DEVELOPMENT OF DEEP SEGMENTATION AND VGG-16-ASSISTED DEEP LEARNING MODEL FOR EFFICIENT BRAIN TUMOUR CLASSIFICATION

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Abstract

In recent days, the mortality rate is occurred due to the rising number of brain tumor patients around the world. The severity of brain tumor is huge while comparing with other cancer types, and thus, there is a need of early identification and precise treatment for saving a life. However, detection of such tumor cells is complicated owing to the formation of the tumor cells, which results in complications regarding brain tumor classification for evaluating the tumors. Various imaging approaches have been utilized for detecting brain tumors in recent studies. On the other hand, there is a complication regarding the extraction of abnormalities in the brain via easy imaging approaches. To alleviate all the challenges, this paper implements a tumor classification model using intelligent segmentation and deep learning techniques. The input images are obtained from benchmark data sources and fed to pre-processing stage, which is accomplished by filtering methods and Contrast Limited Adaptive Histogram Equalization (CLAHE). These images are given to VGG16-Ensemble Network (VGG16-Ensemble) with three classifier models as Auto Encoder (AE), Deep Belief Network (DBN), and Long-Short Term Memory (LSTM), where the results are obtained as normal and abnormal images. The attained abnormal images forward to segmentation. Here, the Convolutional Neural Network (CNN), Modified CNN, and U-Net are used, where the parameters in CNN are optimized to propose modified CNN by Adaptive Distance-based Sea Lion Optimization Algorithm (AD-SLnO) to acquire the segmented images. Finally, the optimized ensemble classification is developed known as OVGG16-Ensemble, in which hyper parameters of VGG16, LSTM, DBN, and AE are tuned optimally by AD-SLnO algorithm. Thus, it is developed for classifying the abnormal images into benign stage or malignant stage. Consequently, the result evaluation is done, and its performance is estimated by diverse measures.

Keywords: Efficient Brain Tumour Classification; Deep Learning-based Segmentation; Deep Belief Network; Convolutional Neural Network; VGG16; Long-Short Term Memory; Auto Encoder; Adaptive Distance-based Sea Lion Optimization Algorithm

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1. Introduction

Human body has the brain as the management center, which is accountable for carrying out various activities via a huge number of neurons and connections [9]. A cluster of irregular cells in the brain is known as brain tumour, which damages brain cells and increases the brain inflammation. The growth of abnormal cells in brain tissue is noticed and considered as the tumor part, which spreads to the other regions of brain. It leads to irregular augmentation of the cells in the brain. [13]. Generally, there are two diverse types of tumors that are non-cancerous and cancerous [10]. The early detection and also treatment planning is more required for patients. The severe brain tumor is assumed as malignant and benign cancers. It is more helpful and determined by taking the experience and knowledge of physician to increase the possibility of survival rate for recovering the patient life [11]. Thus, image segmentation and classification play a significant role in processing the medical images with the motive of detecting the affected area and classified the level of abnormality classes to the given images [12]. Similarly, the identification of the tumor spot in brain images is most required as well as needed to detect the tumor level. The diagnosis process of brain tumor comprises of three stages like tumor detection, segmentation, and classification [14].

Owing to the complicated structure of brain, the detection of brain tumor is challenging. While detecting or diagnosing the tumor cells at an earlier stage with intelligent computer aided systems, a higher level of diagnosis and treatment rate is noticed that increasing the survival rate in comparing with the final stage detection [15]. Surgery, therapy, chemotherapy or combinations of such approaches are most essential for treating tumor patients. The significant factor in detecting the brain tumor is data acquired from the various imaging approaches like Computed Tomography (CT) scans, X-rays, mammograms, Magnetic Resonance Imaging (MRI), etc [17]. Among them, the usage of MRI in brain tumor detection models is complicated regarding their higher resolution in multi-planar MR images. It also suffers from various noises including pepper noise, salt, and rician noise that influence the images, and thus, it is impossible and troublesome for further analyzing the images. Thus, the removal of noise in medical imaging is cumbersome [18]. The next process is feature extraction, which is useful in getting the most essential information from the images and forwarded it to the technique rather than processing the huge dataset that results in higher computation of computational and time resources [19]. Next level of processing step is to use the segmentation of brain tumor. In recent years, the final process of brain tumor detection is to utilize deep learning-based techniques owing to the robust feature learning ability, which is more useful in detecting the tumor cells in brain [20].

An automatic brain tumor classification model is most essential to support medical professions for giving precise decisions on treatment planning. Generally, the discriminative features are extracted using deep neural architecture [21]. The deep architectures are useful in segmenting and classifying the brain tumors, where the most frequently used architecture is CNN. Some studies use cascaded CNN framework to detecting the voxels of tumor. Frequently, the CNN-based approaches are useful to segment the MRI images with the small convolutional kernel. Moreover, the cellular automata and fuzzy c-means algorithm are integrated for performing the brain tumor segmentation. The existing approach on segmenting the brain tumors is done via formulating a novel similarity function with a Gray Level Co-Occurrence Matrix (GLCM) for addressing the seed growing issue [23]. Similarly, a generative technique is used for separating the tumor cells from other cells by considering the earlier statistics for gathering the information. The utilization of deep CNN is recently adopted for the purpose of effective detection rate in detecting the tumors in brain [24]. Moreover, K-nearest neighbours (KNN) and Artificial Neural Network (ANN) classifiers are also generally utilized for classifying the tumors. Moreover, the major issue in computer-assisted diagnosis models is the utilization of fragmented/small medical imaging datasets that is taken from various scanners and so, the researchers try to apply various improvements in existing approaches for classifying the brain tumor [25]. Therefore, this research work tries to detect the tumor area of gathered brain images and classified the tumor level via the intelligent approaches for increasing the accuracy of classification. The research ideas of the designed brain tumor classification model are given here.

- To implement a new research work on efficient brain tumour classification with severity classification by taking the deep segmentation and heuristic-assisted deep learning model for promoting the medical field.
- To design an ensemble deep learning classifier with the adoption of techniques like VGG16, LSTM, DBN and AE networks for categorizing the images into normal and abnormal classes from the gathered standard brain images.
- To present a novel ensemble segmentation approach for segmenting the abnormal images with the heuristic-improvement on U-Net approach along with the adoption of CNN, and Modified CNN networks for precise

segmentation results in terms of precision and accuracy.

- To recommend a new heuristic-derived severity classification framework with the ensemble technique by integrating the optimized networks such as VGG16, LSTM, DBN and AE to get the results in terms of classified images into benign or malignant classes regarding maximization on precision and accuracy.
- To recommend a novel AD-SLnO technique for improving the tumor segmentation and severity classification phases by tuning the learning rate and hidden neuron count in CNN, Epoch in VGG16, hidden neuron count in LSTM, learning rate in DBN, and batch size in AE for increasing the efficiency of tumor segmentation and classification model for brain.

The residual modules in this research work are depicted here. Module III specifies the deep learning-based brain tumor segmentation and classification. Module IV recommends the tumor detection and ensemble deep learning-based tumor segmentation for efficient brain tumor diagnosis. Module V implementing novel AD-SLnO for tumor segmentation and classification for optimal brain tumor diagnosis. Module VI specifies the result and estimation. Module VII concludes this paper.

EXISTING WORKS

A. Related works

In 2022, Jemimma and Vetharaj [1] have implemented a novel automated segmentation and classification framework from the MRI images for brain tumors. It has consisted of diverse phases. The gathered RGB images pre-processed via hue colour transformation. Then, the morphological and thresholding operations were carried out. Next, "Fractional probabilistic Fuzzy C Means (Fr-pFCM)" was used for performing the automated segmentation via integrating the "probabilistic Fuzzy Clustering (probabilistic FCM) and fractional theory for getting the highly precise segments. Further, the feature extraction was done from the segments, where the metrics like theoretic information metrics, wavelet transform, Local Directional Pattern (LDP), Empirical Mode Decomposition (EMD), and descriptors were utilized. Next, the "Whale-Cat Swarm Optimization based Deep Belief Network (WCSO-DBN)" was applied for performing the final classification purpose. The evaluation was done using BRATS database and the analysis was performed and shown the superiority over others. In 2019, Amin et al. [2] have recommended a novel tumor detection framework for precisely segmenting and classifying the malignant and benign tumor. The input images were segmented precisely via the various spatial domain techniques. Then, the classification was done via the Google and Alex networks, where softmax layer has extracted two score vectors and fused and subjected to various classifiers. The experimental analysis was verified on various datasets.

In 2022, Neelima et al. [3] have formulated the automated strategy for tumor classification with MRI images. The normalization of intensity in gathered images was done via the pre-processing along with min-max normalization. The Optimal DeepMRSeg approach was utilized for segmentation and done via new "Sailfish Political Optimizer (SPO)". Then, the feature extraction was done via the CNN and carried out the data augmentation. Next, CNN was utilized for performing data augmentation including adjustment or rotation of contrast, brightness, randomized right or left flipping, and random translation. Further, the classification was carried out using with "Generative Adversial network (GAN), and trained using Conditional Autoregressive Value at Risk-based sailfish political Optimizer (CAViaR-SPO)". Finally, the designed CAViaR-SPO-based GAN for brain tumor classification has provided superior efficiency owing to segmentation accuracy and higher performance.

In 2020, Raja and rani [4] have recommended a new brain tumor classification approach. Firstly, the images were gathered from BRATS 2015 database and fed to the denoising that was done by non-local mean filter. Next, the brain tumor segmentation was done by for precise segmentation and then, the reliable features were extracted using. At the end, Jaya Optimization Algorithm (JOA)-derived Deep Autoencoder (DAE) with a softmax regression was applied for classifying the tumor regions for detecting the brain tumor. Consequently, the result analysis was done and obtained the superior performance over classification accuracy while estimating with existing approaches.

