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DEEP LEARNING TECHNIQUES FOR MRI IMAGE-BASED PERFORMANCE ANALYSIS OF BRAIN TUMOR CLASSIFICATION

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ABSTRACT
Brain tumors can produce symptoms and indicators due to direct tissue death, localized invasion of the brain, or aftereffects from increased intracranial pressure. In order to identify images from the publicly available image dataset, this work combined multiple image feature sources using deep learning algorithms. The architecture of most classic convolutional neural networks (CNNs) consists of convolution modification and max-pooling of layers connected with several completely linked layers. The steps used in this system are pre-processing, segmentation, feature extraction, and classification. The preprocessing procedures of this investigation were used by the modified trimmed median filtering approach. U-Net segmentation is used to carry out the segmentation process. Features are then extracted using the wavelet transform method. In this study, MRI images of brain tumors, including meningnant and benign tumors, were detected and classified using the proposed CNN-based VGG16 model. The convolutional neural network (CNN) architectures employed in this investigation were guided by the VGG-16. The outcomes are assessed in terms of accuracy, precision, recall, and F1-score after the suggested model has been simulated. According on the test findings, the recommended approach may lead to 96.9% maximum recall, 97.4% maximum F1-score, 98.45% maximum accuracy, and 98.1% maximum precision.
Keywords: *Deep Learning, Modified Trimmed Median Filter, 3D Version Of U-Net Segmentation, Discrete Wavelet Transform, Convolutional Neural Network (CNN) Based VGG-16.*

1. Introduction

Brain tumors fall into a number of kinds, the most common being primary and secondary tumors. Whereas secondary cancers go from another part of the body to the brain, primary tumors originate in brain tissue. A significant portion of brain tumors are of the second sort, which is comparable to metastases of the initial form of cancer. The differences in tumor location, shape, and size present a significant obstacle for brain tumor identification. This survey's goal is to assist researchers by providing a thorough literature review on brain tumor detection using magnetic resonance imaging (MRI) was described by Amin et al., (2022). Accurate segmentation and classification are still difficult tasks in this field, despite numerous noteworthy attempts and encouraging results. Cells within or close to the brain can proliferate and become a tumor. Weber et al., (2006) have explained about the brain tissue which can harbor the growth of brain tumors. There is also a possibility of brain tissue being near brain tumors. Near each other along neural connections are the pituitary, pineal, and brain surface membranes. Tissue from the brain can become a tumor. Ravinder et al., (2023) have explained in detail and the brain tumor classification. Seldom can cancerously cells from other sections of the body move to the brain. Secondary or metastatic brain tumors are the terms we use to describe these cancers. Primarily, brain tumors come in many forms. Brain tumors are not always malignant. Benign or noncancerous brain tumors are what these tumors are called. While they expand, non-cancerous brain tumors may compress brain tissue. A malignant brain tumor, often known as a brain malignancy, is another type of brain tumor. Brain tumors spread quickly. Brain tissue can be penetrated by cancer cells and harmed.

Due to its critical importance to both the medical community and mankind at large, brain tumor research is currently very popular in academia. Since the human nervous system is centered in the brain, a brain tumor can be fatal and will likely be the cause of 18,000 adult fatalities were elaborated by Alnaggar et al., (2022). Brain tumors arise from uncontrolled clumps of aberrant cells that eventually build up and destroy the brain's regulatory structure. Depending on how the brain's tissues are harmed by the tumor, it can be determined if a brain tumor is cancerous or not were explained by Kumar et al., (2017).

One of the diseases that can harm the brain and cause death is brain cancer, according to Gore et al., (2020). One method is based on medical imaging to detect brain tumors. According to Suresha et al., (2020), magnetic resonance imaging (MR) is a time-consuming technique for identifying brain tumors, but it is essential for early illness prediction, which is now only dependent on the knowledge of medical professionals. In the current climate, brain tumors are one of the main causes of death, and experts are looking for strategies to slow their spread (Chaudhary et al., 2020). Kumar et al., (2021) list brain tumors as one of the diseases that directly impact the brain. The better soft tissue composition of MR images makes them ideal for brain research. Early brain tumor diagnosis can be challenging for medical professionals, according to Sravanthi et al. (2021). Noise and other environmental disturbances have a greater impact on MRI pictures. As a result, it is challenging for medical professionals to diagnose the tumor and its causes. Computed tomography (CT) or magnetic resonance imaging (MRI) scans are frequently used to identify the presence of cancers (Mittal et al., 2021). The neurologists must use a very challenging and time-consuming procedure to find tiny cancers. Hu et al., (2020) assert that in order to cure and lower the high death rate linked to brain tumors, early diagnosis in the early stages is crucial. Therefore, it may be beneficial to use automated processes for the meticulous inspection of malignancies. A machine learning model that meticulously chooses and extracts features produces more accurate results, claim Halder et al., (2021). Aulia et al., (2022) state that brain tumors are frequently diagnosed with magnetic resonance imaging (MRI). The risk of dying from a future or malignant brain tumor is high. These tumors are more likely to spread from one location to another. Baalamurugan et al., (2022) have described the computer-aided robotic research technology is used to more accurately and efficiently diagnose brain tumors in their early stages. MRI scans can be used to identify tumor cells using a variety of segmentation techniques.

Gravity within the skull can accelerate brain tumor growth, deteriorate overall health, and in the worst situation, result in death. It is usual practice to use MRI data to visually represent the different forms and appearances of brain tumors. Thus, Saxena et al., (2020), conducted an analysis of MRI scan images to determine the tumor's location, size, kind, and grade. This information can be used to assess the tumors and plan future therapy. The patient's condition affects the tumor's shape, size, location, kind, and grade, all of which have an impact on the course of treatment. Therefore, appropriate treatment approaches can benefit from accurate tumor detection.

