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BRAIN TUMOR SEGMENTATION AND CLASSIFICATION USING CNN PRE-TRAINED VGG-16 MODEL IN MRI IMAGES

T. GAYATHRI [1*], K. SUNDEEP KUMAR [2]

[1]*Department of Computer Science and Engineering, Dayananda Sagar University, Bengaluru, India*
[2]*Department of CSE, Geethanjali Institute of Science and Technology, Nellore, India*

**Corresponding author: gayal28@gmail.com*

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ABSTRACT: The formation of a group of abnormal cells in the brain that penetrate the neighboring tissues is known as a brain tumor. The initial detection of brain tumors is necessary to aid doctors in treating cancer patients to increase the survival rate. Various deep learning models are discovered and developed for efficient brain tumor detection and classification. In this research, a transfer learning-based approach is proposed to resolve overfitting issues in classification. The BraTS – 2018 dataset is utilized in this research for segmentation and classification. Batch normalization is utilized in this experiment for data pre-processing and fed to a convolutional layer of CNN for extracting features from Magnetic Resonance Images (MRI). Then, an Adaptive Whale Optimization (AWO) algorithm is utilized to select effective features. This work proposes a Convolutional Neural Network (CNN) based segmentation and a transfer learning-based VGG-16 model for effective classification. The performance of the proposed CNN-VGG-16 technique is analyzed through various tumor regions like TC, ET, and WT. The proposed method attains a Dice score accuracy of 99.6%, 95.35%, and 94%, respectively, when compared to other existing algorithms like CNN, VGG-net, and ResNet.

ABSTRAK: Pembentukan gumpalan sel abnormal dalam otak yang menembusi tisu-tisu jiran adalah dikenali sebagai tumor otak. Pengesanan awal tumor otak adalah penting bagi membantu doktor merawat pesakit kanser bagi meningkatkan kadar jangka hayat. Terdapat banyak model pembelajaran mendalam berkaitan kecekapan pengesanan tumor otak dan pengelasan. Dalam kajian ini, pendekatan pembelajaran berdasarkan pindahan dicadangkan bagi mengatasi isu terlebih padan dalam pengelasan. Set data BraTS – 2018 telah digunakan dalam kajian ini bagi tujuan pensegmenan dan pengelasan. Kelompok normal digunakan dalam eksperimen ini bagi data awal proses dan disalurkan kepada jalur lingkaran CNN bagi mengekstrak ciri-ciri dari Imej Resonan Magnetik (MRI). Kemudian, algoritma Optimalisasi Mudah Suai 'Whale' (AWO) digunakan bagi memilih ciri-ciri berkesan. Kajian ini mencadangkan Lingkaran Rangkaian Neural (CNN) berdasarkan segmentasi dan model VGG-16 berdasarkan pindahan bagi pengelasan berkesan. Prestasi teknik CNN-VGG-16 yang dicadangkan diuji dengan pelbagai bahagian tumor otak seperti TC, ET dan WT. Kaedah yang dicadangkan ini beroleh ketepatan skor Dice sebanyak 99.6%, 95.35% dan 94% masing-masing jika dibanding dengan algoritma sedia ada seperti CNN, VGG-net dan ResNet.

KEYWORDS: *Adaptive Whale Optimization, Brain tumor, Convolutional Neural Network, Magnetic Resonance Images, VGG-16.*

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1. INTRODUCTION

The human brain is an important organ in the nervous system that is responsible for the activities in humans' daily lives [1]. The brain gathers signals from the organs of the body and then handles processing, manages decisions, and gives the resultant data to the muscles [2]. A brain tumor is a collection of unmanaged cancer cells which grow around the brain. Brain tumors are classified into two types, namely, primary tumors, which grow in the spinal cord or brain alone, and secondary tumors, which are also known as brain metastases that grow anywhere in the human body and spread to the brain [3]. There are various types of scan imaging systems, such as Computed Tomography (CT), Electroencephalogram (EEG), and Magnetic Resonance Imaging (MRI), which are used for providing significant information about the vicinity, dimension, and metabolism of cerebrum tumors, assisting decision [4]. These systems are combined to produce the major information about cerebrum tumors [5]. MRI is a non-intrusive system that utilizes the signals of radio recurrence to develop interior images under the influence of an extremely attractive field [6]. The MRI system gives different types of contrast images in tissues, eventually producing significant auxiliary information and analyzing the tumor segmentation within its subregions [7].

