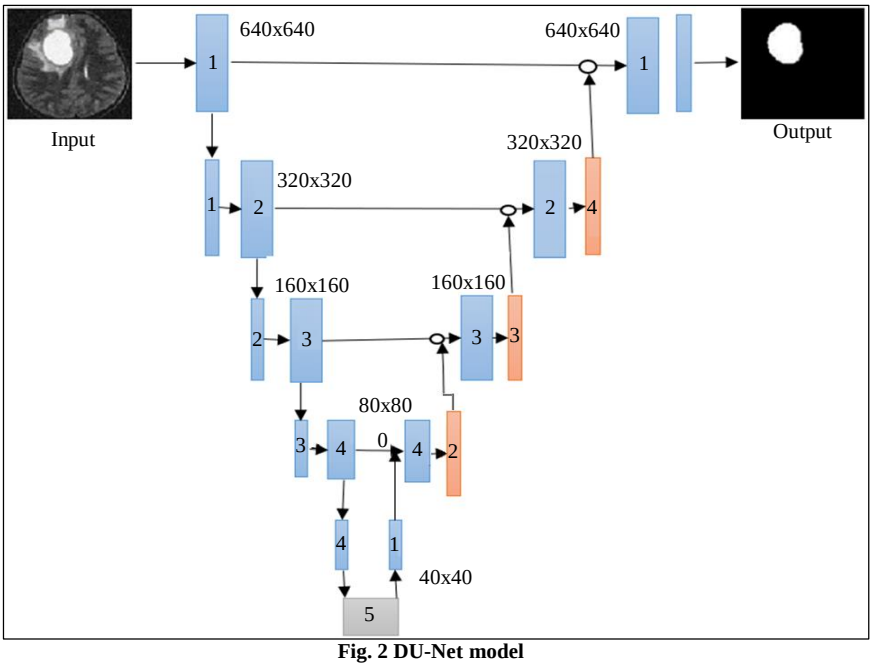

Fig. 2 DU-Net model

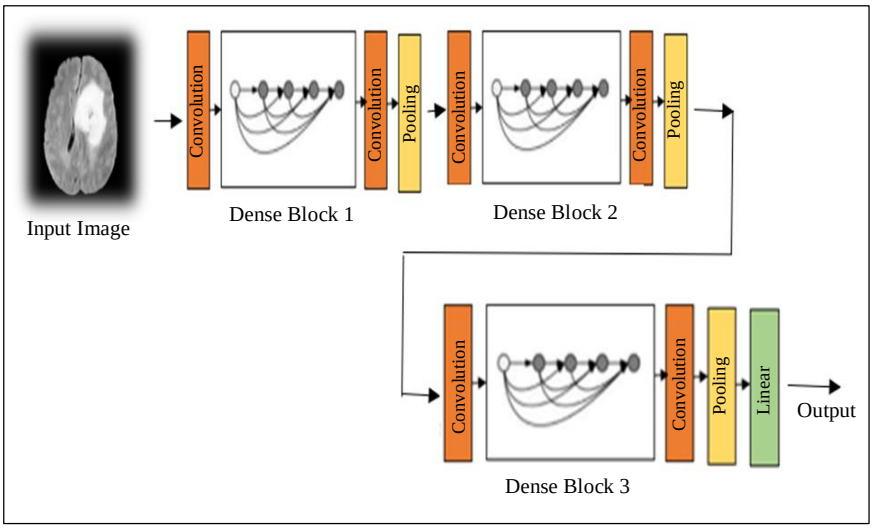

Fig. 3 Feature extraction of DenseNet-121

Rectified Linear Units, 3 × 3 convolution, and Normalization are the further stages in the transition layer. If the sizes of the feature maps are altered, the concatenation process becomes impractical. Therefore, downsampling is used for the layers with various feature map sizes. The 2x2 average pooling and 1x1 convolution transition layers are placed in between two neighbouring Dense Convolution blocks. Seven by seven Conv blocks with stride make up the initial Conv layer. Convolution preserves the relationships between the pixels while learning the attributes of the image.

$$f(x_o) = \max(0, x_o) \quad (5)$$

3.5. Proposed Method VGG-19

The multilayered VGG 19 network architecture is one of the CNN-based architectures that is being considered. It comprises 16 convolutional layers to extract features during training and 19 learnable weights for transfer learning.