A variety of non-invasive techniques for peering inside the body are referred to as medical imaging. Medical imaging comprises several image modalities and procedures to picture the human body for diagnostic and therapeutic reasons were described by Mohanty et al., (2024). As such, it plays a crucial and pivotal role in taking actions to improve people's health. In order to successfully proceed to a higher level of image processing, A crucial and required stage in the image processing process is picture segmentation were explained by Amran et al., (2022). In medical image processing, tumor or lesion detection, effective machine vision, and obtaining appropriate results for additional diagnosis are the key objectives of image segmentation. Enhancing the tumor or lesion's sensitivity and specificity has emerged as a major issue for medical imaging. It gets harder to pinpoint the precise position of the tumor. The use of state-of-the-art techniques makes identifying the aberrant cells more difficult. MRI scan images are used to accurately classify tumors and cancer cells.

A high-performing Initial and accurate brain tumour detection using an efficient VGG-16 tumour diagnosis system. Contribution of this paper.

- To enhance the image quality, a modified trimmed median filter is used at the pre-processing stage.
- Then applied a 3D-U-Net segmentation for segmenting the brain tumor.
- The feature will be extracted using Discrete wavelet transform.
- A CNN based VGG-16 model built on the architecture and optimized for classification of benign and malignant pictures is proposed. The performance metrics Accuracy, Precision, Recall, and F1-score are used to assess the recommended method.

2. Literature Review

A computer-aided method for analyzing MRI pictures and precisely identifying abnormalities is now possible because to advancements in machine learning and rapid processing. In the area of analysis of medical images, picture segmentation has gained popularity and become a focus of research. With the use of a computer-aided identification system, brain anomalies can be swiftly classified, allowing for early treatment which have been described by Sharif et al., (2024). Thorough review of the subject and fresh insights into the various ways that Brain tumors are identified using machine learning and photo segmentation algorithms. Comparing deep learning methods against new methods, the former are more successful in distinguishing cancers from brain MRI images. Bahadure et al., (2017) have determines about the key features of different types of brain tumors, and also identifies many segmentation/classification procedures that are useful for the identification of various brain illnesses. This research gathers all the information required to identify and comprehend tumors, including their advantages, developments, disadvantages, and possible future patterns.

While deep learning algorithms have made significant progress, Soomro et al., (2022) have noted that, in brain tumor the detection is still necessary to have a generic strategy. When the same acquisition properties (intensity range and resolution) are used for training and testing, these approaches perform better; the robustness of the methods is directly impacted by a small difference in the training and testing images. Fusing deep and hand-crafted characteristics can enhance the classification outcomes. Chahal et al., (2020) have explained about various methods for detecting different types of brain tumors using MR imaging are discussed, along with the benefits and drawbacks of each method. Presently available segmentation, classification, and detection methods are also discussed, with an emphasis on the benefits and drawbacks of various medical imaging modalities.

Sharma et al., (2023) have explained about the effectiveness of the ResNet50 approach using performance indicators, and the outcomes were contrasted with those attained using techniques. Utilizing components of the ResNet50 model, the design of the layers in place of the final layer in order to accommodate work requirements. This work uses the upgraded ResNet50 model to assess the accuracy of brain cancer categorization utilizing a unique deep learning strategy based on a transfer learning technique. Abdusalomov et al., (2023) have studied about multiple approaches for the diagnosis of malignancies and brain cancer. An assessment matrix is a certain system for employing the system and the type of which dataset is also included in this study. This research also explores the anatomy of brain tumors, datasets that are available, augmentation techniques, component extraction, and machine learning, transfer learning, and deep learning model classification.

Zeineldin et al., (2020) used a new universal deep learning architecture called DeepSeg and FLAIR MRI data for fully automated brain lesion recognition and segmentation. DeepSeg is a modular decoupling framework. Colucci-D'Amato et al., (2020) state that it is essential for the conversion of synaptic action into long-term synaptic memory. It is thought that BDNF influences dendritic spines and functional plasticity in the central nervous system (CNS) by instructively modulating adult and structural neurogenesis, at least in the hippocampus. The method proposed by Kang et al., (2021) uses a number of pre-trained deep convolutional neural networks and the concept of transfer learning to extract deep features from brain magnetic resonance (MR) images. In order to detect brain tumors and ascertain their stage in the given input image, Praveena et al., (2022) present integrated learning process detection (ILPD), which assesses the tumors' dimensions and shape. To increase the tumor identification rate, Deep Convolutional Neural Networks (DCNN) are combined with better picture filters. The ILPD achieved precision (99.67%), accuracy (98.45%), specificity (99.12%), sensitivity (97.89%), and dice score (98.87).

A large dataset of MRI images labeled with tumor regions is used to train the CNN using data augmentation and transfer learning techniques in the CNN-RNNs and GANs methodology (Kaushik et al., 2023). Experiments show that the proposed approach performs better than the most sophisticated methods for brain tumor detection. In 2023, Singh et al., created a new convolutional neural network (CNN) architecture to classify three different types of brain cancers. Using this ten-fold cross-validation data set method for record-wise cross-validation yields an accuracy percentage of 92.50%. In order to automatically detect brain abnormalities, the logistic regression machine learning technique, as outlined by Gajula et al., (2024), might be used in this work. Performance parameters like accuracy 97%, precision 97.9%, and recall 97% were ultimately achieved; these figures show how much better the methodology is than current models. Kempanna et al., (2024) state that ResNet18, which is well-known for its powerful feature extraction capabilities, was used to assess the MRI images, and targeted loss was used to address class imbalance problems that are commonly found in medical datasets. Following training on a large dataset, the model's accuracy was 95.54%. Pacal et al., (2024) have described the effective and reliable training, transfer learning, and data augmentation methods utilized to improve model performance.