The detection of brain tumors from MRI images is a difficult task because of the requirements of a trademark [8,9]. The accuracy of brain tumor diagnosis is increased by the process of segmentation. In recent times, methods based on deep learning are frequently utilized in medical image segmentation [10]. There is a chance of acquiring many types of noise like salt & pepper, speckle, and Gaussian while obtaining the MRI images [11]. So, the technique of noise removal is important for decreasing the noise. The selection of features plays a major role in the classification stage because it decreases the evaluation time and maximizes the performance of classification [12]. The application of deep learning produces an ideal solution because it extracts more prominent features from the entire image than the manually defined features [13]. The most recently adopted techniques for segmentation depend on deep learning, needing a masked image for an expected outcome [14]. Those labels support and guide the learning process during the segmentation stage, but the process takes more time to compute [15]. From the overall existing analysis, detecting tumors in their early stages was impossible with the previous methods; the low-grade and high-grade tumors were not classified, and without segmented images, the whole image dataset was used for classification, which resulted in neglecting the extraction of objects of interest and restricted the data available. Additionally, the computational cost was high, even when done only for the classification and not segmentation. The very challenging aspect of MRI scans is that they are not like X-ray images (2D). An MRI image is made up of various 3D volumes that represent different parts of the brain. During the segmentation of the image, these 3D volumes are integrated. While integrating different channels of MRI images, some misalignments occur that result in error. To overcome these issues, the process of segmentation should depend on the CNN architecture without utilizing masked images. The extracted features contain redundant noise, which minimizes the classification performance. To remove the redundant features, the feature selection process is required in brain tumor classification. Adaptive Whale Optimization (AWO) algorithm is used to select features from the extracted images in the convolutional layer. The AWO is utilized to overcome the limitations of whale optimization algorithms, which include low convergence speed and less capacity of global optimization, and can easily fall into local optima. The AWO algorithm improves the speed of convergence, and the ability of exploration to ignore falls into the local optima. The AWO consists of three phases: prey search, encircling prey, and bubble-net attacking.

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The significant contributions of the research are given below:

- The Adaptive Whale Optimization (AWO) algorithm is utilized to select the necessary features; the AWO improves the convergence speed of WOA and ignores falling into the local optimum. Using selected relevant features for classification maximizes the classification accuracy.
- The CNN and pre-trained VGG-16 model is proposed for the image segmentation and classification respectively, to reduce overfitting and the time consumed on processing smaller batch sizes.
- The performance of the segmentation process is evaluated using DSC and HD measures, and the classification method is estimated by utilizing accuracy, precision, and f-measure criteria with various tumor regions such as Tumor Core, Enhancing Tumor, and Whole Tumor.

The rest of this research paper is described as follows: the relative research on brain tumor segmentation and classification is given in Section 2. The proposed method for segmentation and classification of brain tumors is explained in Section 3. The outcomes and comparative analysis of the proposed method are given in Section 4, and the conclusion of the paper is given in Section 5.

2. LITERATURE SURVEY

Sharif et al. [16] introduced a four-phased brain tumor prediction model that included lesion enhancement, feature extraction, selection for classification, localization, and segmentation. An inception v3 model was used to extract and select features using Non-Dominated Sorting Genetic Algorithm (NSGA). Two methods were utilized; the transfer learning-based approach was used in the classification phase and a YOLO v2 inception v3 model was used in the localization phase. Another popular method named McCulloch's Kapur entropy was used for segmenting tumor regions. The research was validated on BRATS 2018, 2019, and 2020 datasets, respectively. However, this technique was not suitable for detecting tumors in their early stages, and future work intends to implement a quantum computation algorithm to check the system's efficiency.

Decuyper et al. [17] developed an automatic brain tumor classification and segmentation pipeline model using an MRI of the BRATS 2019 dataset. A 3D U-Net was used to segment the tumor region, followed by extracting the Region of Interest (ROI) from MRI scans. To predict the grade, IDH mutation, and 1p19q at a time, the extracted features were fed into CNN. A multi-class classification enabled the network to train on large datasets and resulted in high classification accuracy. Individual classes were not predicted due to the limitation of only two IDH mutant glioblastoma in the training set, so the classification resulted in combined classes. The future work intends to be a non-invasive evaluation of genetic mutations that help in the process of classification of glioma.

Rajinikanth et al. [18] implemented an architecture of the Deep Learning method for the automatic detection of brain tumors using 2D MRI slices. The pre-trained DL networks like AlexNet, VGG16, ResNet 50, and ResNet 101 were implemented with deep features followed by classification. The classification included implementing popular classifiers like DT, KNN, SVM-linear, and SVM-RBF. To improve the detection accuracy, a VGG19 network was fused in the model, resulting in better accuracy with the help of SVM-RBF. This model was validated on the BRATS and TCIA datasets, thereby achieving better results. However, the low-grade and high-grade tumors were not classified. Future works intend to improve categorization accuracy by adjusting fully connected and drop-out layers.

Tandel et al. [19] presented five DL and ML-based brain tumor detection models for effective classification and detection of brain tumors, which were trained and tested on four sets of natural image datasets. A majority voting ensemble optimization algorithm was introduced to validate and improve the face image classification of males versus females. The five DL models included AlexNet, VGG-16, GoogleNet, ResNet18, and ResNet50. The five ML models included Decision tree, Naïve Bayes, KNN, SVM, and linear discrimination using five-fold cross-validation. The proposed ensemble model achieved better accuracy and promising results. Instead of using segmented images, the whole image dataset was used for classification, which resulted in neglecting extracting objects of interest, which is a major drawback of this work. This was overcome by proposing image segmentation techniques.

Punn and Agarwal [20] introduced an effective $3D$ Deep Neural Network model for the segmentation of brain tumors. A $3D$ inception U-Net model and multi-modalities fusion were used to extract the tumor regions and their patterns along with segmentation. Each tumor region was divided into CT, WT, and ET by using target classes such as necrosis, edema, background, enhancing tumor, and non-enhancing tumor. The class imbalance issues were solved by introducing the loss function of weighted segmentation. The introduced method was validated on BRATS 2017 and 2018 datasets. The performed multi-modality fusion was not applied to the real-time data fusion and cascading. The future work includes a wide range of biomedical applications such as image registration, disease quantification, and other application fields.