It made use of one output layer at the termination and five Fully Connected (FC) layers. To extract characteristics from the inserted photos, the first convolutional layer approximates 64 kernels (3 × 3 filter size). A max-pooling layer has also been added, sandwiched between the convolution layers. The VGG-19 model is shown in Figure 4.

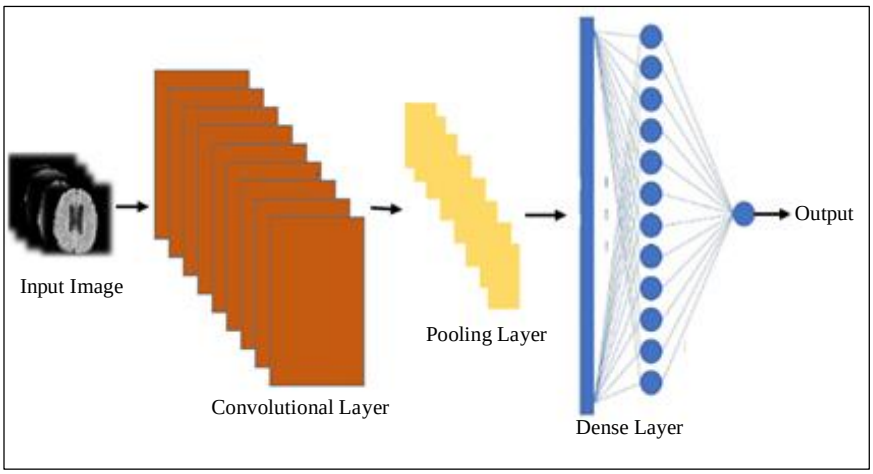

Fig. 4 VGG-19 model

Pseudocode 1
Inputs: No. of epoch,
Tumor detection: training dataset, validation dataset
Tumor classification: training dataset, validation dataset
Outputs
Tumor detection evaluation results
Tumor classification evaluation results
Data Preprocessing
Training process ← preprocess
Validation process ← preprocess
Training for Tumor Detection
θ ←VGG -19 MODEL;(Training dataset, E1)
While θ not converged
For local epoch e ←1 to E1
For b1= (x, y) random to training dataset
Update tumor detection model
$\theta \leftarrow e(\nabla(l(\theta, E1))$
End
End
End
Training for Tumor Classification
∂ ←VGG -19 MODEL;(Training dataset, E2)
While ∂ not converged
For local epoch e ←1 to E2
For b2=(x,y) random to training dataset
Update tumor detection model
$\partial \leftarrow e(\nabla(l(\theta, E2))$
End
End
End
Evaluation Scores of Tumor Detection Model
return

3.6. Performance Measures

For the prediction and classification tasks, numerous evaluation metrics are employed, including F1-measure, accuracy, precision, and recall.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

$$F1 - Measures = 2 \times \frac{Precision \times Recall}{Percision+Recall} \quad (9)$$

4. Experimental Results

Images of cancer are developed in two groups: 20% are used for testing, while the remaining 80% are selected at random for training. The original dataset is then split into training and testing datasets. Table 1 compares the quantity of tests and wet images with the brain tumor's severity.

Table 1. Brain tumor classification system

Class	Total Image	Training	Testing
Benign	90	54	36
Malignant	360	195	165

The dataset used in this study was split up into 2 groups. Every training and testing set contained both benign and malignant photographs. 400 patients' 512x512-pixel-diameter MRI scans were included in the dataset. The photos from the dataset that were utilized as data input are shown in Figure 5.

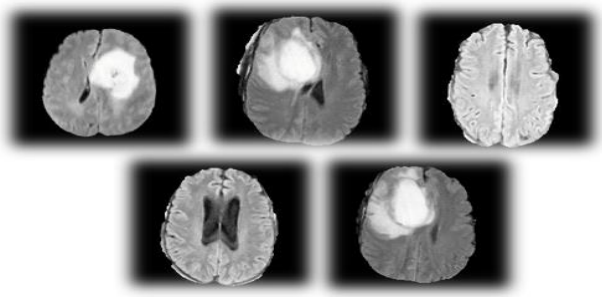

Fig. 5 Input images

4.1. Image Preprocessing

The next step involves applying a Gaussian filter to the brain tumor images in order to improve their quality. The subsequent findings were used in a Gaussian filter-based investigation of noise reduction in brain tumor images (Figure 6). Preprocessing is used on the MRI images to enhance contrast and image quality.