Mahmud et al., (2023) have proposed an effective architecture for convolutional neural networks (CNNs)-based brain tumor diagnostics. a comparison between the proposed architecture and other models, such as Inception V3, VGG16, and ResNet-50. Numerous criteria, such as area under the curve (AUC), loss, accuracy, and recall, are used to assess the models. We were able to establish that our suggested model performed better than Inception V3, VGG16, and ResNet-50 models by contrasting it with these metrics. Using a dataset of 3264 MR images, we found that the CNN model had 93.3% accuracy, 98.43% AUC, 91.19% recall, and 0.25 loss. Mahjoub et al., (2023) have suggested about CNN model for categorizing brain cancers from MRI pictures is a useful tool that could help doctors identify brain tumors quickly and correctly. When compared to other deep neural models, the high accuracy rate of the suggested model shows how well DCNNs classify brain cancers based on MRI data.

Anantharajan et al., (2024) have described how this machine learning technique is extensively used in a variety of applications and has shown to be successful in solving a number of difficult problems. The MRI images are first collected and pre-processed using the median filter and the Adaptive Contrast Enhancement Algorithm. For segmenting the pre-processed images, a fuzzy c-means algorithm is applied. The gray-level co-occurrence matrix is used to extract features such as mean, contrast, entropy, and energy. To characterize the abnormal tissues, the Ensemble Deep Neural Support Vector Machine classifier is proposed. The improved sensitivity (92%), specificity (98%) and accuracy (97.93%) in the strategy's use illustrate its numerical efficiency.

Islam et al., (2024) have determined about the model has potential as a tool in the field of medical image analysis because its architecture is made to achieve optimal performance on medical image datasets. It is critical to recognize the limitations of the proposed model, which include the need to carefully evaluate how applicable it is to different datasets and clinical scenarios, as well as the potential costs related to computing and data requirements. Based on DL and ML, this work proposes a novel MRI brain tumor detection technique.

Research Gaps

In order to design and investigate brain disease detection utilizing deep learning approaches, various research gaps should be addressed based on the literature evaluation above. According to the state of this field's research, we enumerated the research issues.

a) To create reliable and common methods for detecting brain tumors, extracting their quality for medical diagnosis, visualizing them, and predicting their presence.
b) CNN-based picture segmentation and feature extraction that is reliable and scalable while taking into account various dataset types and requiring little computational work.
c) The accuracy and detection time may be improved by using suitable feature extraction and reduction models.

Severity analysis is a crucial component of suitable treatment that has not been taken into account in any contemporary publications.

3. Proposed Methodology

An overview of the suggested methodology for the deep learning technique can be seen below. The procedure for generating the dataset is described in detail after the deep learning models that were used to categorize the different subtypes of brain cancers. Fig. 1, shows the flowchart for the suggested brain tumor classification. Pre-processing is done using modified trim filters. The proposed system performs better when a segmentation strategy based on DU-Net is applied. To extract features, one uses the wavelet transform. The suggested CNN based VGG-16 model distinguishes between malignant and benign brain tumor subtypes.