Agrawal et al. [21] introduced a 3D-UNet deep neural network for the segmentation and classification of brain tumors utilizing the Kaggle dataset. The introduced method depended on the 3D segmentation of MRI images. The images of the brain in the 3D volume were divided into 3D sub-volumes that were fed into the method of segmentation and rejoined into one 3D volume. The advantage of the method was that it represented critical features directly from multiple-modal MRI images of both healthy and tumor brain tissues. The limitation of the introduced method was that the limited data available and the computational cost was high.

Raza et al. [22] presented a hybrid deep learning method named DeepTumorNet for the classification of brain tumors using the CE-MRI dataset. The GoogleNet structure of the CNN method was utilized as a base for the development of the hybrid method. In developing a hybrid DeepTumorNet technique, the final five layers of GoogleNet were deleted, and 15 new layers were added rather than these five layers. The ReLU activation function was utilized in the feature map to maximize the model's expressiveness. The advantage of the presented method was that it computed many discriminative and descriptive data and accurate features for the classification of brain tumors. The limitation of the method was that it carried out only classification and not segmentation, and the segmented images provided higher accuracy.

Haq et al. [23] implemented a hybrid technique dependent on Deep Convolutional Neural network (DCNN) and machine learning classifiers for the segmentation and classification of brain tumors using MRI images. CNN, in the initial stage, was utilized to learn the feature map from the image space of MRI images and the region of the tumor marker. Next, faster region-based CNN was created for the tumor region localization by utilizing a Region Proposal Network (RPN). Finally, DCNN and ML classifiers were combined in series for segmentation and classification. The method attained automatic segmentation and classification of brain tumors without a user interface. However, the limitation of the method was high computational time.

3. PROPOSED METHODOLOGY

In the proposed methodology, the CNN-based VGG-16 pre-trained method is proposed for a better classification of brain tumors. An imaging dataset of BraTS 2018 is utilized for the proposed method. Batch normalization is utilized in the pre-processing stage, and a convolutional layer of CNN is utilized for the extraction of features from MRI images. The AWO algorithm is employed to select the features. The fully connected CNN is employed for image segmentation, and the pre-trained model VGG-16 is employed for effective classification. The flowchart of the proposed methodology is represented in Fig. 1.

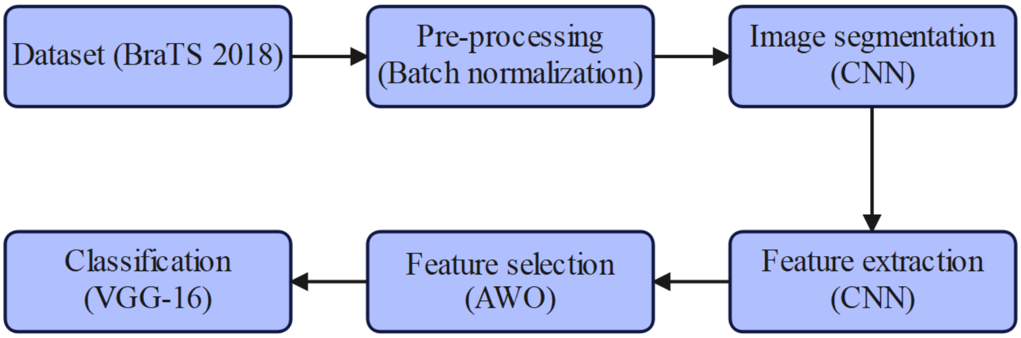

Fig. 1. Workflow of proposed methodology

3.1. Dataset

The imaging dataset utilized for this research is a publicly available dataset named Brain Tumor Segmentation (BraTS-2018) [24] to segment and classify brain tumor MRI images. The dataset has four multiple contrast MRI scans of 477 patients with high or low-grade glioma brain tumors. The four multiple contrast MRI scans generated for every patient are $T1$ (T1-weighted gradient-echo), $T1 - Gd$ (T1-weighted post-gadolinium contrast gradient-echo), $T2$ (T2-weighted gradient-echo) and T2-FLAIR or FLAIR (T2-weighted fluid-attenuated inversion recovery). The sample images of the dataset are represented in Fig. 2.