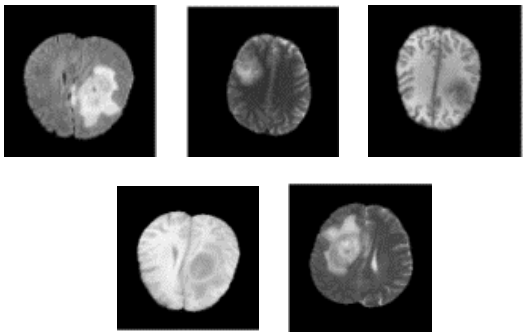

Fig. 6 Preprocessed images

4.2. Image Segmentation

The filter sharpens and smoothens the edges of the image, as shown. The image's pixel quality is enhanced and segmented after pre-processing procedures are applied, and the segmented image is shown in Figure 7.

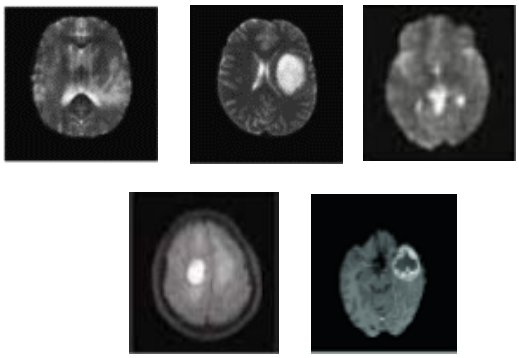

Fig. 7 Segmented images

4.3. Feature Extraction

After the features have been separated with the help of the segmented picture, the features are recovered using the DenseNet-121 approach. The form features in the binary image are the abnormality index, irregularity index, and distance from the lesion. Figure 8 shows an extraction of features.

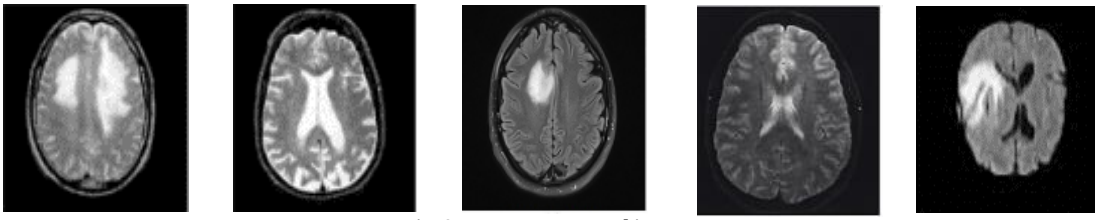

Fig. 8 Features extracted images

4.4. Performance Measures

In order to determine the efficacy of the suggested methodology, assessed the results of deep learning methods were assessed for both image segmentation and classification. Using the VGG-19 models, the accuracy, precision, recall, and F1-score metrics are determined in order to evaluate the performance of the recommended classifiers in this section. Table 2 displays the results of the recommended approach. According to the table, for the "Benign" category, the values for Precision, Recall, F1-measure and Accuracy were 98.7%, 98.5%, 97.9%, and 97.8%, respectively. Conversely, for the "Malignant" category, the values for Precision, Recall, F1-measure, and Accuracy were 97.9, 98.9%, 98.3% and 98.5% respectively.

Table 2. The suggested VGG-19 model results for tumor

	Precision (%)	Recall (%)	F1-Measure (%)	Accuracy (%)
Benign	98.7	98.5	97.9	97.8
Malignant	97.9	98.9	98.3	98.5
Average	98.3	98.7	98.1	98.15

4.5. Classification

The VGG-19 image segmentation and classification results were analyzed in order to assess the efficacy of the suggested methodology. An overview of current techniques for the classification of brain tumors based on various characteristics is provided in Table 3. In this instance, a comparative analysis is employed; note that the majority of the research is concentrated on the accuracy attained.

