1. Simy Mary KURIAN[1], 2. Sujitha JULIET[2*]

Mangalam College of Engineering (1), Karunya Institute of Technology and Sciences (2)
ORCID: 1.0000-0003-1680-1382; 2. 0000-0001-6214-9431

doi:10.15199/48.2024.07.49

Enhanced Frost Self Organizing Map Segmentation Based Gradient Boost Classification for brain tumour Detection

***Abstract**. Brain tumor detection is a crucial field of research in medical imaging. Specifically, the application of soft computerized techniques in brain tumor detection facilitates the medical experts for diagnosis and critical treatment of brain cancer. An early and accurate tumor classification system is a pressing necessity to support radiologists and physicians to detect brain tumors. In this regard, this paper proposes a novel technique called Enhanced Frost Preprocessed Kohonen Self Organizing Map Segmentation based Intensified Gradient Boosting Classification (EFSOM-GB) for accurate brain tumor detection with higher accuracy and lesser time consumption. The proposed technique is designed with aid of preprocessing, segmentation and ensemble classification. The input MRI image is preprocessed using Enhanced Frost Filter to eradicate noisy artifacts and offer higher PSNR ratio. Next, Kohonen Self Organizing Map Segmentation process is utilized to segment the preprocessed image for extracting features like texture, color, shape, and intensity. An intensified Gradient Boosting Classification is performed to categorize MRI images as normal or tumor. The experimental evaluation is performed with different metrics such as peak signal-to-noise ratio, tumor detection accuracy, error rate and tumor detection. The proposed model provides significant improvement interms of tumor detection accuracy, tumor detection time and reduced error rate when compared to existing methods.*

Streszczenie.** Wykrywanie guzów mózgu jest kluczową dziedziną badań w obrazowaniu medycznym. W szczególności zastosowanie miękkich technik komputerowych w wykrywaniu guza mózgu ułatwia ekspertom medycznym diagnozowanie i krytyczne leczenie raka mózgu. Wczesny i dokładny system klasyfikacji nowotworów jest pilną koniecznością, aby wspierać radiologów i lekarzy w wykrywaniu guzów mózgu. W tym kontekście w artykule zaproponowano nowatorską technikę zwaną ulepszoną, wstępnie przetworzoną metodą Frost, samoorganizującą się mapą Segmentacji Kohonena, opartą na intensywnej klasyfikacji wzmacniania gradientu (EFSOM-GB), służącą do dokładnego wykrywania guza mózgu z większą dokładnością i mniejszym czasochłonnością. Proponowana technika została zaprojektowana z wykorzystaniem wstępnego przetwarzania, segmentacji i klasyfikacji zespołowej. Wejściowy obraz MRI jest wstępnie przetwarzany przy użyciu ulepszonego filtra Frost w celu wyeliminowania zakłóconych artefaktów i zapewnienia wyższego współczynnika PSNR. Następnie wykorzystuje się proces samoorganizującej się segmentacji mapy Kohonena w celu segmentacji wstępnie przetworzonego obrazu w celu wyodrębnienia takich cech, jak tekstura, kolor, kształt i intensywność. W celu sklasyfikowania obrazów MRI jako prawidłowych lub nowotworowych przeprowadza się wzmocnioną klasyfikację ze wzmocnieniem gradientu. Ocenę eksperymentalną przeprowadza się przy użyciu różnych wskaźników, takich jak szczytowy stosunek sygnału do szumu, dokładność wykrywania nowotworu, poziom błędu i wykrywanie nowotworu. Proponowany model zapewnia znaczną poprawę dokładności wykrywania nowotworu, czasu wykrywania nowotworu i zmniejszonego poziomu błędów w porównaniu z istniejącymi metodami.* (Ulepszona, samoorganizująca się mapa Frost oparta na segmentacji mapy, klasyfikacja wzmocnienia gradientowego do wykrywania guza mózgu***)

Keywords: Brain Tumor Detection, Enhanced Frost filter-based preprocessing, Kohonen Self Organizing Map segmentation/
Słowa kluczowe: Wykrywanie guza mózgu, ulepszone przetwarzanie wstępne oparte na filtrze Frost, segmentacja samoorganizującej się mapy Kohonena

Introduction

Brain serves as the central control unit of the human body, orchestrating a multitude of functions through extensive neuronal connections. A brain tumor, stemming from abnormal cell proliferation within the brain, is among the most severe conditions. Many studies have been invetigated for MRI based tumor detection and classification. For treatment process, early and accurate detection of brain tumors is important. Based on this motivation, a novel tumor detection method is introduced to precisely diagnose and treat brain tumors in medical field.