In 2019, Gumaei et al. [5] have implemented precise brain tumor detection model. The brain images were preprocessed for enhancing the contrast of brain regions and edges. Next, the hybrid features were extracted and Regularized Extreme Learning Machine (RELM) was applied for brain tumor classification. Then, the result execution was done on a public dataset of brain images and compared with traditional techniques. The simulation analysis was done to effectiveness over other algorithms regarding accuracy, and specificity. In 2022, Jemimma and Raj [6] have recommended a new approach for classifying the brain tumor using Deep CNN. Here, the images from standard dataset were pre-processed for eliminating the artifacts and noise in them. Then, the tumor regions were segmented. The features were extracted from the segmented regions. The deep CNN was used for extracting the features for determining the cells. Then, the Deep CNN was applied for final brain tumor classification outcomes regarding various metrics.

In 2021, Ramya et al. [7] have promoted a new approach of image segmentation and classification especially for brain tumor by processing the MRI images. The Laplacian cellular automata filtering approach was used for image pre-processing and then, the ensemble approach was utilized for segmenting the images from tumor regions and their outcomes were estimated. The segmented results were attained as the ensemble cluster label and the abnormalities were classified via deep super learning. At last, the experimental analysis and evaluation has shown the superior detection performance when estimating with traditional approaches on standard "BraTS brain image dataset". In 2021, Fayaz et al. [8] have recommended a classification with the help of binary classification framework, where the features were extracted, and the number of features was reduced via the statistical feature extraction and a blended ANN was applied for classifying the MRI images. It has finally obtained the superior classification performance and analyzed over existing methods regarding simplicity and accuracy.

B. Problem specification

Automatic tumor classification model is requires to classify the cancerous images. Yet, having the different types of tumor causes the challenging one when implementing the segmentation and classification approach. Since tumors contain distinct size, various shapes and location, it tends to become critical to diagnose and treating the patients. Table I provide the advantages and disadvantages regarding traditional brain tumor segmentation and classification. WCSO-DBN [1] attains more accuracy, sensitivity and specificity value. But, it may produce imprecise value when the cluster groups are apriority specified. Alex and google network [2] flexible to implement and renders the higher results. However, it does not provide the exact results when it deals with sub-tumoral region. and also does not utilize the way of coronial and saggital views. CAViaR-SPO-based GAN [3] obtains higher classification and segmentation rate. Yet, it falls into the problem of premature convergence and gradient. DAE [4] reaches the higher accuracy. But, it does not suit for ensemble-based classifier model. RELM [5] enhances the accuracy performance and provides effective results when it implements with large number of datasets. It does not include other standard algorithms for performance improvement. DCNN [6] maximizes the accuracy, sensitivity and specificity. But, it generates the hardware dependency problem and longer training time. Deep Super Learning [7] yields the desired classification and segmentation rate. However, it causes the time and space complexity while it contains large size of features. Blended ANN [8] improves the robustness of model in terms of various measures. On the other hand, due to extract distinct types of features, the complexity arises and overfitting problem. In order to overcome the challenges, it is suggested to develop a deep learning based classification model for brain images.

Table 1. Advantages and issues of existing brain tumor segmentation and classification models

Author [citation]	**Methodology**	**Features**	**Challenges**
Jemimma and Vetharaj [1]	WCSO-DBN	• Attains more accuracy, sensitivity and specificity value.	• It may produce imprecise value when the cluster groups are apriority specified.
Amin et al. [2]	Alex and Google network	• Easy to implement. • Renders the higher results.	• It does not provide the exact results when it deals with sub-tumoral region. • Does not utilize the way of coronial and saggital views.
Neelima et al. [3]	CAViaR-SPO-based GAN	• Obtains higher classification and segmentation rate.	• It gives the problem of premature convergence and gradient.
Siva Raja and Viswasa rani [4]	DAE	• Reaches the higher accuracy.	• It does not suit for ensemble-based classifier model.

Gumaei et al. [5]	RELM	• Accuracy performance is enhanced. • Provides effective results when it implements with large number of datasets.	• It does not include other standard algorithms for performance improvement.
Jemimma and Raj [6]	CWCSO-DCNN	• Maximizes the accuracy, sensitivity and specificity.	• It generates the hardware dependency problem. • It takes longer training time.
Ramya et al. [7]	Deep Super Learning	• Yields the desired classification and segmentation rate.	• It causes the time and space complexity while it contains large size of features.
Fayaz et al. [8]	Blended ANN	• Improves the robustness of model in terms of various measures.	• Due to extract distinct types of features, the complexity arises. • Becomes overfitting problem.

Deep learning-based “brain tumor segmentation and classification”

C. Proposed Brain Tumor Diagnosis Model

Medical image processing has been generally considered a fundamental way of offering clinical treatment and medical research purposes including image-based applications, medical robots, medical record data management, computer-aided diagnosis, etc. Further, it also helps in proper guidance for a medical specialist with the aim of understanding the diseases and investigating medical limitations for enhancing the quality of health care. The research community gets more attention toward medical image analysis for timely treatment. Thus, brain tumor image analysis also gains considerable attention in medical image analysis research works. Although various research works have been designed for precise tumor segmentation and brain tumor detection, they still suffer from a lack of accuracy in segmenting and detecting tumors. Some common challenges for the abovementioned issue are data imbalance, annotation bias, low contrast imaging, morphological uncertainty, location uncertainty, etc. Consequently, the recent research approaches continuously try to promote performance via intelligent methods like deep learning techniques, which help in extracting the feature representations in an automated way, and thus, it is more helpful in classifying the diseases effectively [26]. Predominantly, the focus of precise brain tumor detection must be given to the segmentation process, which is essential in any image processing approach. It has the objective of generating the precise delineation of tumor regions. However, the segmentation results are affected by low contrast among the neighbouring tissues and uncertainty in voxel information. On the other hand, segmentation is demanding while processing the unpredictable appearance and shape of the tumour parts. Thus, the huge requirement of the brain tumor detection model is to achieve better segmentation performance via suitable approaches. Secondly, the brain tumor detection stage is most required for getting tumor detected outcomes like normal and abnormal classes. Conversely, it suffers from differentiations in tumor size, shape, and location. The deep learning-derived brain tumor detection approaches require large memory and higher computing power. Moreover, the better approach is necessary for getting the accurate brain tumor detection methods. Some approaches only gets or detects the brain tumor regarding normal brain images and abnormal tumor images. However, not all the models focus on classifying the tumors regarding benign or malignant stages of tumor. The architectural representation of designed brain tumor diagnosis model is given in Fig. 1.

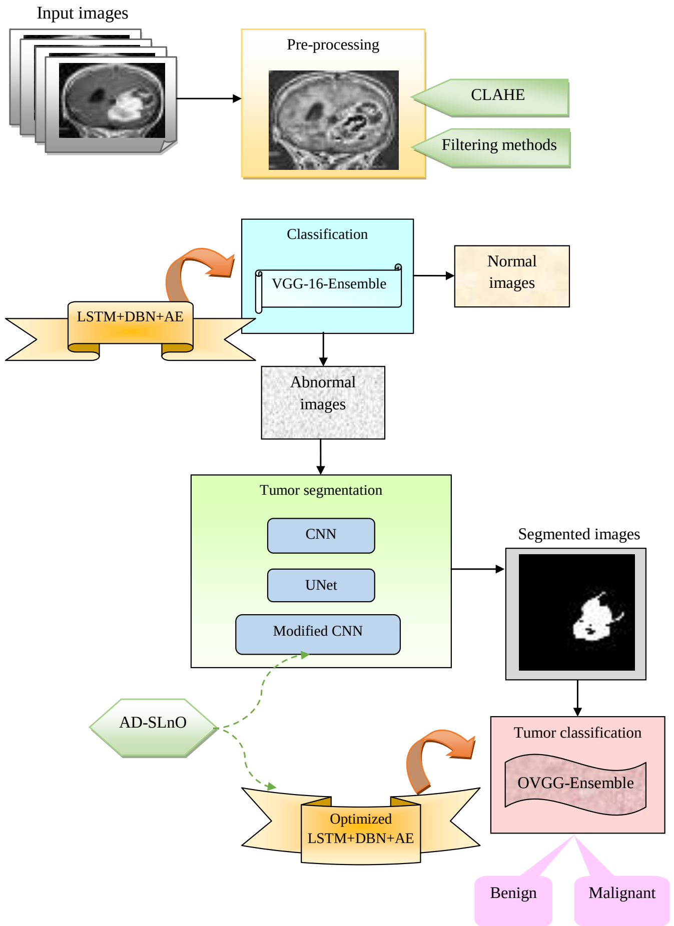


Fig. 1. Architectural representation of designed brain tumor diagnosis model using deep learning techniques

A new brain tumor classification model is implemented in this research work using segmentation and tumor detection phases. Here, the input images from standard data sources are collected. The attained images are pre-processed via filtering methods like median filtering, Gaussian filtering, bi-lateral filtering and CLAHE techniques and fed to VGG16-Ensemble Network for detecting the tumor images, which is designed by adopting various classifiers and results are attained as normal and abnormal images. With the aid of acquired abnormal images, the segmentation step is carried out by ensemble learning with the integration CNN, Modified CNN and U-Net are utilized, where the parameters in CNN are optimized to propose modified CNN by AD-SLnO to acquire the precise segmented images through taking the averaging among these three classifiers. At last, the tumor classification is done by developing OVGG16-Ensemble, in which hyper parameters of VGG16, LSTM, DBN and AE are tuned optimally by AD-SLnO algorithm for classifying the segmented images into benign stage or malignant stage for promoting the medical treatments in timely manner.

D. Pre-processing of Raw MRI Images

The acquired MRI images H_g are given into pre-processing stage and performed using the filtering techniques and CLAHE as follows.

Median filtering [27]: The sharp edges are preserved by median filtering, which is better for pre-processing medical images. It is more effective in smoothing the spiky noise and salt and pepper noise from images. The computational process of the median filtering is derived in Eq. (1).

$$H_g^{MF}(a,b) = MED\left\{ \begin{matrix} H_g(a+cj, b+dj), \\ (cj, f) \in w \end{matrix} \right\} \quad (1)$$

Here, term (a,b) is formulated from $[1,2,\ldots,Sa] \times [1,2,\ldots,Ta]$, the width of the image is known as Ta and the height of the image is specified by Sa. Further, the coordinate set over the window is derived as w.