Comparing that, the VGG-19 categorization yields superior outcomes. With the recommended method, 98.3% precision, 98.7% F1-score, 98.1% recall, and 98.15% accuracy were attained. A comparison table is shown in Table 3, and the graphical representation is shown in Figure 9.

4.5.1. Accuracy vs. Epoch

The accuracy vs. epoch graph that was found during the training and testing phase is explained. It shows why the suggested VGG-19 approach is worthwhile. Figure 10 shows how accurate the suggested model is throughout training and testing.

4.5.2. Loss vs. Epoch

The loss vs. epoch graph generated during the training and testing stage is shown in Figure 11. The loss curve shows the suggested VGG-19 model's best performance over a 100-epoch period, along with the least amount of loss. The loss graph of training and testing of VGG-19 is shown in Figure 11.

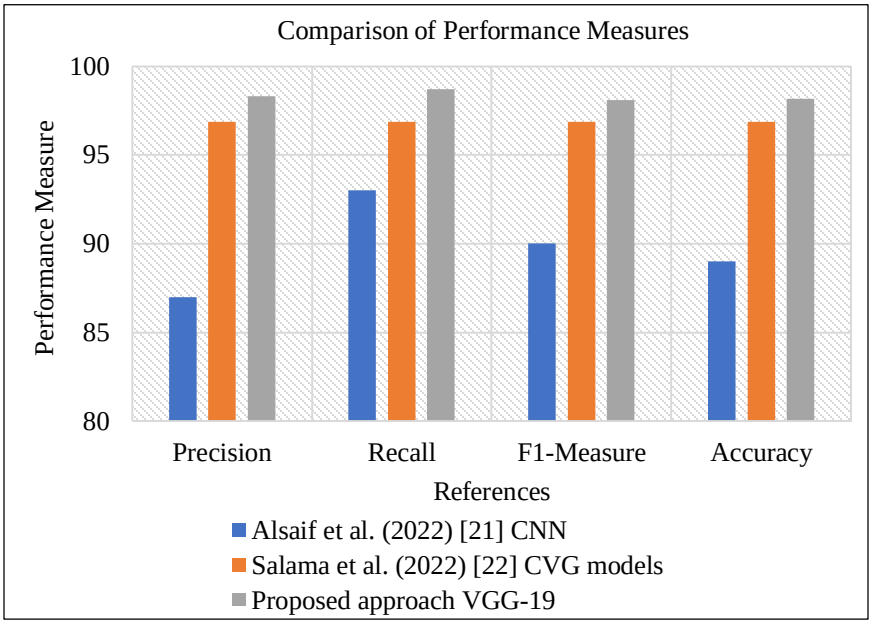

Fig. 9 Comparison of different classification model

Table 3. Comparison table

Reference	Techniques	Precision	Recall	F1-Measure	Accuracy
Alsaif et al. (2022) [21]	CNN	87	93	90	89
Salama et al. (2022) [22]	CVG Models	96.88	96.88	96.88	96.88
Proposed Approach	VGG-19	98.3	98.7	98.1	98.15