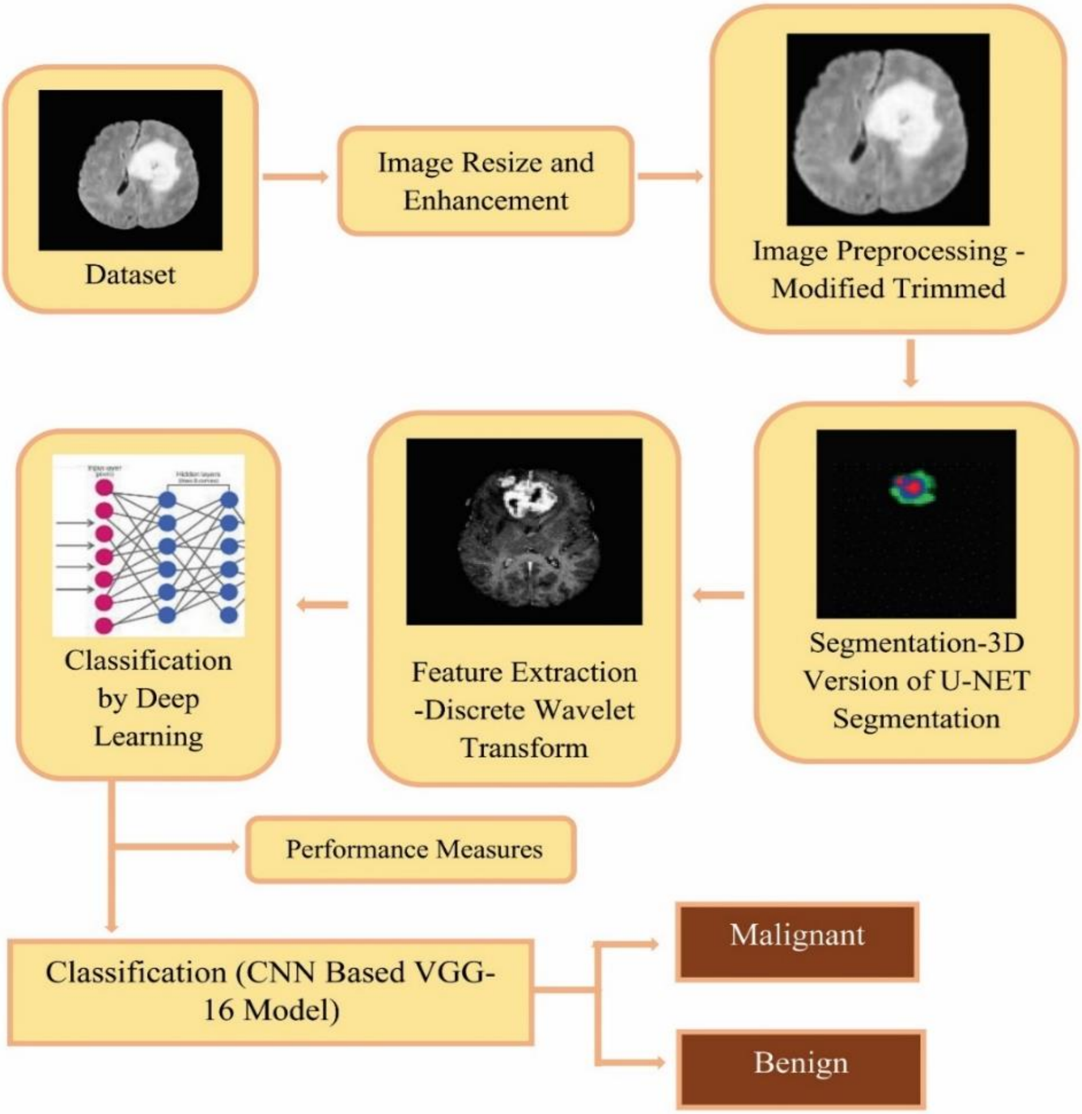

Fig. 1. Flowchart of proposed methodology

It is well known that to get an optimal solution for any linear programming problem using the direct simplex algorithm should be processed to be in standard form, the simplex method for solving an LP problem requires the problem to be expressed in the standard form. But not all LP problems appear in the standard form. In many cases, some of the constraints are expressed as inequalities rather than equations;

3.1 Dataset

This investigation used the dataset on brain tumors from (https://www.kaggle.com/datasets/jakeshbohaju/brain-tumor) to assess pictures of brain tumors. An image from this dataset is used to represent each category. There are 3762 MRI scan images in all in the collection. The collection featured a diversified range of brain tumor photographs from various users, assuring a broad representation of tumor kinds and features. The data set consists of roughly 450 photos, of which 285 are used for testing and the remaining 165 for training.

3.2 Image preprocessing

Prior to classification, one technique for filtering the image is the modified trimmed median filter. This method selects a weighted median filter for each component based on the form of the filter function. The ability of this method to modify images while taking the filter's kernel center into consideration led to its selection. Noise that is dispersed regularly can be successfully removed with this filter.

This section explains the suggested noise removal algorithm, or Modified Trimmed Median Filter (MTMF). In this instance, a 3x3 window for the image, and inside of it, the processing pixel is examined to determine whether or not noise has deteriorated it. It must determine from the pixel value that a pixel is considered non-noisy or noise free if its value falls between the image's highest and lowest gray level values; otherwise, it is noisy. In the event that the processing pixel turns out to be noise-free, it stays unchanged. A pixel is considered noisy when its processing value is the lowest and maximum gray level value in the image. If it is the noisy pixel, you can use the MTMF that was generated for this window in its place. In this case, N(i,j) which represents the noisy image and K(i,j) is represents the restored image.
Below is a description of each of the MTMF's many steps.

Steps
1. Read the noisy N(i,j) input image.
2. Choose a processing pixel Nij. If Nij is kept constant and 0<nij Step Three: Nij serves as both the processing pixel and the center element in this arrangement.
3. Choose a 3x3 2D window.
4. Nij is a degraded pixel. The next two instants are feasible when Nij is either 0 or 255. These two scenarios rely on every element in the window that has been selected.
5. The only characters in the chosen 3x3 window are 0s and 255s. Nij can then be substituted with the average of every element in the 3x3 frame.
6. The chosen 3x3 window contains more than just 0s and 255s; remove the 255s and 0s from the window and substitute the average of the mean and median values found for the window's most notable sections for the Nij.
7. Repeat steps 1 through 3 until all of the image's pixels are covered in order to obtain the restored image K(i,j).

3.3 Image Segmentation

The foundation of our system is the U-Net structure, it is made up of a symmetric expanding path to go back to the initial resolution and a contracting path to study the entire image. In the field of medical picture segmentation, the U-Net structure has been applied extensively and demonstrated to perform competitively. Several studies show that a 3D version of U-Net with 3D volumes as input can perform better than a fully 2D design. The input's increasingly abstract representation is encoded by the contracting path, while the original resolution is restored by the expanding path the network's depth "level." more levels reflect features with more dimensionality but with lower spatial resolution, and vice versa. The contracting path receives a 128x128x128 voxel block with 4 channels as input. Five levels make up the contractual course.

Every level, with the exception of the first, is made up of two S3D blocks. Transition blocks connect the several layers, reducing the feature map resolution while increasing the number of channels. The transition module consists of instance normalization after a 3x3x3 convolution with stride 2. After contracting, the feature maps' dimensions are lowered to 8x8x8. Fig. 2, shows that the 3D version of U-Net Segmentation