The pre-processed images using the median filtering are shown by H_g^{MF}, which is further fed to the Gaussian filtering.

Gaussian filtering [29]: This process takes the input as median filtered images H_g^{MF} and is a linear smoothing filter and helpful in removing the noise attained from a normal distribution. It performs by assigning a weighted value for every pixel and is chosen via the shape of the Gaussian function. It has the responsibility of minimizing the high and low signals from distortion. It also eliminates the illuminations and noise from the images and performed as Gaussian low pass filter for removing the high frequency components in the images. This filter on median filtered images H_g^{MF} is done via Eq. (2).

$$H_g^{GF}(a,b) = Hs(a,b) * gc(a,b) \tag{2}$$

Here, the final Gaussian filtered images are known as H_g^{GF}, the channel component is specified as $Hs(a,b)$, and the convolution is denoted as $*$ and the Gaussian function is termed as $gc(a,b)$.

Bi-lateral filtering [30]: The bilateral filtering is used for eradicating the unnecessary noises in the Gaussian filtered images. It is helpful in preserving the edge features and improving the denoising efficiency by filtering the approximate coefficients. The images are smoothed by preserving the images. It works by replacing every pixel via a weighted average of their neighbors and it is dependent on the two constraints like the contrast of the features to be preserved and point to the size.

The bilateral filtering is defined as given here.

$$s(y) = l^{-1}(y) \| \int_{-\infty}^{\infty} q(\varphi) cf(\varphi, y) sg(cf(\varphi), cf(y)) d\varphi$$
(3)

Here, $l(y) = \int_{-\infty}^{\infty} q(\varphi) cf(\varphi, y) sg(cf(\varphi), cf(y)) d\varphi$, where the bilateral filtering is derived by combining both range and domain filtration. Moreover, the "photographic resemblance between the pixel at the neighborhood center" y and that of close by point φ is known as $sg(cf(\varphi), cf(y))$, and the geometric closeness among the neighborhood center y and a nearby point φ is known as $cf(\varphi, y)$, and the normalization constant is specified as $l^{-1}(y)$. At last, the bilateral filtered images H_g^{BF} are given to next process.

CLAHE [28]: The bilateral filtered images H_g^{BF} are fed to enhance the images by deriving the histogram value. The unique gray scale mapping is used for image enhancement via CLAHE. The adaptive histogram equalization mechanism is applied to compute the mapping function to every pixel over the gray scale. The contrast enhancement is carried out on all pixels in the images, in which the iteration number of the approach specifies the pixel count of the images. CLAHE uses threshold for contrast enhancement in images. Thus, CLAHE performs precise image enhancement and reduce the noise level. Finally, the contrast enhanced images are more suitable for further level of processing to get the final detection outcomes.
The CLAHE gets pre-processed images and known as H_g^{CLAHE}.

E. Dataset Details

The proposed brain tumour classification approach gathers the images through the link "https://www.kaggle.com/code/nabamitachakraborty/brain-tumor-detection-cnn/data: access date: 03-09-2022". The gathered dataset includes 253 MRI images under the normal and abnormal categories.

The obtained MRI images from the Kaggle dataset are known as H_g, where $g = 1,2,3,\cdots,G$ and the final set of images considered for processing is referred to as G.

Tumor Detection and Ensemble Deep Learning-Based Tumor Segmentation for Efficient Brain Tumor Diagnosis

A. VGG16-Ensemble-based Tumor Detection

In this proposed model, a new tumor detection framework is adopted with the help of VGG16-Ensemble technique, which is designed by adopting the techniques like VGG16, LSTM, DBN and AE classifiers. This ensemble learning promotes the performance of the tumor detection while taking the input as pre-processed images from CLAHE are known as H_g^{CLAHE}. These images are separately fed to each classifier and retrieve the output in terms of normal and abnormal classes and taken averaging for getting the final outcomes.

VGG16 [33]: This network takes the input as pre-processed images from CLAHE H_g^{CLAHE} and classifies the outcomes in terms of normal and abnormal classes.

It is one of the highest-performing CNN approaches owing to its simplicity. It helps in detecting the tumors regarding brain tumors with accurate, efficient, and quicker decisions. It is known as a 16-layer CNN model, which is the most efficient and best model rather to other architectures. It does not have various parameters, and consequently, it has a 3×3 kernel size with ConvNet layers. The kernel function is considered owing to the reason of getting the non-linearity into the output neurons. These neuron functions are worked together with the bias, weight, and concerning training process. By considering the inaccuracy in outputs, the neuron's function of the neural network gets altered. However, the input gets the non-linearity regarding the activation function and the input layer, which results in learning and accomplishing complicated tasks. It has two major processes including object localization in images and image classification. Initially, the objects in the images are detected and then, the classification of images is done on every labelled class. This classifier gets the outcomes in terms of normal and abnormal classes.

LSTM [31]: This network also considers the input as pre-processed images from CLAHE H_g^{CLAHE} and classifies the outcomes in terms of normal and abnormal classes.

LSTM has the ability to select the higher-level constraints and also dealt with unlocking the specific memory positions in a spatial context and problems of vanishing gradients. It is an improved version of RNN for capturing the sequence dependencies of the global input data. It also has the unique framework of detecting hidden outcomes in complicated image sequences owing to the processing of spatio-temporal constraints. LSTM takes the input as pre-processed images and the temporal dependencies were ascertained. Generally, LSTM has three major parts "the forget gate, the input gate, and the output gate". These steps are explained here. The forget gate takes the input as the input value of the current instant and the output value of the last instance and the result of the forget gate is derived in Eq. (4).

$$fg_t = \delta\left(Wg_{fg} \cdot \left[hs_{t-1}, \left(H_g^{CLAHE}\right)_t\right] + k_{fg}\right) \tag{4}$$

In Eq. (4), the resultant value of the last instant is known as hs_{t-1}, the input value of the present instant is derived as $\left(H_g^{CLAHE}\right)_t$, the sigmoid activation function is known as δ, the bias of the forget gate is specified as k_{fg}, the weight of the forget gate is mentioned as Wg_{fg} and the range of fg_t is noted as (0, 1).

Next, the resultant value of the last instant and the input gate gets the input as the input value of the present time is given. The input gate is derived with candidate cell and state output value as correspondingly formulated in Eq. (5) and Eq. (6).

$$\widetilde{C}c_t = \tanh\left(Wg_{cc} \cdot \left[hs_{t-1}, \left(H_g^{CLAHE}\right)_t\right] + k_{cc}\right) \tag{5}$$

$$ip_t = \delta\left(Wg_{ip} \cdot \left[hs_{t-1}, \left(H_g^{CLAHE}\right)_t\right] + k_{ip}\right) \tag{6}$$

Here, the weight of the input gate is derived as Wg_{ip}, the bias of the candidate input gate is known as k_{cc}, the weight of the candidate input gate is derived as Wg_{cc} and the bias of the input gate is known as k_{ip}.

The next process is for updating the current cell state as shown in Eq. (7).

$$Cc_t = fg_t \times Cc_{t-1} + ip_t \times \widetilde{C}c_t \tag{7}$$

The output gate is formulated at time t by taking the input as the output and value of hs_{t-1} and $\left(H_g^{CLAHE}\right)_t$, which is derived in Eq. (8).

$$op_t = \delta\left(Wg_{op} \cdot \left[hs_{t-1}, \left(H_g^{CLAHE}\right)_t\right] + k_{op}\right) \tag{8}$$

In Eq. (8), the weight of the output gate is derived as Wg_{op} and the bias of the output gate is known as k_{op} ,. Finally, the LSTM computes the output value through the determination of output of the state of the cell and output gate as derived in Eq. (9).

$$hs_t = op_t \times \tanh\left(Cc_t\right) \tag{9}$$

Here, the activation function is denoted as $\tanh$. At last, the memory state stores the computed information. Thus, LSTM classifies the outcomes in terms of normal and abnormal classes.

DBN [32]: This network considers the input as pre-processed images from CLAHE H_g^{CLAHE} and classifies the outcomes in terms of normal and abnormal classes.

DBN is chosen here for its superior performance in recent detection models in terms of accuracy rate. DBN has two layers including "Restricted Boltzmann Machines (RBM) and Multi-Layer Perception (MLP)". The RBM has two layers that interconnect the neurons. These neurons process the inputs with the available weights among the DBN layers. DBN has the input as the pre-processed images, where these images are processed by the suitable weights in the consecutive layers of DBN. Each RBM layer has an input layer, and a hidden layer, where the hidden layer of RBM layer 1 is fed to the input layer of RBM layer 2, which is further subjected to the input of the MLP layer. Similarly, the MLP layer has "the input layers, the hidden layer, and the output layer" and generated the outputs. The training of DBN is carried out by initializing the weights. It is helpful for ensuring the effectiveness of data process to preserve the fine details of the images. The training of DBN is done to classify the absence or presence of a tumor and attained the class labels as output regarding normal and abnormal classes. The gradient descent algorithm is generally used for generating and formulating the weights. Based on the derived weights, the training is done. At last, DBN classifies the outcomes in terms of normal and abnormal classes.

AE [34]: This network assumes the input as pre-processed images from CLAHE H_g^{CLAHE} and classifies the outcomes in terms of normal and abnormal classes.

AE is an unsupervised learning method that processes the pre-processed images via hidden layers and attained the results as normal and abnormal classes from the output layer. It initially extracts the features from the images and fed to the output layer. It has two modules including an encoder and decoder with hidden layers, where the encoding of input images is performed among the input layer and hidden layer, and the decoder operation is performed among the hidden layer and output layer. The decoder increases the size of the data. Additionally, the hidden layer processes the features of input images. Moreover, the noise in images is reduced by this AE model. Next, backpropagation is used in AE for minimizing the error rate. The possibility of getting superior efficiency with a lower error rate is noticed by updating the weight parameters. Moreover, the compressed features are recreated by using the loss functions.

The objective of reducing the loss rate is done by converging the value of variable e' towards e as derived in Eq. (10).

$$LF(e,e') = \|e - e'\|^2 \tag{10}$$

The hidden layer value V is computed in Eq. (11).

$$V = \ell(\omega e + r) \tag{11}$$

The value of output layer is formulated in Eq. (12).

$$e' = \ell'(\omega' e + r') \tag{12}$$

In the aforementioned equations, the bias vector is known as r, the weight matrix is indicated as ω and the activation function is denoted as ℓ.