Many researchers have contributed for brain tumor detection in recent years. Abdul A et al., presented an automated method for segmenting brain tumors on MRI Images [1]. CNNs and genetic algorithm (GA) for tumor detection was proposed [2] by extracting significant features. The designed algorithms failed to yield better performance for larger datasets. Similarly, for image segmentation and classification of tumors, CNN was used [3]. The Facial Expression Recognition (FER) techniques based on deep learning [4] is compared based on the number of expressions recognized and the difficulty of algorithms in CNN. The research has investigated the performance of Berkeley wavelet transformation (BWT) for segmentation [5] to lessen the tumor classification time. The Fuzzy c-means (FCM) technique [6] could not increase the performance of tumor detection. Brain tumor detection with CNN using MRI images was proposed [7]. However, the designed method has higher time consumption for tumor detection. Ge T et al., propsed a model for brain lesion segmentation based on joint constraints of Low-Rank representation and sparse representation [8]. In recent years, principal component analysis (PCA) and normalized gastrointestinal stromal tumor (NGIST) descriptor with regularized extreme learning machine (PCA-NGIST with RELM) classifier was introduced to categorize the type of tumors [9]. A hybrid feature selection method that uses Normalized GIST descriptor with PCA (PCA-NGIST) is used to extract the significant features from brain images without using any kind of image segmentation. Hu et al. developed multi-cascaded convolutional neural network (MCCNN) for brain tumor segmentation [10]., in which multilevel priority feature selection for automated tumor detection was performed. For brain tumor identification and segmentation, Johnpeter et al., designed co-active adaptive neuro-fuzzy inference system (CANFIS) [11]. A framework of marker-based watershed [12] algorithm and multilevel priority features selection was proposed. However, the hybrid method failed to achieve higher accuracy for tumor detection. Feature selection based on hybrid optimization for MRI brain tumor classification and segmentation [13] was investigated by Kharrat A et al. The Deep CNN proposed by Kumar et al., used maximum entropy classifier to identify and locate the tumour from the input image [14]. Brain Tumour Detection by Gamma DeNoised Wavelet segmentation was introduced [15]. Entropy Classifier for better accuracy was investigated. Deep learning technique was designed to segment brain tumors from fluid attenuation inversion recovery (FLAIR) [16] by using a fully convolutional neural network (FCNN). A deep Wavelet Auto encoder based deep Neural Network (DWA-DNN) was introduced for tumor detection [17]. The method achieved higher accuracy, specificity and sensitivity than the existing methods. The designed technique failed to perform segmentation process with lesser time consumption. A fuzzy C-means with Super-Resolution and Convolutional Neural Networks with extreme learning machine algorithms (SR-FCM-CNN) was designed [18] for automatic brain tumor detection. The model used Super Resolution Fuzzy-C-Means (SR-FCM) approach for tumor detection. In this model, feature extraction is performed by pretrained SqueezeNet architecture from convolutional neural network (CNN) and classification is carried out with extreme learning machine (ELM). However, the performance of detection was not improved.. An automatic and intelligent brain tumor detection using Lee sigma filtered histogram segmentation [19] model was introduced to improve detection time and accuracy. Shree and Kumar [20] analyzed a probabilistic neural network classifier was designed to enhance accuracy of brain tumor location recognition. But the classifier failed to effectively perform the segmentation and feature extraction for achieving higher accuracy. Rajan et al., introduced brain tumor detection by intensity adjustment [21]. Tripartite Generative Adversarial Network (Tripartite-GAN) proposed by Z hao et al., accurately detected the tumor. But the time analysis was not solved. Transform based image analysis for MRI and CT images were performed for telemedicine applications [23]. Ragupathy B et al., illustrated U-Net convolutional neural network classification technique [24] for brain tumor detection. Optimized vessel detection in marine environment using hybrid adaptive cuckoo search algorithm introduced for enhance accuracy [25]. The authors proposed simulated Annealing-Genetic Algorithms for choosing the optimal relevant feature. In order to increase the accuracy. An improved deep neural learning classifier was investigated for brain tumor detection [26]. Gray bimodal histogram segmentation has been carried out to segment the image into different regions to minimize the tumor detection time.

Segmenting MRI images poses a significant challenge in various medical imaging applications, with extensive prior research in the field. In the process of feature extraction, numerous relevant features are computed for subsequent classification. However, these extracted features often include noise, which can adversely affect classification accuracy. To mitigate this issue, the development of a precise classification model becomes imperative. Grounded on this motivation, the authors propose a method, specifically designed to enhance the accuracy and reduce processing time in identifying tumor regions within MRI images

The proposed research work aims to perform preprocessing, segmentation and ensemble classification on MRI images for tumor detection. The success of the proposed technique can be attributed to several underlying mechanisms:

- The proposed EFSOM-GB method aims to achieve early-stage brain tumor detection with improved accuracy and reduced processing time by incorporating preprocessing, segmentation, and ensemble classification.
- The novelty of the proposed enhanced Frost filtering technique lies in its utilization of a unique window filtering approach to eliminate noisy pixels and enhance image quality, ultimately leading to a reduction in mean square error and an enhancement in peak signal-to-noise ratio."
- A Kohonen Self-Organizing Map Segmentation process is employed to segment input images, extracting various image features such as texture, color, shape, and intensity, resulting in reduced tumor detection time.
- The novel intensified gradient boost technique is utilized for the classification of MRI images as normal or tumor, offering improved accuracy based on the extracted feature results.
- A novel likelihood ratio test is applied to calculate class means and features, contributing to the classification outcomes.
- The application of gradient descent step-size in EFSOM-GB is essential for determining the optimal classifier outcomes with minimal training loss.
- The proposed EFSOM-GB technique is subjected to a comparative analysis, encompassing both quantitative and qualitative assessments, against various state-of-the-art algorithms, using different metrics.