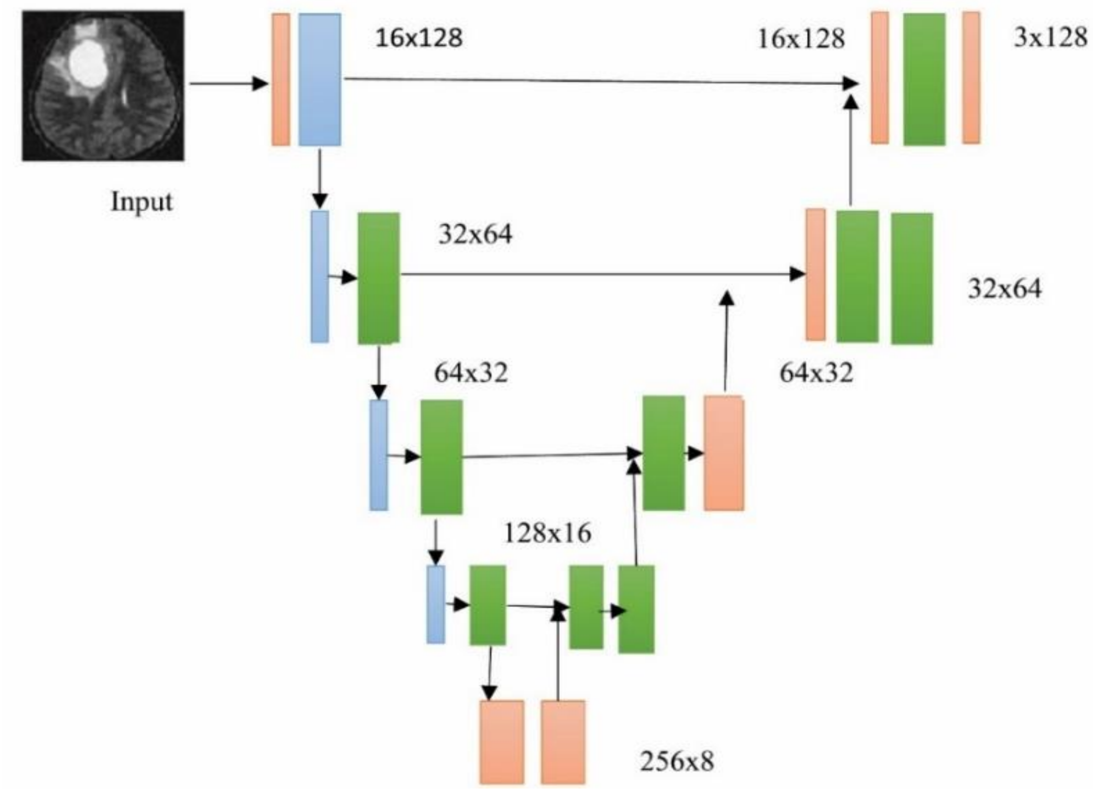

Fig. 2. 3D Version of U-Net segmentation

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3.4 Feature extraction

After the segmentation process, Discrete wavelet transform is used to extract features. In terms of mathematics, the wavelet transform is the outcome of convolutional signal x(t) with the wavelet function (t). Next, connect scaling functions to orthonormal dyadic discrete wavelets I(t). Approximation coefficients S can be obtained by convolving the signal and the scaling function. Here is an expression for the discrete wavelet transform (DWT) in notation:

$$Ta,b = \int_{-\infty}^{\infty} x(t)\varphi_{a,b}(t)dt \tag{1}$$

Reconstructing the original requires using an orthonormal wavelet basis. The signal's approximation coefficients at scale m can be shown as follows:

$$S_{a,b} = \int_{-\infty}^{\infty} x(t)\emptyset_{a,b}(t)dt \tag{2}$$

Our discrete input signal $S_{a,b}$ has a finite length in practice, which is equal to an integer power of two, $\emptyset_{a,b}$. The signal's discrete approximation can be shown as,

$$m_o(t) = m_x(t) + \sum_{x=1}^{X} d_x(t) \tag{3}$$

In this case, the scale m mean signal approximation is

$$m_x(t) = S_X \emptyset_{x,n}(t) \tag{4}$$

Thus, given a finite length signal, the detail signal approximation corresponding to scale m is defined as follows:

$$d_x(t) = \sum_{x=0}^{m-x} T_{a,b}\varphi_{a,b}(t) \tag{5}$$

By adding the approximate signal at scale index m to the sum of all detail signal components across scales, one can also approximate the original signal at scale index 0. The signal approximation at a specific scale was created by combining the approximation with detail at the next lower scale.

$$m_x(t) = x_{m-1}(t) - d_x(t) \tag{6}$$

It can be demonstrated that the signal approximation is provided by if scale m_3 is selected.

$$m_3(t) = m_o(t) - d_1(t) - d_2(t) \tag{7}$$

Representing the progressive removal of high frequency data (found in the dx (t)) from the initial signal at each stage. This is the foundation of our process and is known the analysis of a signal utilizing wavelet transform.