At last, AE classifies the outcomes in terms of normal and abnormal classes.

VGG-16-Ensemble: A new VGG-16-Ensemble architecture is designed with the integration of the techniques like VGG16, LSTM, DBN and AE classifiers. These pre-processed images from CLAHE are known as H_g^{CLAHE} are separately fed to each classifier and retrieved the results in terms of normal and abnormal classes. Finally, the averaging among VGG16, LSTM, DBN and AE classifiers is taken for getting the final outcomes. This ensemble learning promotes the performance of the tumor detection in terms of normal and abnormal classes. The abnormal images are further fed to the next stage. The framework of designed VGG-16-Ensemble is included in Fig. 2.

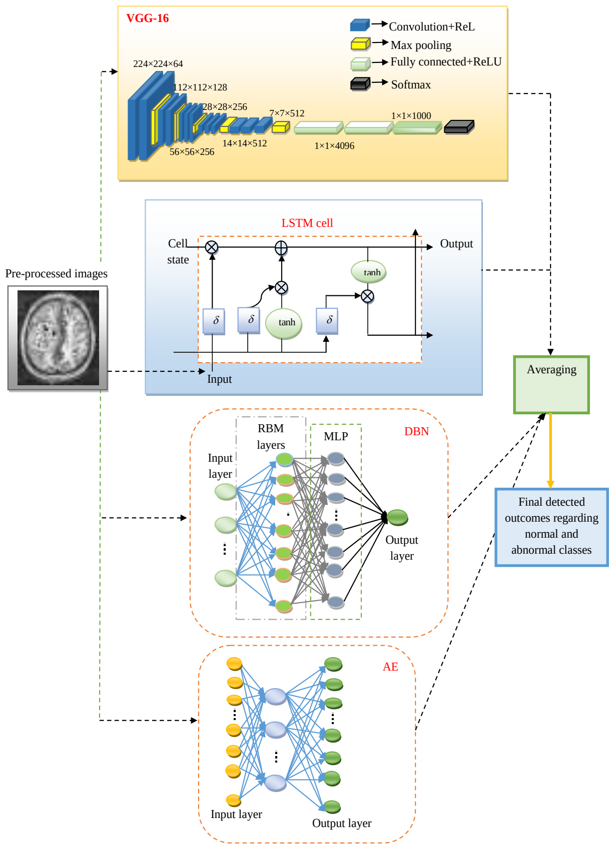


Fig .2 Architecture of VGG16-Ensemble-based Tumor Detection

B. Tumor Segmentation using Deep Learning

In the recommended efficient brain tumour classification framework, the design of ensemble technique is implemented for the purpose of segmenting the tumor in the gathered abnormal images using VGG-16-Ensemble. The abnormal images are directly fed into the techniques like CNN, U-Net and modified CNN networks with the aim of precisely segmenting the tumors in the gathered abnormal images, where the modified CNN is recommended with the parameter optimization in CNN using a newly recommended AD-SLnO technique. Finally, the segmented outcomes of each network are taken averaging and retrieved the results regarding the tumor segmented images and attained the superior performance via the ensemble approach.

CNN [39]: CNN takes the input as abnormal images and retrieved the outcomes as segmented images. CNN is one of the recent and eminent deep learning approaches broadly used for image processing tasks, which is also known as a feed-forward neural network.

CNN comprises neurons with biases and learnable weights. Here, every neuron receives the various inputs and considers a weighted sum over them and fed to the activation function, and responded with the output. CNN is operated like a neural network, where a vector is taken as the input that is the acquired abnormal images. It has the ability of automatical the learning of a hierarchy from complicated features. Initially, it obtains the feature maps by convolving the images with the kernels, where weights in the kernel try to connect every part of the feature map to the earlier layers. This process is carried out during the training process to enhance the attribute of the input images. CNN is initialized for getting better convergence. It focuses on managing the gradients at the specified levels to solve the gradient explosion. Next, the activation function is derived for transforming the data in a nonlinear way. Here, one of the eminent activation function is Rectifier linear units (ReLU) and formulated in Eq. (13).

$$o(ys) = \max(0, ys) + \beta \min(ys) \tag{13}$$

The pooling layer in CNN integrates the features attained via the feature maps and aids in reducing the computational load by solving the redundant features. Next, regularization is carried out for decreasing overfitting. Then, the fully connected layer forces the process of learning superior representations to prevent the co-adaptation of the features. However, a fully connected layer takes more parameters for training than other layers. The loss function is formulated during the training phase for getting the final precise outcomes.

Thus, the CNN gets the final outcomes as segmented images.

U-Net [40]: This network takes the input as abnormal images and retrieved the outcomes as segmented images. It is a fully connected CNN used for segmenting the images. Thus, for getting superior outcomes, the designed model uses U-Net for getting tumor segmented images. An AE form is derived in U-Net, which copies the inputs to their outputs. A compressed depiction of the images is derived by this AE via a latent-space illustration that shows the closest data points. Then, the output is produced by reconstructing the compressed data. AE has two networks like encoder and a decoder. U-Net utilizes an autoencoder framework with convolutional form, where the encoding is performed via convolutional layers and the input images are decoded. Moreover, this network has two paths like "a contraction path (encoder) and a symmetric expanding path (decoder)". The context of the input images is captured by the encoder path and performs like a serial way of consequent layers. On the other hand, for the accurate localization of tumors in the images, the transposed convolutions are used by the decoder path. U-Net has stacked the max-pooling layers and convolutional layers. This promotes the network for learning more accurate features from the compressed input images.

Finally, the U-Net gets the final outcomes as segmented images.

Modified CNN using AD-SLnO technique: A new modified CNN is designed from the traditional CNN by altering or tuning the parameters in CNN by AD-SLnO technique. This network takes the input as abnormal images and retrieved the outcomes as segmented images. Here, the learning rate and hidden neuron count in CNN is optimized using AD-SLnO algorithm. This modification promotes the performance of segmentation while comparing with traditional CNN. Although, CNN has better performance on segmentation in recent studies, it also has some challenges including class imbalance exploding gradient, and overfitting problems. It is also a slower network owing to the max pooling operation. It also takes more computational time while process the huge-scale dataset. Thus, a new AD-SLnO is adopted into CNN for maximizing the segmentation efficiency.

Finally, the precise segmented outcomes are attained by modified CNN using AD-SLnO technique.

Deep learning-based Tumor segmentation: The primary concern of any brain tumor classification model is tumor segmentation, which distinguishes normal tissues from abnormal tissues. However, the segmentation process is more complicated regarding the size, shape location, and diversity of tumors. The segmentation process generally divides the images into diverse regions, in which every region is categorized based on similar characteristics. In recent days, various techniques have been suggested especially for segmenting the MRI images. Some techniques with their challenges are discussed here. Level-set algorithm has higher computational complexity whereas the contour-based segmentation technique is computationally expensive and has not attained satisfactory results, especially for high-intensity, non-uniform and noisy images. K-means clustering faces complications regarding the process of intensifying features in images. Fuzzy c-means clustering cannot determine the lower and upper approximation value for the roughness measure and also higher computational complexity. Thresholding suffers from selecting the optimal threshold value. Region growing takes higher execution time [41]. These challenges promote the researchers in considering the deep learning methods for promoting segmentation performance. The deep learning-based medical image segmentation has attained superior efficiency, which promotes the performance regarding application prospects, accuracy and feasibility. Thus, this research recommends new ensemble learning-based tumor segmentation for performing the precise segmentation of tumors in the gathered abnormal images.

The abnormal images are directly fed into the techniques like CNN, U-Net and modified CNN networks for segmenting the tumors, where the modified CNN is recommended using a recommended AD-SLnO technique. Finally, the segmented outcomes of each network are taken averaging and retrieved the final results regarding the tumor segmented images and attained the superior performance via the ensemble approach regarding outcomes.

The framework of proposed deep learning-based tumor segmentation is given in Fig. 3.

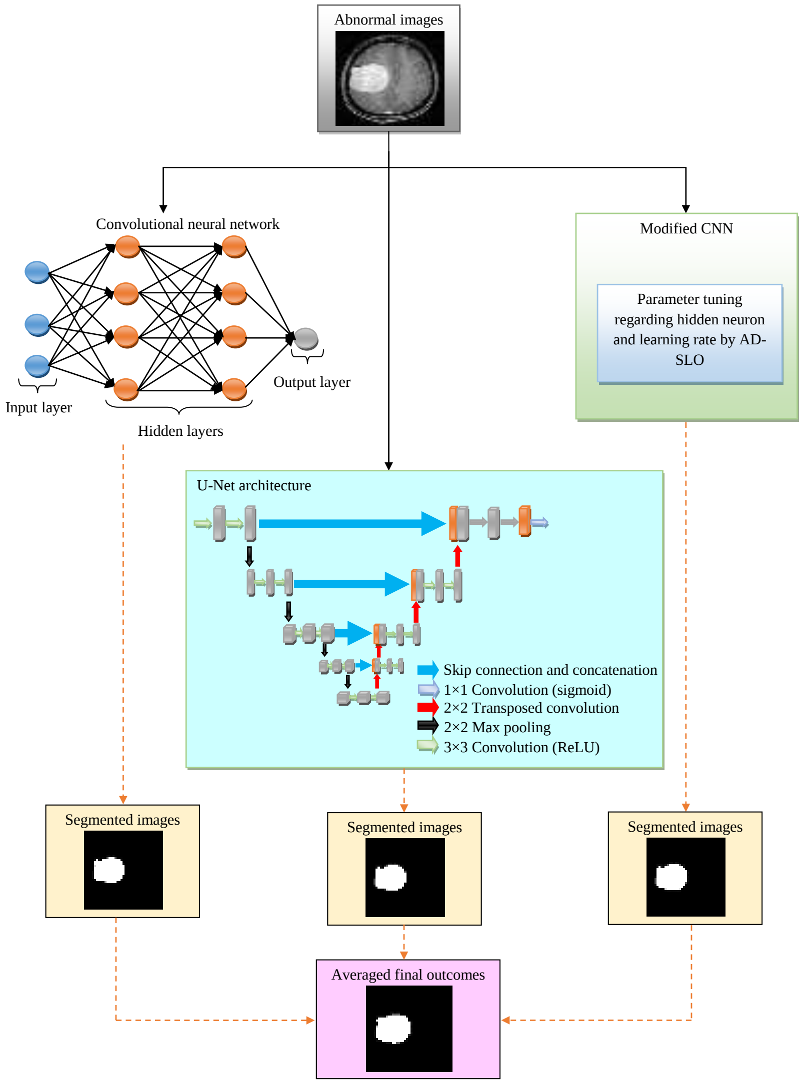


Fig.3 Architecture of tumor segmentation using deep learning

C. Processing Results of MRI Images

Some sample images attained from the execution are specified in Fig. 4.