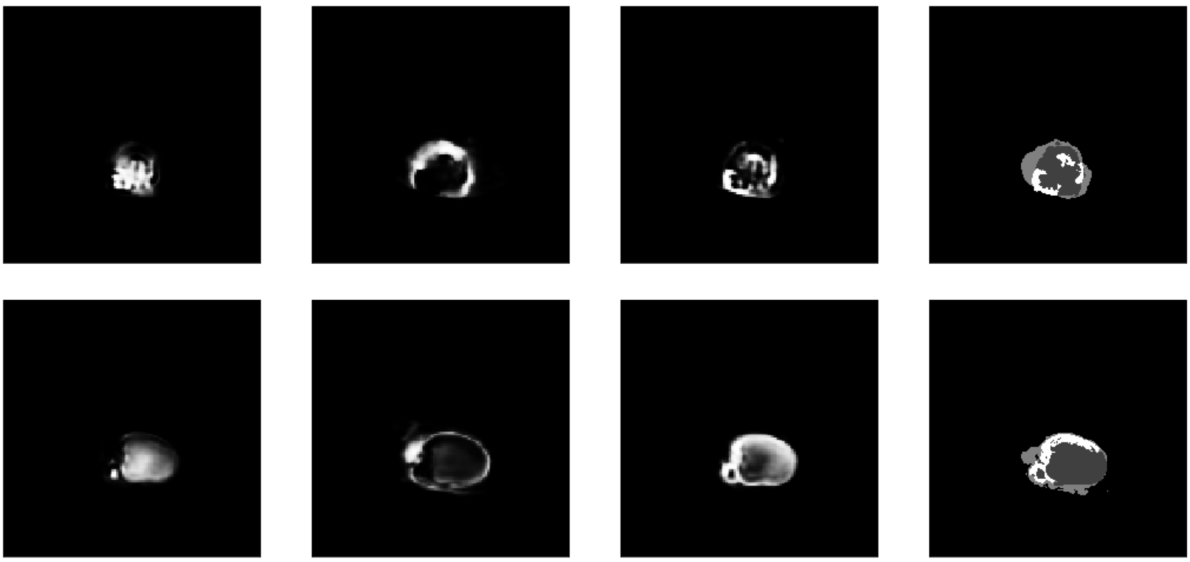

Fig. 2. Sample images of dataset

3.2. Data Pre-processing

The batch normalization is a pre-processing method in this research; here, the term 'batch' represents a set of input data and processes performed in terms of batches. Normalization is used to change numerical data to a general scale while protecting their shapes. In other words, it is a procedure of converting data to 0 as an average value and 1 as standard deviation. Batch normalization is a process of making neural networks quicker with huge stability by including additional layers in deep neural networks. The standardizing and normalization processes are processed through a new layer by taking values of the prior layer.

The mean and standard deviation (SD) of hidden activation is measured by considering batch input along layer h as Eq. (1) and Eq. (2).

$$\mu = \frac{1}{m}\sum h_i \tag{1}$$

$$\sigma = \left[\frac{1}{m}\sum(h_i - \mu)^2\right]^{1/2} \tag{2}$$

Where, μ is the mean, σ represents SD, and m represents the number of neurons in the layer h.

By utilizing Eq. (1) and Eq. (2), hidden activations are normalized. The average value is subtracted along every input, and then an entire value is divided with the addition of standard deviation and smoothing term (ε). Smoothing makes sure to keep the numerical values stable within the process by protecting separation by zero and is measured using Eq. (3).

$$h_{i(norm)} = \frac{(h_i - \mu)}{\sigma + \varepsilon} \tag{3}$$

After the stage of pre-processing, the training set's size is maximized to overcome the overfitting problem. The pre-processed information is fed to the fully connected CNN for segmentation of brain MRI images.

3.3. Image Segmentation

In image processing, a neural network is the most powerful method to perform segmentation. MRI is the major imaging technique for capturing brain images. Automatic segmentation is a difficult task due to the variability of structure and large spatial area. So, the research implements an automatic segmentation technique based on CNN with 3×3 Kernels [25]. The Kernels of smaller size help to develop the deep architecture by utilizing a smaller number of weights in the network. Kernels are shared through whole units of similar feature maps, and the conv layer contains smaller weights for training than dense FC layers, thus making the CNN suitable for training, leading to low overfitting.

The following are concepts that are significantly deployed in the CNN segmentation:

3.3.1. Initialization

Initialization is significant for attaining quick convergence. By utilizing the initialization, the activations and gradients are managed in the control stages or else, the back-propagated gradients disappear.

3.3.2. Activation Function

The activation function is manageable for information transformed non-linearly. Rectifier linear units (ReLU) are represented by Eq. (4).

$$f(x) = max(0, x) \tag{4}$$

The activation function is found for attaining superior results than traditional sigmoid, as well as to fasten the training. However, establishing a constant 0 damages the flow of gradient and successive weight adjustments. To overcome these limitations, utilize a Leaky Rectifier Linear unit (LeakyReLU) which implements a little slope on the function's negative part. The function is represented as Eq. (5).

$$f(x) = max(0, x) + \alpha\, min(0, x) \tag{5}$$

where, α represents the parameter of leakiness, and a fully connected layer is utilized as a softmax.

3.3.3. Pooling

Pooling combines the dimensions of close features in feature maps. The integration of possible unnecessary features makes the portrayal much more compact and invariable to little changes of the image, such as unwanted information, which also reduces the estimation load of the next phases. To merge features, it is typical to utilize max-pooling.

3.3.4. Regularization

Regularization is utilized to minimize overfitting. The dropout is utilized in a fully connected layer. In every training stage, it deletes nodes from the network with the possibility. Like this, it forces each node of fully connected layers to learn the best data description, protecting nodes from cooperating. Every node is used at the testing stage while the dropout is represented as an ensemble of various networks and bagging form, since all networks are trained with the training data portion.

3.3.5. Loss Function

Loss function is the process that needs to be decreased in the training phase. The research deploys a categorized Cross-entropy described as Eq. (6).

$$H = -\sum_{j \in voxels} \sum_{k \in classes} c_{j,k}\, log\left(\hat{c}_{j,k}\right) \tag{6}$$

Where, $\hat{c}$ represents the prediction of probabilistic (after the softmax) and c represents the target.