3.5 Proposed CNN based VGG-16 method

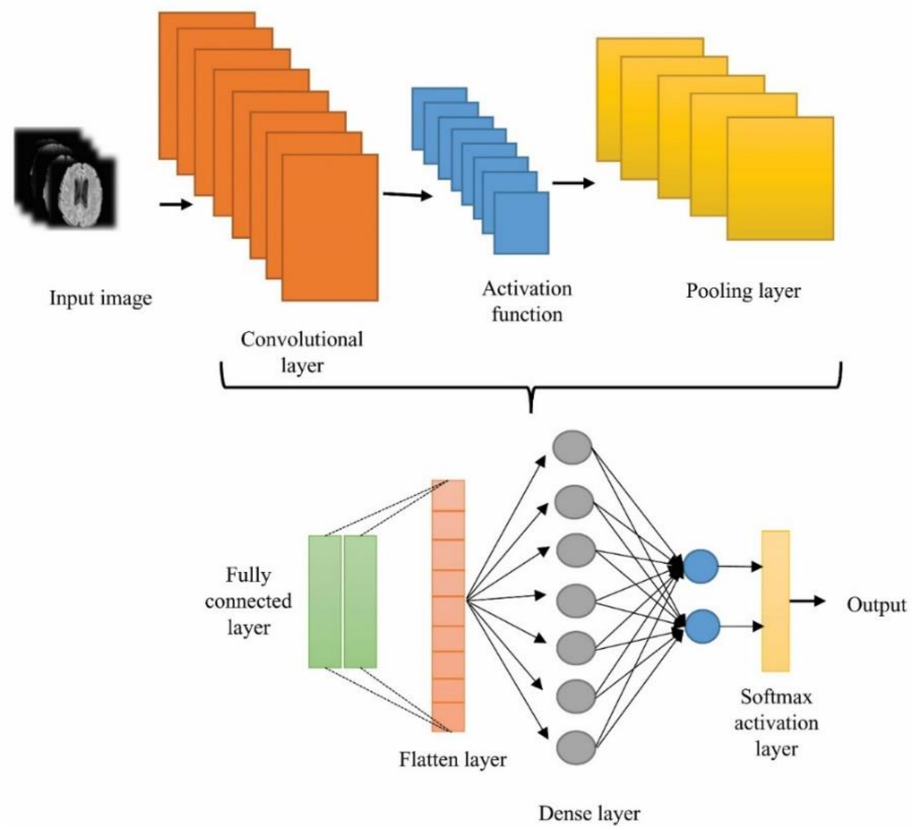

Fig. 3. Proposed Architecture of CNN based VGG-16

Among the most popular deep learning architectures is VGG-16. Fig. 3, presents the proposed architecture of CNN based VGG-16. It comprises 41 layers that are disrupted, including 13 convolutional layers among them. VGG16 implements a tiny 3x3 kernel on every Convolutional Layer having one stride. Convolutional layers are always followed by max pooling layers. Fixed 224x224 three-channel images are fed into the VGG-16. The final layer, which represents the class label number in the dataset, has a channel size of 1000, whereas the first two have the same channel size of 4096. The probability for the input image is determined by the soft-max layer, also known as the output layer.

Like other pre-trained models, VGG-16 requires substantial training and testing randomly. Therefore, transfer learning (TL) strategies are generally applied in CCN models. TL is a mechanism that applies some of the same training to a second task that is comparable to the first. Then train a CNN model on a similar problem to the one under consideration, i.e., one in which the input is the same but the result may differ.

Algorithm: CNN Based VGG-16

Input: No. of epoch-E, batch size-b, brain tumor training data X_{TRAIN} ,Brain tumor test dataset-X_{TEST},

Output: The assessment metrics are computed on the dataset
Initialize deep learning model of VGG-16
Deep learning
for epoch $e \leftarrow 1$ to E do
 for b=$(a, b) \in$ random batch X do

optimize model parameters

$\omega_a \leftarrow \omega_a - \delta(\nabla(\alpha(\omega_a, b)))$

end

end

Initialize upper layers of classification model parameters with trained model

Tumor classification

Preprocess brain tumor dataset

$X_{TRAIN} \leftarrow Pre_{DATA}(X_{TRAIN})$

$X_{TEST} \leftarrow Pre_{DATA}(X_{TEST})$

while θ has not converged do

for epoch $e \leftarrow 1$ to E do

for S=(a,b) random batch of X_{TRAIN} do

update model parameters

$\theta_a \leftarrow \theta_a - \delta(\nabla(\alpha(\theta_a, S)))$

end

end

end

Evaluated trained model with brain tumor test $P_{TEST} \leftarrow compute_{METRICS}(\theta, X_{TEST})$

return P_{TEST}

3.6 Performance metrics

For the prediction and classification problems, various assess metrics are employed, including accuracy, precision, recall, and F1-measure. The following evaluation measures are used to gauge how effective the suggested model is.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

$$Recall = \frac{TP}{TN+FN} \tag{10}$$

$$F1 - Measures = 2\ x\ \frac{Precision+Recall}{Percision+Recall} \tag{11}$$

4. Experimental Results and discussion

Two sets of tumor images are created: 20% are used for testing, while the other 80% are chosen for training from the dataset. Next, for additional processing, the original dataset is divided into training and testing datasets. The number of tests and wet images compared to the severity of the brain tumor are shown in Table 1.

Table 1 - Brain tumor classification system

Class	Total image	Training	Testing
Benign	80	62	18
Malignant	370	196	174

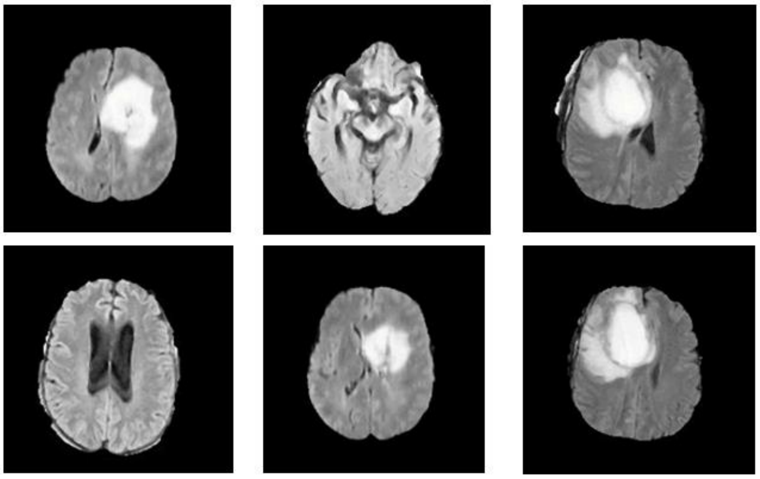
Fig. 4. VGG-16 Input images

Two groups of the dataset were used in this investigation. Both benign and cancerous photos were included in every training and testing set. The dataset contained 512x512-pixel-diameter MRI scans from 450 patients, of which 285 were used for testing and the remaining 165 for training. Fig. 4, displays the images from the dataset that were used as data input.