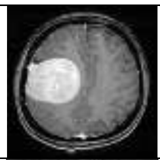
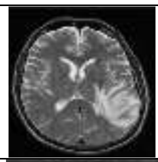
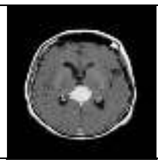
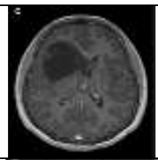
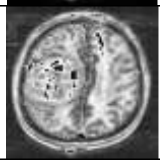
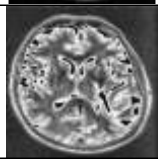
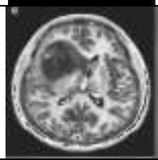
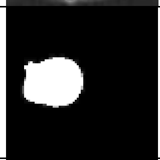
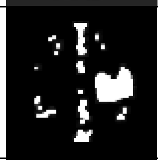
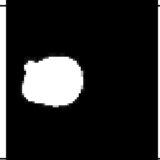
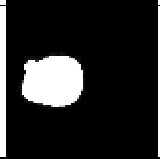
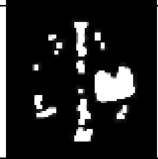
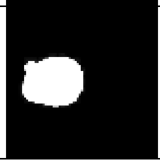
Image description	1	2	3	4
Gathered images from dataset				
Pre-processed images				
Tumor segmented images using CNN				
Tumor segmented images using UNet				
Tumor segmented images using Modified CNN				
Tumor segmented images using Ensemble (CNN+modified CNN+UNet)				

Fig. 2. Processing results of MRI images from different stages

Implementing Novel AD-Slno for Tumor Segmentation and Classification for Optimal Brain Tumor Diagnosis

D. OVGG16-Ensemble-based

Tumor Classification

In this recommended tumor classification model, a new heuristic-derived severity classification framework is suggested with the ensemble technique by integrating the optimized networks such as VGG16, LSTM, DBN and AE to get the results in terms of classified images into benign or malignant classes regarding maximization of "precision and accuracy". Here, the OVGG16-Ensemble network is designed by optimizing the Epoch in VGG16, hidden neuron count in LSTM, learning rate in DBN, and batch size in AE using AD-SLnO technique for increasing the efficiency of classification model. Here, each optimized network takes the input as the tumor segmented images using ensemble method (CNN+modified CNN+UNet) and achieved the outcomes as benign or malignant classes. The objective of designed OVGG16-ensemble based tumor classification framework is derived in Eq. (14).

$$Fv = \underset{\{lr_{CNN}, hn_{CNN}, eh, Hn_{LSTM}, \ell_{DBN}, Bs_{AE}\}}{\arg\max} Ar + pn \tag{14}$$

Here, learning rate in CNN is denoted as lr_{CNN} in the range of [0.01, 0.99], and hidden neuron count in CNN is derived as hn_{CNN} in the range of [5, 255], which are used for segmentation whereas for classification, the Epoch in VGG16 is known as eh in the range of [50, 100], hidden neuron count in LSTM is mentioned as Hn_{LSTM} in the range of [5, 255], learning rate in DBN is formulated as ℓ_{DBN} in the range of [0.01, 0.99], and batch size in AE is derived as Bs_{AE} in the range of [2, 256], which are optimized by AD-SLnO technique. Here, "precision is termed as pn, and equated in Eq. (14).

$$pn = \frac{m}{m+p} \tag{15}$$

Moreover, accuracy is termed as Ar and formulated in Eq. (15).

$$Ac = \frac{(m+n)}{(m+n+p+q)} \tag{16}$$

Here, terms q, n, p, and m "refer to the false negatives, true negatives, false positives, and true positives respectively". Thus, the optimal parameter tuning the designed OVGG16-Ensemble network helps in promoting the performance when comparing with other traditional methods, which is exhibited in result section. The framework of the designed OVGG16-Ensemble network for tumor classification is stated in Fig. 5.

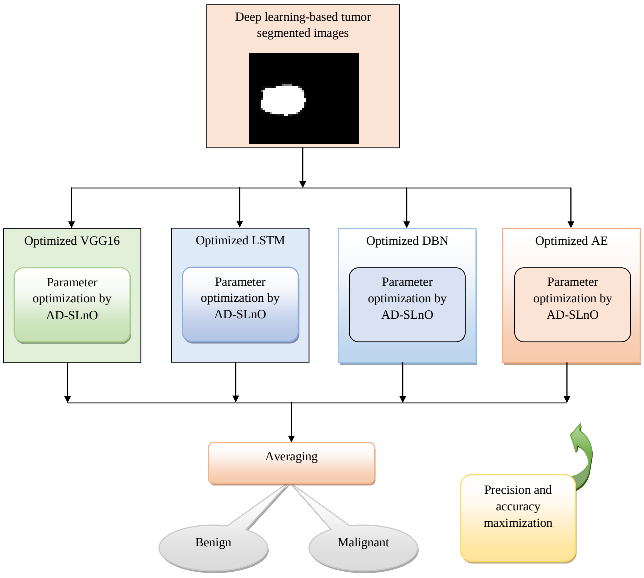


Fig. 3. Architecture of designed OVGG16-Ensemble network for tumor classification

E. Proposed AD-SLnO

A new AD-SLnO technique is suggested in this research work on detecting brain tumors to maximize the performance of proposed model. It assists in enhancing the performance regarding accuracy and precision rates. This algorithm is derived from the concept of new fitness derived formulation for the existing parameter in SLnO, which tries to promote the performance regarding higher convergence rate.

It is inspired and developed from the SLnO [38] algorithm as it holds vast features like superior performance is observed by testing with 23 eminent test functions and achieved superior function to reach the optimal solutions. However, the convergence rate of SLnO must be enhanced and thus, a new fitness derived formulation is implemented here to achieve higher convergence rate to improve brain tumor segmentation and tumor classification processes. This AD-SLnO technique is formulated for optimizing the rate and hidden neuron count in CNN, Epoch in VGG16, hidden neuron count in LSTM, learning rate in DBN, and batch size in AE to promote segmentation and classification purposes.

SLnO is motivated by considering the hunting behavior of sea lions with their properties like "better hunting property, lucid vision and quick movement". The SLnO algorithm has diverse stages like "tracking, social hierarchy, attacking and encircling prey". Sea lions are intellectual animals that live in larger ranges with various numbers of members. Thus, it has its hierarchy with various subcategories. It travels towards prey by considering properties like function, gender, and age and immediately reacts to the fish's movement. It also has the capability of sensing the fishes in the ocean and also in dark water. Next, the hunting is carried out by chasing, encircling and attacking the prey.

"Chasing of prey": Sea lions chase the prey by Eq. (17).

$$\vec{Z}(i+1) = \vec{Q}(i) - \vec{D}i \cdot \vec{R} \tag{17}$$

$$\vec{D}i = \left| 2\vec{A} \cdot \vec{Q}(i) - \vec{P}(i) \right| \tag{18}$$

In the aforementioned derivations, the random vector is derived as $\vec{R}$ that is linearly minimized between 0 to 2 via getting the optimal or close to the optimal solutions, term i specifies the current iteration, $\vec{A}$ is the random value in the boundary of [0, 1], the terms $\vec{Q}(i)$ and $\vec{P}(i)$ correspondingly indicates the position vectors of sea lion and the target prey, the next iteration is indicated as $(i+1)$, and the distance $\vec{D}i$ is formulated among the target prey and the sea lion. The target prey is assumed as the solution that is closer to optimal solution or recent best solution.

"Vocalization phase": Different vocalizations are used for making the communication among sea lions by taking hunting and chasing behaviors. The sea lions have the ability of detecting the sounds in above and under water surface. Hence, after identifying the prey by some sea lions, it intimates to the other sea lions and then, performs the encircling and attacking behaviors and derived in Eq. (19).

$$\vec{L}_{leader} = \left| \frac{\vec{U}_1 \left(1 + \vec{U}_2\right)}{\vec{U}_2} \right| \tag{19}$$

$$\vec{U}_1 = \sin\theta \tag{20}$$

$$\vec{U}_2 = \sin\phi \tag{21}$$

Here, the speed of sounds in water and in air is correspondingly known as $\vec{U}_1$ and $\vec{U}_2$, the "speed of sound of sea lion leader" is equated as $\vec{L}_{leader}$ and the refraction angle and reflection angle are correspondingly derived as ϕ and θ.

Exploitation: After attacking the prey, the recent candidate best solution is considered as the target prey. Two methods like "Dwindling encircling method and Circle updating position" are used for exploitation phase. Dwindling encircling approach is done via the random value $\vec{R}$, which is decreased from 2 to 0 for moving the sea lions towards the prey and for encircling it. Next, the upcoming position of a search agent can be determined between the position of the leader agent and the position of the recent best agent. Next, the circle updating position is followed for updating the solutions. The exploitation phase is done via Eq. (22).

$$\vec{Z}(i+1) = \left|\vec{Q}(i) - \vec{P}(i)\right| \cdot \cos(2\pi b) + \vec{Q}(i) \tag{22}$$

Here, a random number is given as b that lies in a range of [-1, 1], the absolute value is termed as $|\ |$, and the distance among the target prey and search agent is derived as $\left|\vec{Q}(i) - \vec{P}(i)\right|$. While the hunting procedure is carried out in circular motion, the mathematical derivation uses $\cos(2\pi b)$ in Eq. (22).