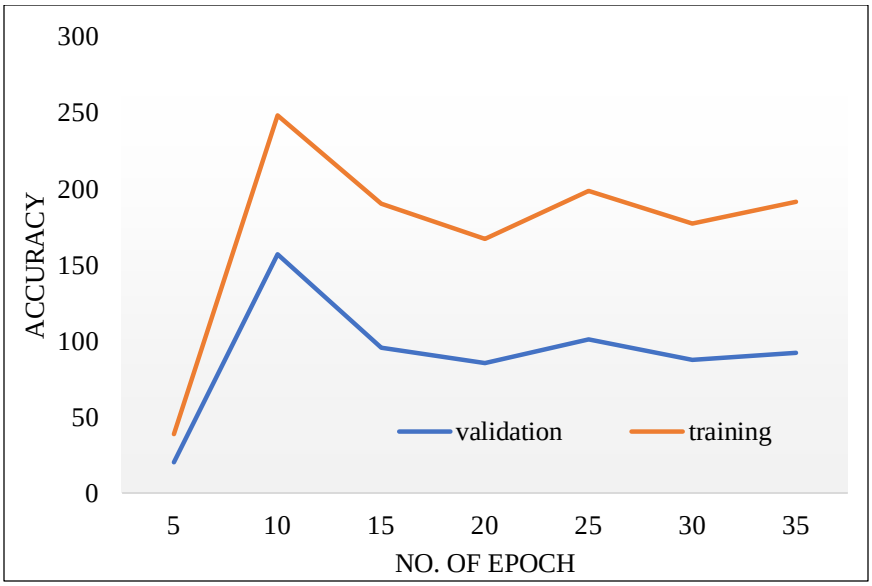

Fig. 10 Accuracy graph of training and testing of VGG-19 model

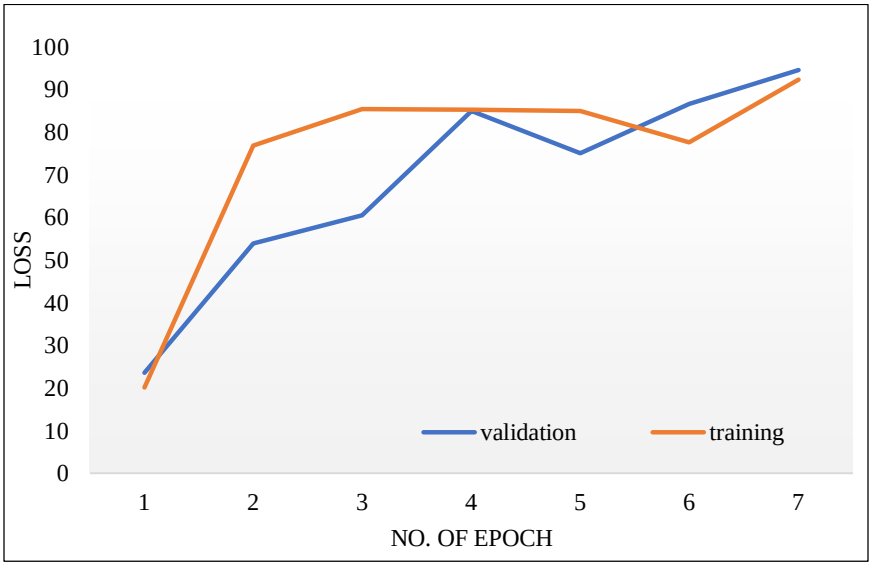

Fig. 11 Loss graph of training and testing of VGG-19

4.5.3. Confusion Matrix

The confusion matrix obtained at the classification stage is shown in Figure 12. 47 of the 90 benign cases are mistakenly diagnosed as malignant, while 43 of the 90 benign cases are accurately classified as benign. 304 cases were appropriately diagnosed as malignant, while 56 of the 360 malignant cases that were reviewed were incorrectly labeled as benign. The accuracy rate of the suggested technique is 98.15% in properly classifying tumors as malignant or benign. The results of the VGG-19 Model is shown are in Figure 12.

43	47	97.7%
56	304	97.6%
98.5%	96.8%	98.15%

Fig. 12 Results of VGG-19

5. Conclusion

This study suggests using VGG-19 to categorize tumor types as benign or malignant. Accurately classifying MRI brain tumors is challenging, and the challenge grows with the type of classification. The proposed approach functions in this manner and uses tumor data from several patients. Pictures feature a lot of contrast. Gaussian filtering techniques are employed during preprocessing to eliminate noise from images. DU-Net segmentation was used to preprocess pictures for segmentation. 98.7% precision, 98.3% F1-score, 98.1% recall, and 98.15% accuracy were obtained using the suggested approach. The experiment results show that the suggested VGG-19 method outperforms state-of-the-art methods in terms of accuracy and other performance parameters.