By utilizing the fully connected CNN model, the tumor-affected MRI brain images are segmented, and the segmented images are fed into the convolutional layer of the CNN model for extracting features.

3.4. Feature extraction

Feature extraction is a process of converting original information into numerical features which are processed while protecting data in the original dataset. Feature extraction provides superior outcomes as opposed to applying the raw data directly to machine learning. The conv layer is a fundamental layer of CNN structure which performs feature extraction, including the combination of linear and non-linear operations. In this research, CNN is used to extract features that input features of image classification, based on various neural networks. The 3D volume dimensions such as N, 155, 240, and 4 are extracted by the conv layer. The extracted features contain redundant noises as features that minimize the performance of classification. To remove the redundant features, the feature selection process is required in brain tumor classification. The features extracted through convolutional layers are fed into the AWO algorithm for selecting features.

3.5. Feature Selection

Adaptive Whale Optimization (AWO) algorithm is utilized to select features from images extracted from the Convolutional layer. The AWO is utilized to overcome the limitations of WOA, such as low convergence speed, reduced ability to optimize globally, and the ability to easily fall into local optima. The AWO algorithm improves the speed of convergence and increases the ability of exploration to avoid falling into local optima. The AWO consists of three phases: prey search, encircling prey, and bubble-net attacking [26].

3.5.1. Encircling prey

In encircling the prey stage, every agent processes an optimum agent at a distance that depends on A acquired by Eq. (8), and a value is minimized linearly with the iteration. Due to a linear decrease in the size of the step, the performance of the agent exploration also decreases at this phase. To maximize group diversity and avoid falling into the local optimum, the research utilizes AWO in the encircling phase. The AWO is multiplied by the current agent target prey to create a new target and modify the AWO by the agent's fitness. The improved encircling prey phase is represented in Eq. (7).

$$X_i(t+1) = w_i(t) \cdot X^*(t) - A \cdot |C \cdot X^*(t) - X_i(t)| \tag{7}$$

$$A = 2a \cdot r - a \tag{8}$$

$$C = 2 \cdot r \tag{9}$$

Where, X represents the position vector, X^* represents the position vector of the optimum solution obtained, t represents a present iteration, $A\ and\ C$ represent the coefficient of vectors, which are measured using Eqs. (8) and (9).

The components of a are linearly minimized from $2\ to\ 0$ and r represents a random number between $(0,1)$. The convergence's adjustment is decided by the operator $w_i(t)$, range of $w_i(t)\ \in [0,1]$ which is modified by the present agent's position. While the position of the agent in the solution space is matchable, the AWO is maximized.

3.5.2. Bubble-net attacking

This technique mimics the whale's behavior when detecting its prey during the bubble-net hunting phase. The whale positions itself near the prey, using a prey in the central point, resulting in being gradually unconscious in the target. This strategy involves a whale encircling the prey, primarily gauging the distance between itself and its target before veering towards it in a curved manner. The improved bubble-net attacking phase is represented in Eq. (10).

$$X(t+1) = D' \cdot e^{bl} \cdot cos(2\pi l) + X^*(t) \tag{10}$$

$$D' = |CX^*(t) - X(t)| \tag{11}$$

where, D' represents the distance of the i^{th} whale to the optimum solution obtained and D' is calculated as Eq. (11). b describes a constant that defines the shape of the curl, and l represents the random number in $[-1,1]$. That is considered when the whale moves around a prey in the outer circle, which decreases the radius of the enclosure as well.

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3.5.3. Prey search

In prey search, whales utilize a score of A to manage them if they are in the encircling stage. When $|A| > 1$, whales can not acquire effective data on prey and require simultaneous attempts to identify a track of clues of prey along random routes. The numerical representation of a changed strategy of hunting is represented in Eq. (12) and Eq. (13).

$$D = |C \cdot X^{rand}(t) - X(t)| \tag{12}$$

$$X(t+1) = X^{rand}(t) - A \cdot D \tag{13}$$

where, X^{rand} represents randomly choosing a vector of position in the whale.

3.5.4. Quasi-Oppositional Solution

For maximizing the search ability after initialization, a quasi-oppositional solution is developed. The solution is utilized for minimizing execution time and also improves the convergence capacity of WOA.

The numerical expression for the opposite solution S_0 for an arbitrary solution is given as Eq. (14).

$$S_0 = u + v - S \tag{14}$$

The mathematical expression for multiple dimension search space is given as Eq. (15).

$$S_0^i = u^i + v^i - S^i; \;\; i = 1,2, \dots, d \tag{15}$$

The numerical equation in an arbitrary solution of the quasi-opposite solution is given as Eq. (16).

$$S_{q0} = rand\left(\frac{u+v}{2}, S_0\right) \tag{16}$$

The numerical expression for multi-dimensional search space is given as Eq. (17).

$$S_{q0}^1 = rand\left(\frac{u^i+v^i}{2}, S_0^i\right) \tag{17}$$

Using Adaptive Whale Optimization, the necessary features are selected, thereby minimizing the method's executional cost and the model's performance. These selected features are fed to a pre-trained VGG-16 model for effective classification. Fig. 3 represents the process of AWO for feature selection.