"Exploration phase or searching for prey": In recent days, the search procedure is carried out randomly. Hence, the random value $\vec{R}$ is derived. The global search agent is attained and utilized to reach the global optimal solutions while taking $\vec{R} > 1$, and this behavior is derived in Eq. (23).

$$\vec{Z}(i+1) = \vec{Z}_{rnd}(i) - \vec{D}i \cdot \vec{R} \tag{23}$$

The major modification in the designed AD-SLnO technique is to suggest the new fitness mathematical formulation for the existing distance parameter in exploration phase of SLnO, which is derived in existing algorithm by taking the random value and random sea lion chosen from the recent population $\vec{Z}_{rnd}$. The new distance formula is given in Eq. (24).

$$\vec{D}i = NP \times \left(\frac{Ft_{best}(i)}{Ft(i)} \right) \tag{24}$$

Here, the number of population is noted as NP and the recent fitness among solutions and best fitness solution derived are correspondingly specified as $Ft(i)$ and $Ft_{best}(i)$.

Thus, this new fitness-derived distance function for updating the exploration phase of AD-SLnO helps in getting global optimal solutions with higher convergence rate, which aids in promoting the segmentation and classification of brain tumor phases.

In Algorithm 1, the pseudo code of proposed AD-SLnO algorithm is shown.

Algorithm 1: Proposed AD-SLnO
Derive the sea lion population Choose $\vec{Z}_{rnd}$ Determine fitness for every solution Determine the distance among prey and sea lion for exploration phase using Eq. (24). While $(i < i_{\max})$ Determine $\vec{L}_{leader}$ using Eq. (19) if $\vec{L}_{leader} < 0.25$ if $\vec{R} < 1$ Update solutions using Eq. (17). else Update the individuals using Eq. (23).

end if
else
Update the solutions using Eq. (22).
end if
end while
Return best solutions

The flowchart of the designed AD-SLnO algorithm is depicted in Fig 6.

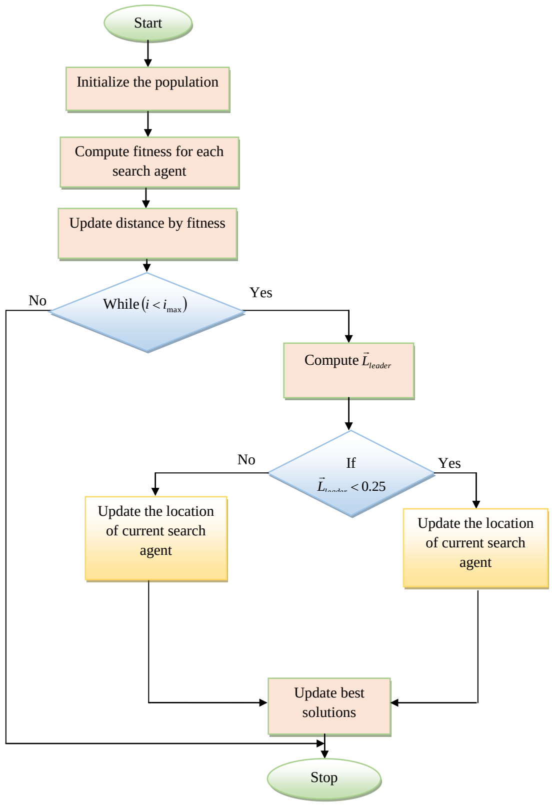


Fig.4 Flowchart of the suggested AD-SLnO algorithm for brain tumor segmentation and classification

2. Result and Estimation

A. Experimental setup

The designed model was evaluated in Python and the performance analysis was carried out over several metrics. The "execution was done by taking the number of populations as 10, chromosome length as 2 and maximum iteration as 10". The performance analysis was conducted over "traditional algorithms such as Coyote Optimization Algorithm (COA) [37], Wolf Optimization (GWO) [36], Particle Swarm Optimization (PSO) [35], Grey SLnO [38] and classifiers like LSTM [31], DBN [32], VGG16 [33], and AE [34] techniques.

B. Evaluation measures

The measures utilized for showing the performance of the designed brain tumor classification model are depicted here.

(a) F1 score is equated in Eq. (25).

$$F1-score = \frac{2m}{2m+p+q} \tag{25}$$

(b) Mathews correlation coefficient (MCC) is equated in Eq. (26).

$$MCC = \frac{m \times n - p \times 1}{\sqrt{(m+p)(m+q)(n+p)(n+q)}} \tag{26}$$

(c) Negative Predictive Value (NPV) is derived in Eq. (27).

$$NPV = \frac{n}{q+n} \tag{27}$$

(d) False Discovery Rate (FDR) is formulated in Eq. (28).

$$FDR = \frac{p}{p+m} \tag{28}$$

(e) False positive rate (FPR) is given in Eq. (29).

$$FPR = \frac{p}{p+s} \tag{29}$$

(f) False Negative Rate (FNR) is shown in Eq. (30).

$$FNR = \frac{q}{m+n} \tag{30}$$

(g) Sensitivity is derived in Eq. (31).

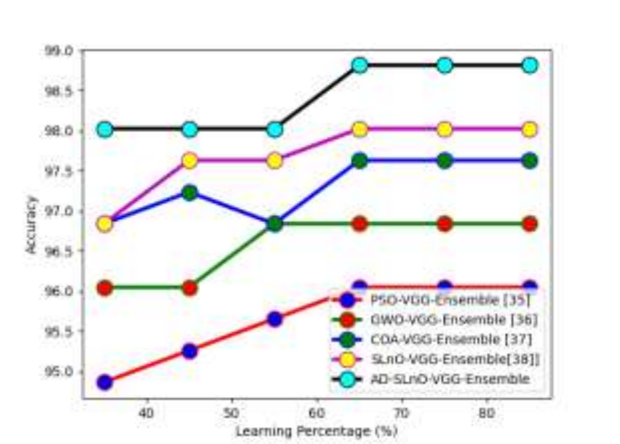
$$Se = \frac{m}{m+q} \tag{31}$$

(h) Specificity is formulated in Eq. (32).

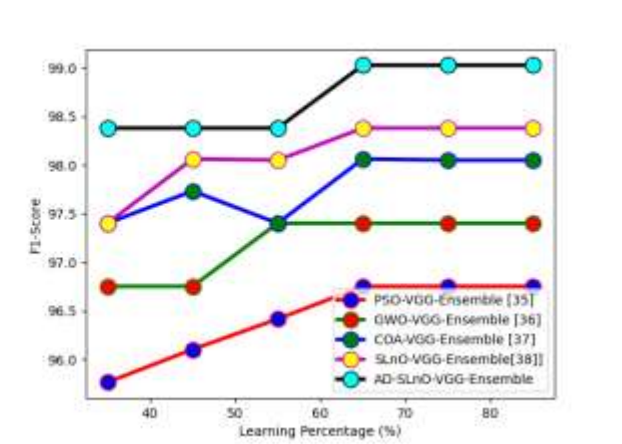
$$Sp = \frac{n}{n+p} \tag{32}$$

C. Investigation on tumor classification over heuristic approaches

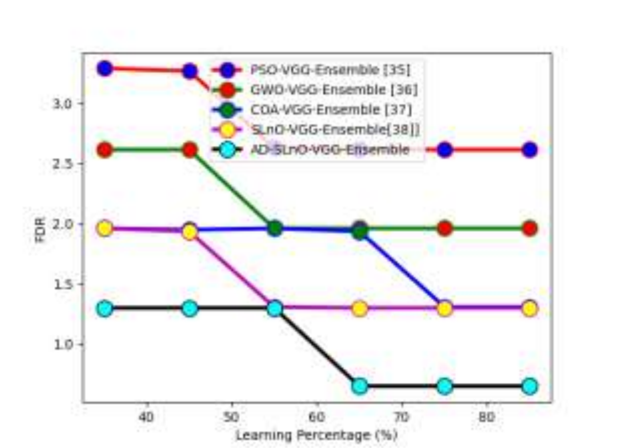
The performance is evaluated on the designed model with comparing diverse existing algorithms as given in Fig. 7. The execution depicts the superior performance of the designed tumor classification model using AD-SLnO-VGG-Ensemble over other methods. For example, while considering the accuracy on detection, the AD-SLnO-VGG-Ensemble achieves superior rate and it is consistently maintained upto to the 85%. This learning percentage-based analysis helps in evaluating the designed model. The precision of the designed AD-SLnO-VGG-Ensemble-based tumor classification is 2%, 1.4%, 0.6% and 0.6% correspondingly superior to PSO-VGG-Ensemble, GWO-VGG-Ensemble, COA-VGG-Ensemble and SLnO-VGG-Ensemble at 75%. Thus, the superior efficiency using AD-SLnO-VGG-Ensemble-based tumor classification is ensured.