4.1 Image preprocessing

The following stage entails enhancing the quality of the brain tumor images by using a modified trimmed median filter. A median filter was used for the following findings were applied to a study on noise reduction in images of brain tumors. To enhance contrast and clarity, the MRI images are pre-processed. Fig. 5, shows the pre-processed images.

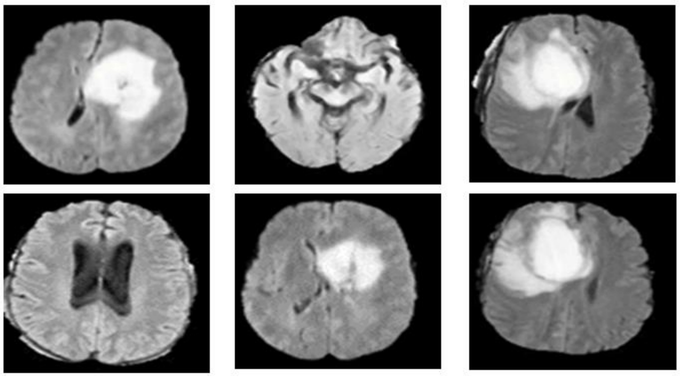
Fig. 5. Pre-processed images

4.2 Image segmentation

As shown, the filter smoothened and sharpens the image's edges. Pre-processing methods are applied to enhance and divide the pixel quality of the image. The U-Net segmentation procedure is used to carry out the segmentation. The segmented images were shown in Fig. 6.

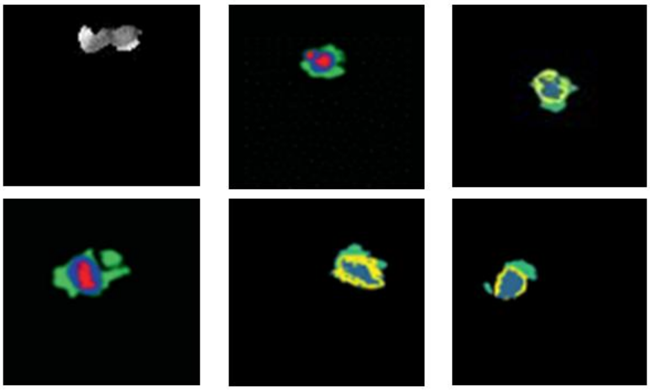
Fig. 6. Segmented images

4.3 Feature extraction

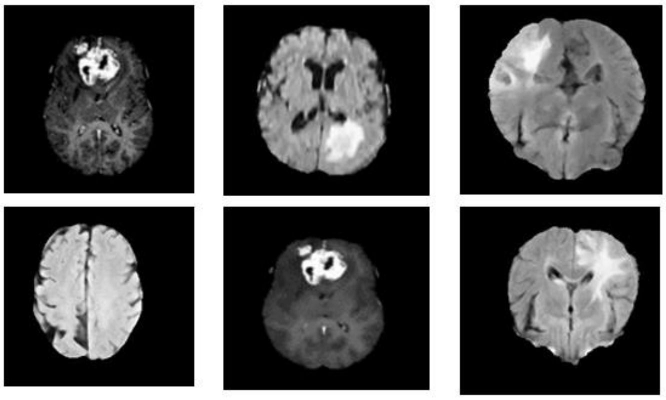

Fig. 7. Feature extracted images

The features are recovered using the discrete wavelet transform technique after they have been separated with the aid of the segmented picture. The abnormality index, irregularity index, and distance from the lesion are the form features in the binary image. A feature extraction is shown in Fig. 7.

4.4 Performance measures

Here, the deep learning approach is used to assess the efficacy of the suggested methodology for both image segmentation and classification. By applying CNN-based VGG-16 models to generate the accuracy, precision, recall, and F1-score metrics, the effectiveness of the suggested classifiers in this section is examined. Table 2, displays the results of the suggested strategy.

Table 2 - The suggested VGG-16 model results for tumor

	Accuracy (%)	Precision (%)	Recall (%)	F1-measure (%)
Benign	98.7	98.3	96.5	97.7
malignant	98.2	97.9	97.3	97.1
Average	98.45	98.1	96.9	97.4

For Benign, the comparable figures were 98.7%, 98.3%, 96.5%, and 97.7% for accuracy, precision, recall, and F1-measure. The malignancy was detected with 97.9% precision, 97.3% recall, 97.1% F1-measure, and 98.2% accuracy. An analysis was conducted on the VGG-16 image classification data to evaluate the effectiveness of the proposed methodology. 98.1% precision, 97.4% F1-score, 96.9% recall, and 98.45% accuracy were obtained using the suggested approach. Table 3, describes the comparison between the proposed model and references. Fig. 8, represents the graphical representation of comparison with suggested methods.

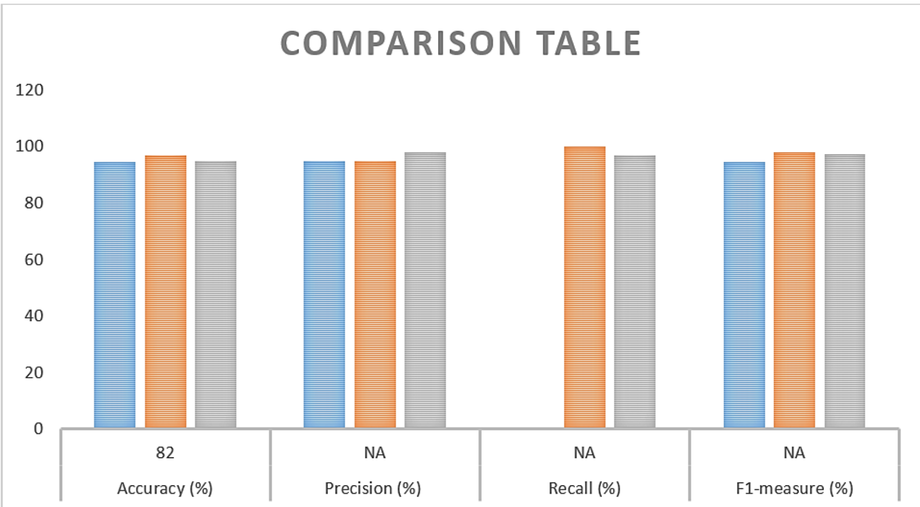

Fig. 8. Graphical representation of comparison table.