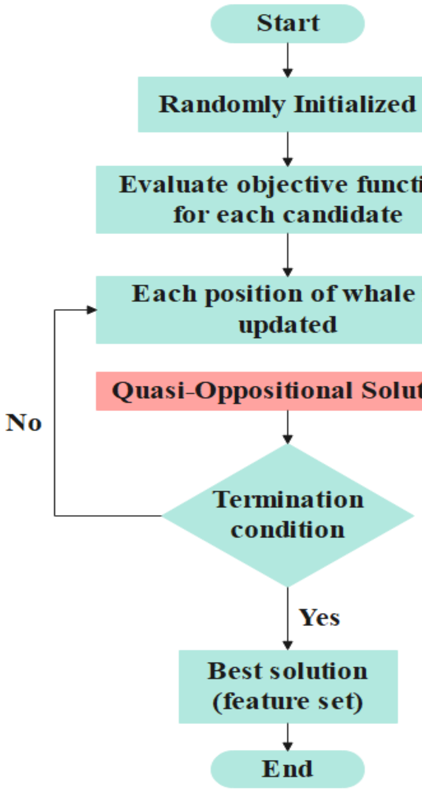

Fig. 3. Process of AWO in feature selection

3.6. Classification

The pretrained CNN structure is deployed for classification, utilizing various labeled images for model training acquired from a feature selection phase. The pretrained CNN structure utilized for the classification is VGG–16. The dense layer is an important part of the classification of brain MRI images, which depends on the results from convolution layers. This gives output from the previous layer to every neuron; every neuron generates a single outcome to the next layer (rework this sentence). Fig. 4 represents the process of VGG-16.

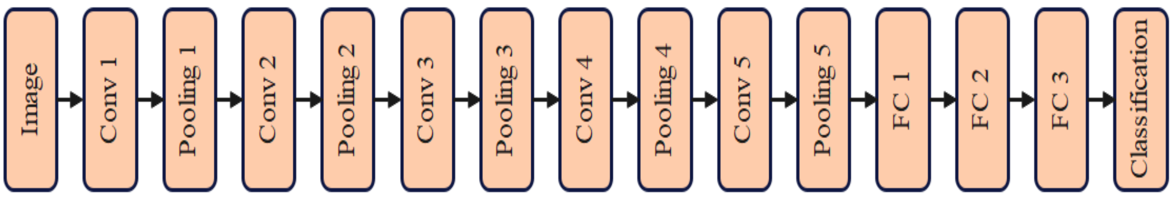

Fig. 4. Pictorial representation of the Classification process of VGG -16

The VGG–16 pre-trained CNN method is employed for classification since there are fewer images in the dataset and in order to overcome the overfitting issue. The method is fine-tuned by frosting certain conv layers. The VGG–16 pretrained CNN method contains 16 convolution layers. The method considers brain MRI images as input along the dimension of $224 \times 224 \times 3$. The method has conv layers with fixed filter size of 3×3 and 5 max-pooling layers of dimension size of 2×2 within the network. The method has the activation function of ReLU and two fully connected layers, having a softmax output layer. The VGG–16 model is a wide network that includes approximately 138 million hyperparameters. The method

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assembles multi-conv layers to develop deep neural networks that improve its capacity for learning handcrafted features, which is invisible. Fig. 2 represents the overall classification process of CNN based pre-trained VGG-16 model. By utilizing the CNN-based pre-trained method of VGG-16, types of brain tumors are classified into primary or secondary brain tumors.

4. PERFORMANCE ANALYSIS

The performance of the proposed technique is simulated in the Python environment with these system requirements: processor - Intel core i7, Operating System - Windows 10 (64 bit), and RAM - 16GB. The performance of the developed CNN-VGG-16 technique is analyzed in terms of segmentation and classification with actual features after selecting the features. The performance of the proposed CNN-VGG-16 is compared with the existing techniques like CNN, VGG-net, and ResNet. The outcomes of the segmentation and classification are discussed below as subsections.

4.1. Evaluation for Segmentation

The segmentation process using CNN with actual features is analyzed by performance metrics like Dice Score Coefficient (DSC) and Hausdorff Distance (HD) for various tumor regions such as Tumor Core (TC), Enhancing Tumor (ET), and Whole Tumor (WT). The CNN involves analyzing features extracted from the image to process tasks like segmenting tumors. VGG-16 stacked multiple convolutional and FC layers efficiently capture data and classify the tumors. Table 1 and Fig. 5 represent the performance of the segmentation process along with actual features. The proposed CNN-VGG-16 method for the segmentation process accomplishes DSC of 98%, 98.5%, and 97% for various dice coefficient values, resulting in higher performance than the existing techniques.