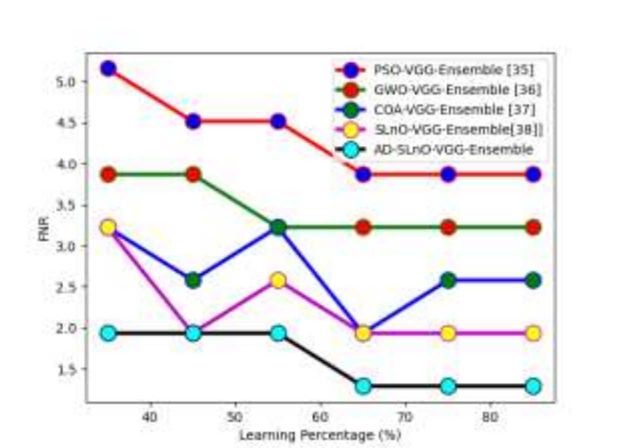
(a)



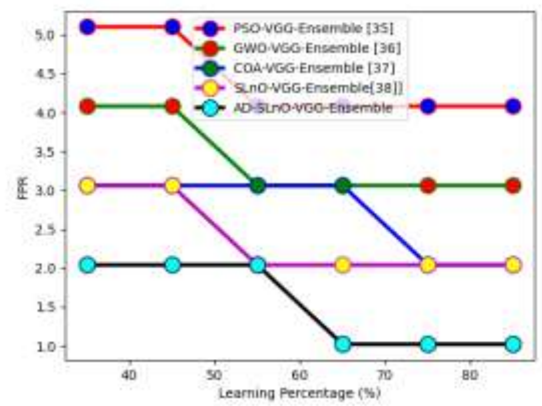
(b)



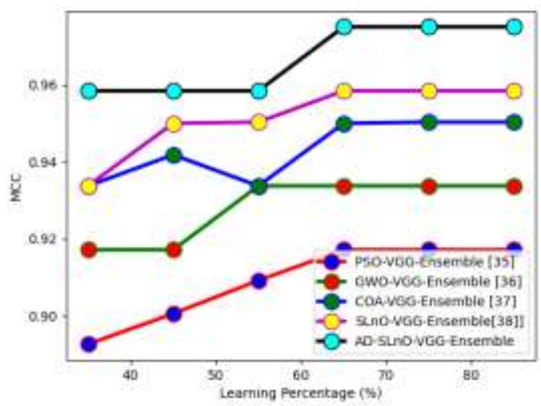
(c)



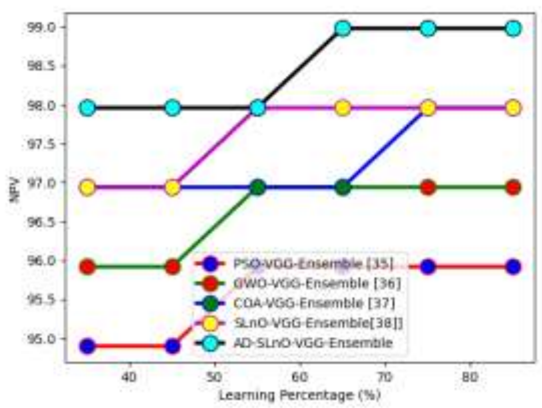
(d)



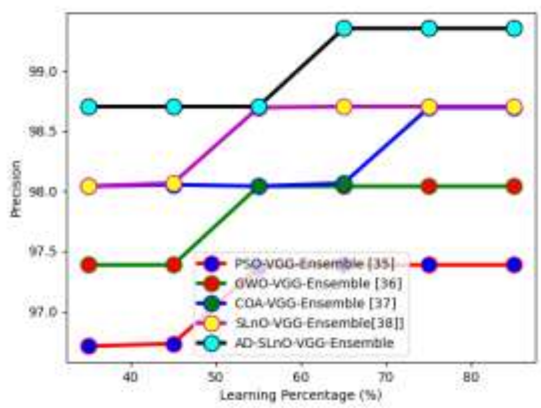
(e)



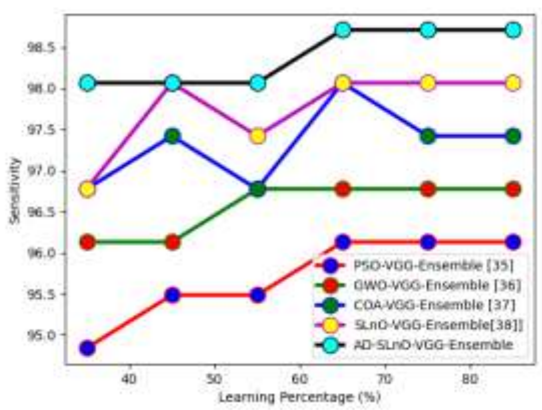
(f)



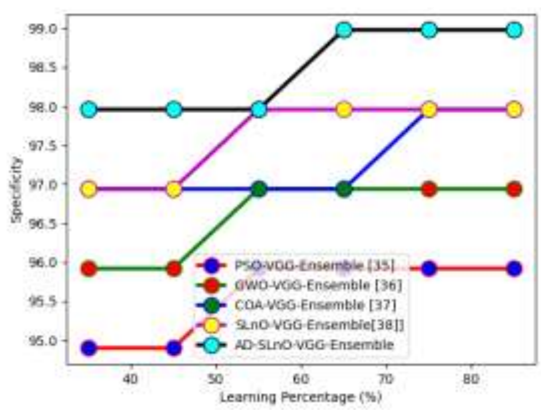
(g)



(h)



(i)

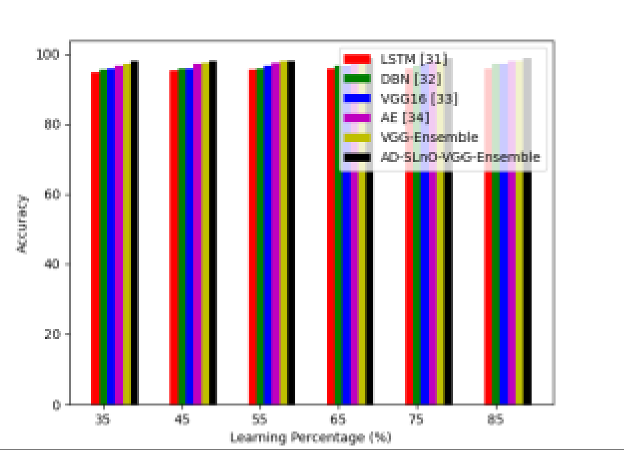


(j)

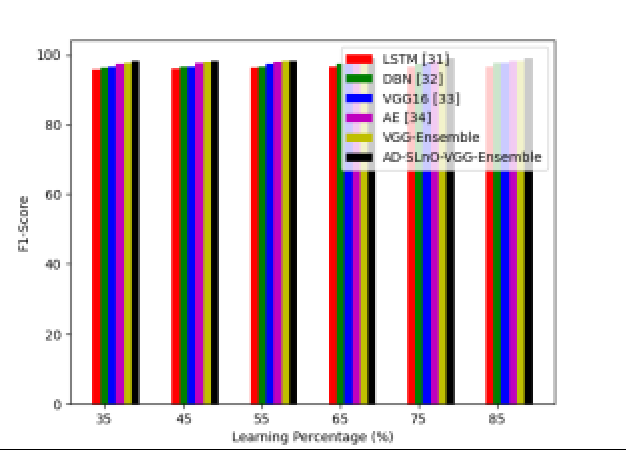
Fig.5 Investigation on the recommended brain tumor classification model over optimization approaches regarding "(a) Accuracy, (b) F1-Score, (c) FDR, (d) FNR, (e) FPR, (f) Precision, (g) MCC, (h) NPV, (i) Sensitivity and (j) Specificity"

D. Examination on tumor classification over classifiers

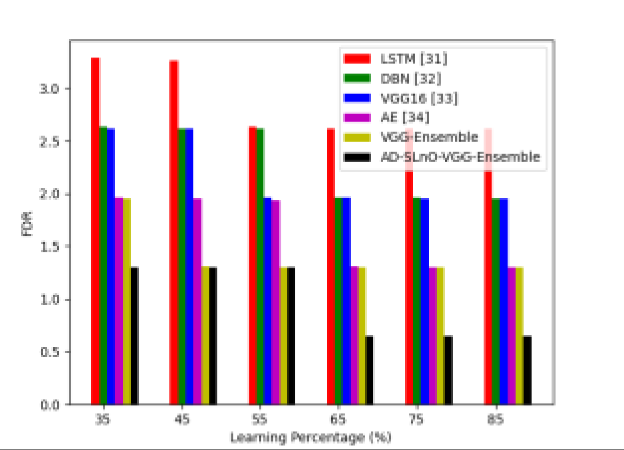
The performance investigation on the designed classification model is performed by comparing diverse classifiers as depicted in Fig. 8. The execution outcomes regarding graphs show the considerable performance enhancement using AD-SLnO-VGG-Ensemble over conventional tumor classification models. The FPR of the designed AD-SLnO-VGG-Ensemble is 75%, 66%, 66%, 50% and 50% correspondingly better than LSTM, DBN, VGG16, AE and VGG-Ensemble at 85%. Finally, the better efficiency is ensured using AD-SLnO-VGG-Ensemble-based tumor classification.


LSTM [31]
DBN [32]
VGG16 [33]
AE [34]
VGG-Ensemble
AD-SLnO-VGG-Ensemble
Accuracy
0
20
40
60
80
100
35
45
55
65
75
85
Learning Percentage (%)

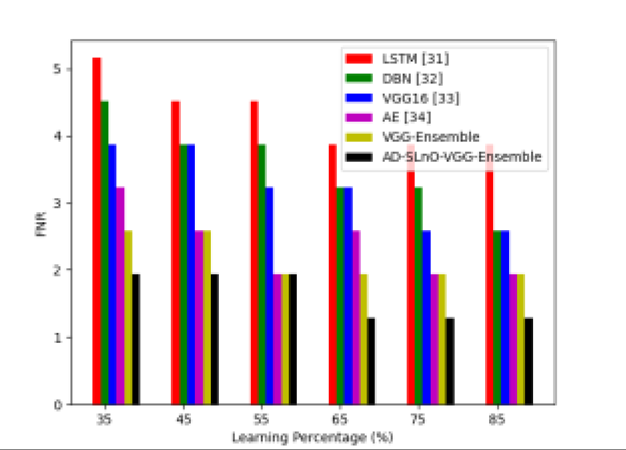
(a)


LSTM [31]
DBN [32]
VGG16 [33]
AE [34]
VGG-Ensemble
AD-SLnO-VGG-Ensemble
F1-Score
0
20
40
60
80
100
35
45
55
65
75
85
Learning Percentage (%)

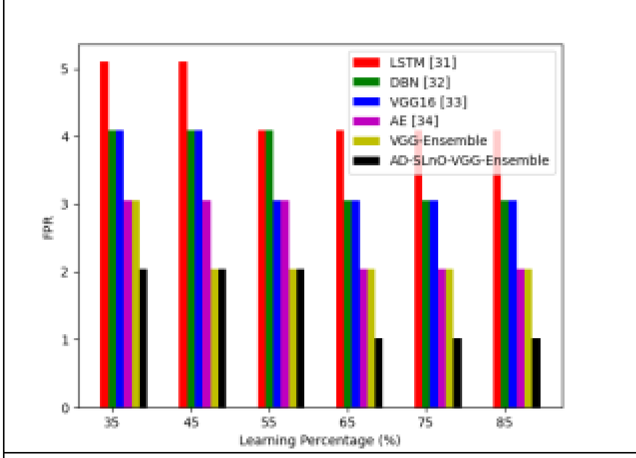
(b)