Acknowledgments

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

References

[1] Sarang Sharma et al., "Deep Learning Model for Automatic Classification and Prediction of Brain Tumor," *Journal of Sensors*, vol. 2022, pp. 1-12, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] W. Li, "Image Classification of Brain Tumor Based on Enhanced VGG 19 Convolutional Neural Network," *Clinical Oncology*, vol. 6, pp. 1-10, 2023. [Google Scholar]

[3] Sri Sai Meghana Alla, and Kavitha Athota, "Brain Tumor Detection Using Transfer Learning in Deep Learning," *Indian Journal of Science and Technology*, vol. 15, no. 40, pp. 2093-2102, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Rashmi Ashtagi et al., "Image Fusion of MRI and CT Scan for Brain Tumor Detection Using VGG-19," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 10s, pp. 369-377, 2024. [Google Scholar] [Publisher Link]

[5] Nitish Zulpe, and Vrushsen Pawar, "GLCM Textural Features for Brain Tumor Classification," *International Journal of Computer Science Issues*, vol. 9, no. 3, pp. 354-359, 2012. [Google Scholar] [Publisher Link]

[6] S. Sai Meghana et al., "A Deep Learning Approach for Brain Tumor Segmentation Using Convolution Neural Network," *International Journal of Scientific and Technology Research*, vol. 8, no. 12, pp. 1697-1702, 2019. [Google Scholar] [Publisher Link]

[7] Yiran Wei et al., "Predicting Isocitrate Dehydrogenase Mutation Status in Glioma Using Structural Brain Networks and Graph Neural Networks," *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, pp. 140-150, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Minakshi Sharma, and Sourabh Mukharjee, "Brain Tumor Segmentation Using Genetic Algorithm and Artificial Neural Network Fuzzy Inference System (ANFIS)," *Advances in Computing and Information Technology*, pp. 329-339, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[9] Navid Ghassemi, Afshin Shoeibi, and Modjtaba Rouhani, "Deep Neural Network with Generative Adversarial Networks Pre-Training for Brain Tumor Classification Based on MR Images," *Biomedical Signal Processing and Control*, vol. 57, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] N. Veni, and J. Manjula, "VGG-16 Architecture for MRI Brain Tumor Image Classification," *Futuristic Communication and Network Technologies*, pp. 319-328, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Tahia Tazin et al., "A Robust and Novel Approach for Brain Tumor Classification Using Convolutional Neural Network," *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1-12, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] Rakibul Islam, Amatul Bushra Akhi, and Farzana Akter, "A Fine Tune Robust Transfer Learning-Based Approach for Brain Tumor Detection Using VGG-16," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 6, pp. 3861-3868, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Tanzila Saba et al., "Brain Tumor Detection Using Fusion of Hand Crafted and Deep Learning Features," *Cognitive Systems Research*, vol. 59, pp. 221-230, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[14] Aman Nath et al., "Novel Deep Neural Network Model for Brain Tumor and Breast Cancer Classification to Promote E-Health," *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, pp. 1303-1309, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[15] Mohammad Shahjahan Majib et al., "VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection on MRI Images," *IEEE Access*, vol. 9, pp. 116942-116952, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Chetana Srinivas et al., "Deep Transfer Learning Approaches in Performance Analysis of Brain Tumor Classification Using MRI Images," *Journal of Healthcare Engineering*, vol. 2022, pp. 1-17, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Saif Ahmad, and Pallab K. Choudhury, "On the Performance of Deep Transfer Learning Networks for Brain Tumor Detection Using MR Images," *IEEE Access*, vol. 10, pp. 59099-59114, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[18] Abdullah Şener, and Burhan Ergen, "Enhancing Brain Tumor Detection on MRI Images Using an Innovative VGG-19 Model-Based Approach," *Sakarya University Journal of Science*, vol. 27, no. 5, pp. 1129-1141, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Deependra Rastogi, Prashant Johri, and Varun Tiwari, "Augmentation Based Detection Model for Brain Tumor Using VGG 19," *International Journal of Computing and Digital Systems*, vol. 13, no. 1, pp. 1227-1237, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Swaraja Kuraparthi et al., "Brain Tumor Classification of MRI Images Using Deep Convolutional Neural Network," *Traitement du Signal*, vol. 38, no. 4, pp. 1171-1179, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[21] Haitham Alsaif et al., "A Novel Data Augmentation-Based Brain Tumor Detection Using Convolutional Neural Network," *Applied Sciences*, vol. 12, no. 8, pp. 1-16, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Wessam M. Salama, and Ahmed Shokry, "A Novel Framework for Brain Tumor Detection Based on Convolutional Variational Generative Models," *Multimedia Tools and Applications*, vol. 81, no. 12, pp. 16441-16454, 2022. [CrossRef] [Google Scholar] [Publisher Link]