Table 1. Performance of segmentation with actual features

Methods	DSC (%)			HD (mm)		
	TC	ET	WT	TC	ET	WT
CNN	80	70	85	25.4	18.89	20.11
VGG-net	89	81	90	17.45	15.36	18.19
ResNet	94	95	91	16.77	13.49	15.99
CNN-VGG-16	98	98.5	97	12.37	11.58	17.54

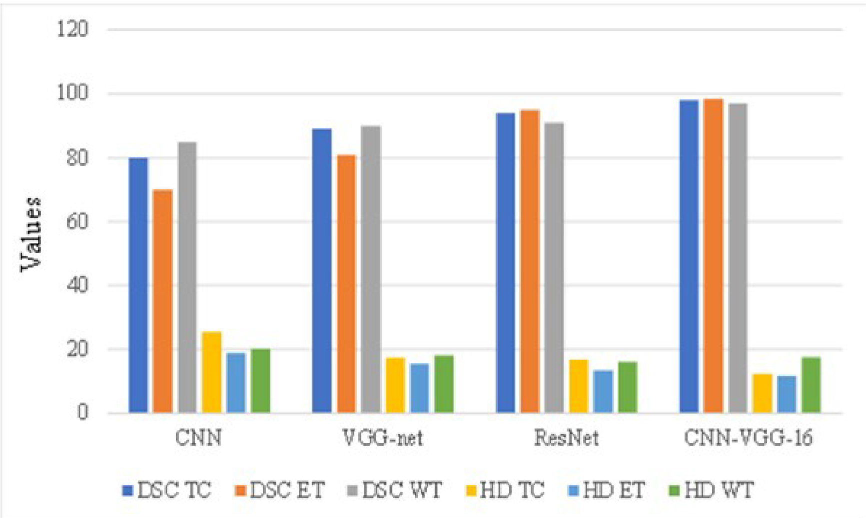

Fig. 5. Performance of segmentation with actual features

The segmentation process by CNN after feature selection is analyzed by performance metrics like DSC and HD with various tumor regions such as TC, ET and WT. Table 2 and Fig. 6 represent the performance of the segmentation process after feature selection. The proposed CNN-VGG-16 method for the segmentation process accomplishes DSC of 98%, 98.5%, and 97% for various dice coefficient values, which is superior to the existing techniques.

Table 2. Performance of segmentation after feature selection

Methods	DSC (%)			HD (mm)		
	TC	ET	WT	TC	ET	WT
CNN	82.5	72	86.6	26.57	21.81	21.99
VGG-net	92	82.9	91.2	18.78	17.24	19.59
ResNet	96.9	97	93.5	19	16.47	17.85
CNN-VGG-16	99.4	99.5	99.7	14.14	13.53	18.63

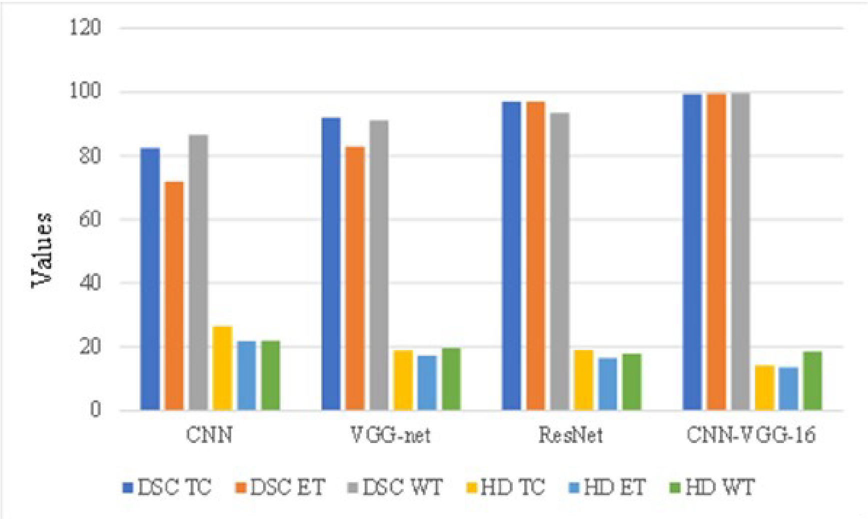

Fig. 6. Performance of segmentation after feature selection

4.2. Evaluation for Classification

The classification process by CNN-VGGnet with default features is analyzed through performance metrics like Accuracy, Precision and F-measure with various tumor regions like TC, ET, and WT. Table 3 and Fig. 7 represent the performance of the classification process with actual features. The proposed CNN-VGG-16 method for a classification process achieves an accuracy of 98%, 94%, and 91% for various dice coefficient values, being comparatively more robust than the existing techniques.

Table 3. Represents the performance of classification with default features

Methods	Accuracy (%)			Precision (%)			F-measure (%)		
	TC	ET	WT	TC	ET	WT	TC	ET	WT
CNN	85	77	82	80	69	84	90	91	94
VGG-net	92	88	88	87	78	90	94	94	96
ResNet	95	92	89	92	87	94	96	95	96
CNN-VGG-16	98	94	91	93	89	97	97	96	97