LSTM [31]
DBN [32]
VGG16 [33]
AE [34]
VGG-Ensemble
AD-SLnO-VGG-Ensemble
FDR
0.0
0.5
1.0
1.5
2.0
2.5
3.0
35
45
55
65
75
85
Learning Percentage (%)

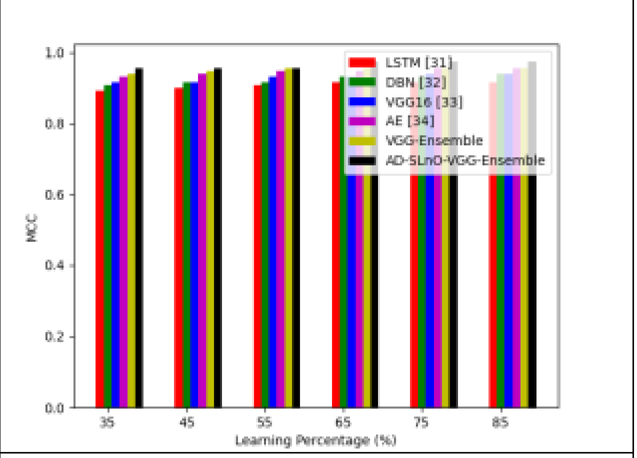
(c)


LSTM [31]
DBN [32]
VGG16 [33]
AE [34]
VGG-Ensemble
AD-SLnO-VGG-Ensemble
FNR
0
1
2
3
4
5
35
45
55
65
75
85
Learning Percentage (%)

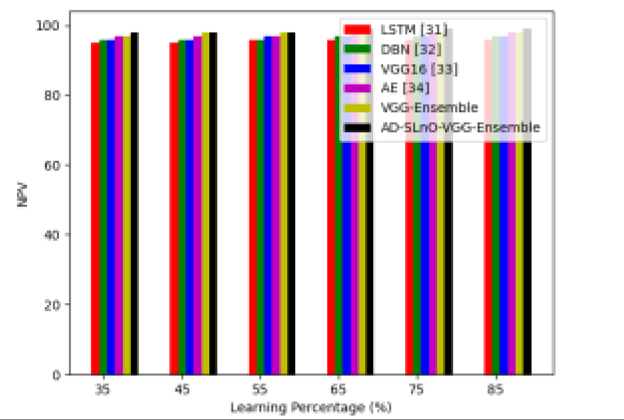
(d)


LSTM [31]
DBN [32]
VGG16 [33]
AE [34]
VGG-Ensemble
AD-SLnO-VGG-Ensemble
FPR
0
1
2
3
4
5
35
45
55
65
75
85
Learning Percentage (%)

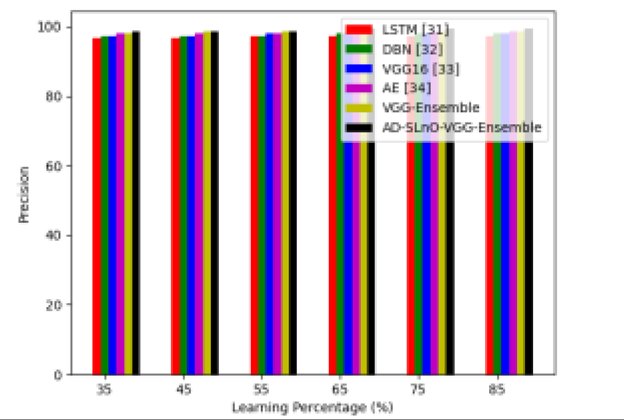
(e)


LSTM [31]
DBN [32]
VGG16 [33]
AE [34]
VGG-Ensemble
AD-SLnO-VGG-Ensemble
MCC
0.0
0.2
0.4
0.6
0.8
1.0
35
45
55
65
75
85
Learning Percentage (%)

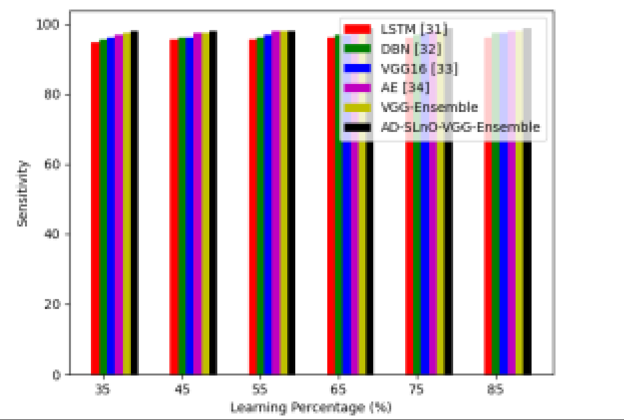
(f)



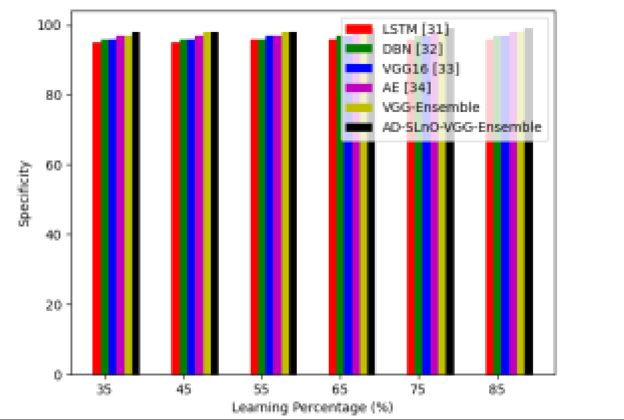
(g)



(h)



(i)



(j)

Fig.6 Investigation on the recommended brain tumor classification model over traditional classifiers regarding "(a) Accuracy, (b) F1-Score, (c) FDR, (d) FNR, (e) FPR, (f) Precision, (g) MCC, (h) NPV, (i) Sensitivity and (j) Specificity"

E. Comparative analysis

Table II demonstrates the outcomes obtained by the proposed brain tumor classification model. Here, the precision of the designed AD-SLnO-VGG-Ensemble is 2%, 1.3%, 1.3%, 0.6% and 0.04% correspondingly enhanced than LSTM, DBN, VGG16, AE and VGG-Ensemble at 85%. At last, the recommended approach using AD-SLnO-VGG-Ensemble is more suitable for brain tumor diagnosis.

Table .2 Investigation on the recommended brain tumor classification model over heuristic approaches

Measures	**PSO-VGG-Ensemble [35]**	**GWO-VGG-Ensemble [36]**	**COA-VGG-Ensemble [37]**	**SLnO-VGG-Ensemble [38]**	**AD-SLnO-VGG-Ensemble**
"Accuracy"	96.83794	97.2332	98.02372	98.81423	99.20949
"Sensitivity"	96.77419	97.41935	98.06452	98.70968	99.35484
"Specificity"	96.93878	96.93878	97.95918	98.97959	98.97959
"Precision"	98.03922	98.05195	98.7013	99.35065	99.35484
"FPR"	3.061224	3.061224	2.040816	1.020408	1.020408
"FNR"	3.225806	2.580645	1.935484	1.290323	0.645161
"NPV"	96.93878	96.93878	97.95918	98.97959	98.97959
"FDR"	1.960784	1.948052	1.298701	0.649351	0.645161
"F1-score"	97.4026	97.73463	98.38188	99.02913	99.35484
"MCC"	0.933755	0.941847	0.958472	0.975097	0.983344

Table .3 Investigation on the recommended brain tumor classification model over classifiers

Measures	**LSTM [31]**	**DBN [32]**	**VGG16 [33]**	**AE [34]**	**VGG-Ensemble**	**AD-SLnO-VGG-Ensemble**
"Accuracy"	96.44269	96.83794	97.2332	98.02372	98.81423	99.20949

"Sensitivity"	96.77419	96.77419	97.41935	98.06452	98.70968	99.35484
"Specificity"	95.91837	96.93878	96.93878	97.95918	98.97959	98.97959
"Precision"	97.4026	98.03922	98.05195	98.7013	99.35065	99.35484
"FPR"	4.081633	3.061224	3.061224	2.040816	1.020408	1.020408
"FNR"	3.225806	3.225806	2.580645	1.935484	1.290323	0.645161
"NPV"	95.91837	96.93878	96.93878	97.95918	98.97959	98.97959
"FDR"	2.597403	1.960784	1.948052	1.298701	0.649351	0.645161
"F1-score"	97.08738	97.4026	97.73463	98.38188	99.02913	99.35484
"MCC"	0.925222	0.933755	0.941847	0.958472	0.975097	0.983344

3. Conclusion

A new brain tumor diagnosis method was implemented using intelligent approaches. The brain MRI images were collected and fed to the pre-processing stage, in which the filtering methods and CLAHE approaches were utilized. Next, these images were fed to VGG16-Ensemble with three classifier models as LSTM, DBN and AE, where the outcomes were acquired as normal and abnormal images. Then, the attained abnormal images were subjected to segmentation step. In segmentation, the deep learning models like CNN, Modified CNN and U-Net were utilized, where the parameters in CNN were optimized using AD-SLnO for precisely getting the segmented images. At last, the OVGG16-Ensemble was suggested, where hyper parameters of VGG16, LSTM, DBN and AE were optimally tuned by same AD-SLnO algorithm to get the results regarding abnormal images into benign stage or malignant stage. Here, the accuracy of the designed AD-SLnO-VGG-Ensemble is 2.8%, 2.4%, 2%, 1.2% and 0.4% correspondingly enhanced than LSTM, DBN, VGG16, AE and VGG-Ensemble at 85%. The studied brain tumor detection and classification model using AD-SLnO-VGG-Ensemble has adopted as more suitable one. However, the future work will be exploring the multiple standard dataset evaluation for promoting the research work.

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