Table 3 - Comparison with other suggested methods

Reference	Method	Accuracy (%)	Precision (%)	Recall (%)	F1-measure (%)
Padma Nanthagopal et al., (2013)	PNN	97.5	NA	NA	NA
Garg et al., (2021)	KNN	94.7	94.9	NA	94.6
Shamshad et al., (2024)	VGG-16	97	95	100	98
Proposed method	CNN-VGG 16	98.45	98.1	96.9	97.4

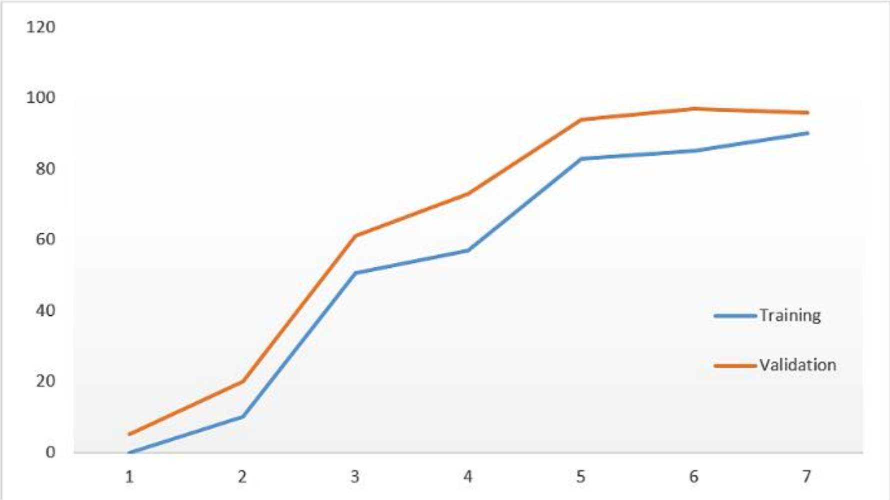

Fig. 9. Accuracy graph of training and testing of VGG-16 model.

Accuracy vs. Epoch

An explanation is given for the accuracy vs. epoch graph that was discovered during the testing and training stages. It demonstrates why the recommended VGG-16 method is beneficial. The accuracy of the proposed model during training and testing is displayed in Fig. 9.

Loss vs epoch

Fig. 10, displays the loss vs. epoch graph that was created throughout the testing and training phases. The suggested CNN-based VGG-16 model's best performance and least amount of loss are shown across an epoch by the loss curve.

The expected accuracy with VGG-16 is shown in Fig. 9 and Fig. 10, together with, in that sequence, accuracy and loss. The training and validation accuracy of the VGG-16 model is positive and tends to increase with each epoch interval. On the other hand, the validation loss increases steadily at various points during each epoch before starting to decline until the last epoch. While validation deals with classifying the images using the dataset, training accuracy assesses the proposed model's capacity to differentiate between the two images during the trained dataset.

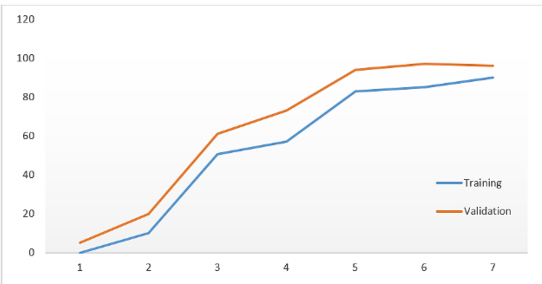

Fig. 10. Loss graph of training and testing of VGG-16

4.5 Confusion matrix

80	18	96%
174	370	97.5%
97.5%	98.1%	98.45%

Fig. 11. Confusion matrix.

Fig. 11, shows the confusion matrix, which shows the prediction performance generated by the VGG-16 classification model. The predicted accuracy of the model is evaluated using this sample, which includes 370 out of 174 non-tumorous photos and 80 out of 18 tumorous images that are accurately classified.

Out of the 80 benign cases, eighteen are correctly categorized as benign, but forty-seven of them are misdiagnosed as malignant. 196 malignant instances that were analyzed had been mistakenly classified as benign, whereas 370 cases had received the accurate diagnosis of malignancy. The proposed method has a 98.45% success rate in correctly categorizing tumors as benign or malignant.

5. Conclusion

This study proposes to classify tumor types as benign or malignant using VGG-16, a Convolutional Neural Network based classification system. It is difficult to accurately categorize MRI brain tumors, and the difficulty increases with the type of classification. In this way, the suggested method operates and makes use of tumor information from multiple patients. Images have a great deal of contrast. Images are pre-processed using modified trimmed median filtering algorithms to reduce noise. Images were pre-processed for segmentation using a 3D version of U-Net segmentation. Using the Discrete Wavelet Transform technique, features are extracted. With the proposed method, 98.1% precision, 97.4% F1-score, 96.9% recall, and 98.45% accuracy were attained. The experiment's results show that the suggested CNN-based VGG-16 algorithm outperforms state-of-the-art methods in terms of accuracy and other performance measures. The accuracy and classification rate results showed that the suggested method functioned more accurately and efficiently than the PNN, KNN, VGG-16 models.

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