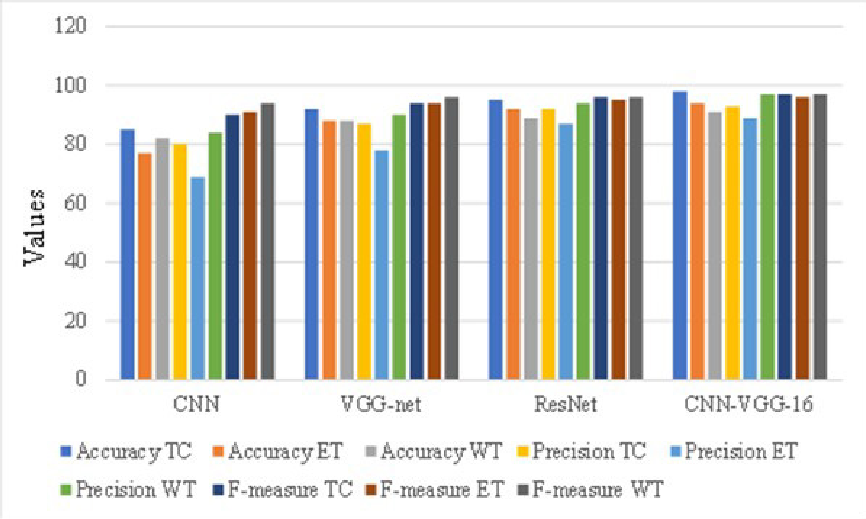

Fig. 7. Performance of classification with actual features

The classification process by the CNN-VGG-16 method after feature selection is analyzed on the basis of performance metrics like accuracy, precision, and F-measure with various tumor regions like TC, ET, and WT. Table 4 and Fig. 8 represent the performance of the classification process after feature selection. The proposed CNN-VGG-16 method outperforms the previous methods for the classification process by achieving an accuracy of 99.6%, 95.3%, and 94% for various dice coefficient values.

Table 4. Represents the performance of classification after feature selection

Methods	Accuracy (%)			Precision (%)			F-measure (%)		
	TC	ET	WT	TC	ET	WT	TC	ET	WT
CNN	87.1	79	84	81.8	70.3	85.9	92.7	92.6	96.8
VGG-net	93.8	89.1	90.2	88.4	80.5	92.7	96.4	95.4	98.2
ResNet	96.2	93.3	91.7	94.1	89.6	95.1	98.9	96.8	97.7
CNN-VGG-16	99.6	95.3	94	94.2	91.4	99	99.7	98.3	99

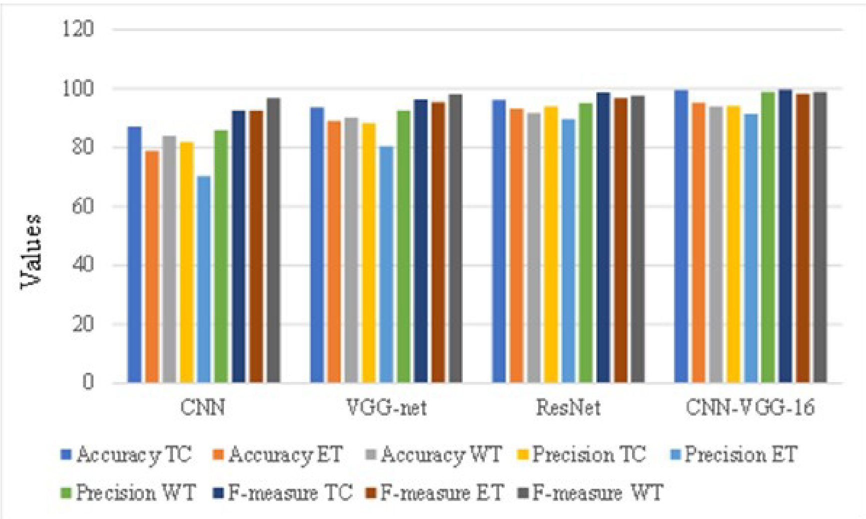

Fig. 8. Represents the performance of classification after feature selection

4.3. Comparative Analysis

The comparative analysis of the proposed technique is described in this section. The performance of the proposed CNN-VGG-16 is compared to existing models like softmax ensemble methods [16] and the SVM-RBF classifier [18] in terms of accuracy, specificity, and sensitivity. As shown in Table 5, the proposed method achieves an accuracy of 99.6%, which is comparatively higher than other existing methods, such as softmax ensemble, which attains 99.1%, and SVM-RBF, which attains 97.70%.

Table 5. Comparative Analysis with Other Methods

Author	**Method**	**Accuracy (%)**	**Specificity (%)**	**Sensitivity (%)**
Sharif et al. [16]	Softmax ensemble	99.1	99.00	100
Rajinikanth et al. [18]	SVM-RBF	97.70	98.00	97.25
Proposed method	CNN-VGG-16	99.6	99.00	99.7

5. CONCLUSION

The early detection of brain tumors is necessary to aid doctors in treating cancer patients to increase their survival rate. In this research, the transfer learning-based approach is proposed to resolve the overfitting problem in classification. The BraTS – 2018 dataset is utilized in this research for segmentation and classification. Batch normalization is utilized in this experiment for data pre-processing, which normalizes the data in terms of batches. The CNN segments the images into specific parts, which makes classification effective, and the relevant features are extracted by the conv layer of CNN. Next, the AWO algorithm is utilized for effective feature selection, which selects relevant features for classification. After selecting relevant features, they are classified by VGG-16 with high accuracy. The performance of the proposed CNN-VGG-16 technique is analyzed on various tumor regions like TC, ET, and WT. The proposed method achieves a Dice score accuracy of 99.6%, 95.35% and 94%, outperforming the previously existing techniques like CNN, VGG-net, and ResNet. In the future, the hyperparameter tuning of the classification model will be performed to improve classification efficiency.

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