Method

In this section, the proposed EFSOM-GB technique is introduced for accurate brain tumor detection. This technique includes three major steps. The input to the proposed model is MRI brain images and output is classification of brain tumor as normal or tumor.

The flow process of EFSOM-GB technique is clearly illustrated in fig.1 with various processing steps. At first, the MRI images $I_1, I_2, I_3 \ldots\ldots I_m$are applied to Enhanced frost filter to smoothen the images by eliminating the noises. Then the segmentation process divides the images into number of areas based on the similar characteristics which reduces the difficulty of feature extraction. Followed by, the feature extraction process is carried out to extract multiple features. Finally, classification is carried out with the extracted features using Intensified Gradient Boosting Classification.

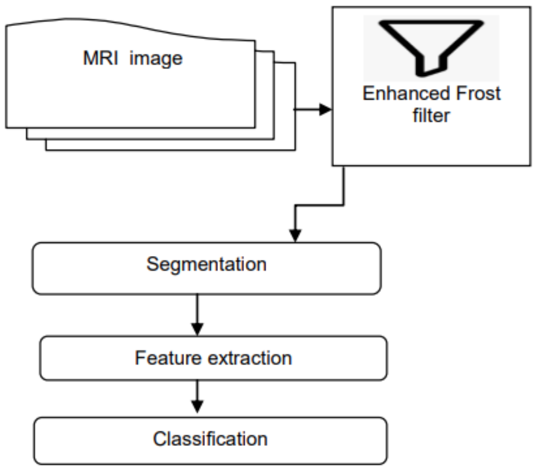

Fig. 1 Flowchart of the proposed EFSOM-GB technique

Enhanced frost filter-based image preprocessing

The first step involved in the EFSOM-GB technique is a preprocessing of input MRI brain image. With the objective of designing a noise-free image, an enhanced frost filter is presented in the EFPKSOMS-IGBC technique. Initially, the input MRI image$I_1, I_2, I_3 \ldots\ldots I_m$is taken from the database.

The pixels of the MRI image are denoted by$r_1, r_2, r_3, \ldots r_n$ and arranged in a filtering window in the form of ascending order. These pixels are arranged in terms of row and columns asgiven below,

(1) $$r_{ij} = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}$$

From (1),r_{ij} indicates the pixel arrangements in a filtering window with the kernel size of$3*3$. After arranging the pixels, the center value is selected for identifying the noisy pixels. In case of any even number of pixels located in filtering window, the averages of these two pixels are taken as center value. Then center pixel value is replaced by the average values of all neighborhoods in the filtering window. The enhanced frost filter is applied to remove the noisy pixels as follows,

(2) $$F = \sum_{s*s} \beta\, \varphi\, e^{-(\varphi\, t)}$$

From (2), F indicates the filtering output, βdenotes a normalized constant, 's' indicates the size of the filter window, φ be the coefficient of variation,$t = (x_2 - x_1) + (y_2 - y_1)$ indicates a distance coordinates from the center pixel to its neighbors in the filtering window. Therefore, the coefficient of variation 'φ' is measured as the ratio of local deviation and the local mean.

(3) $$\varphi = \left[\frac{\mu^2}{\sigma^2}\right]$$

From (3), μ^2 denotes a local mean, σ^2 refers to the local deviation of the filtering window. Finally, the noisy pixels in the filtering window are altered by the average of values of the neighboring of the entire pixels. As a result, the noises are removed and obtain quality enhanced images. Therefore, the enhanced frost filter enhances peak signal to noise ratio and lessen mean square error.

Algorithm 1 describes the process of enhanced frost filtering technique to achieve the quality enhanced image for accurate disease identification. At first, the pixels of input MRI images are given in filtering window in the form of row and columns format. After that, the center value is taken and analyzed with the neighboring pixels. Then, the filtering technique is utilized to replaces the center value by average of neighboring pixels in the window. To evaluate the accuracy of tumor detection, the two significant metrics are used namely Mean Square Error and Peak Signal to Noise Ratio. Major results are achieved with minimum MSE which further leads to improved performance accuracy.

\\ Algorithm 1: enhanced frost filter based noise removal

Input: MRI brain images $I_1, I_2, I_3 \dots .. I_m$

Output: Preprocessed image

Begin

For each image (I_i)

Sort the intensity of pixels $r_{1,}r_2, r_3, \dots r_n$in an ascending order

Take center value'r_{ij}'

Apply the filter 'F'

Replace center pixels by averages of neighboring pixels

End for

Obtain quality enhanced image

End

Kohonen Self Organizing Map Segmentation (KSOMS)

With the enhanced image, the next step in the proposed EFSOM-GB technique is the segmentation process for efficiently dividing the total images into different regions to lessen tumor detection time.

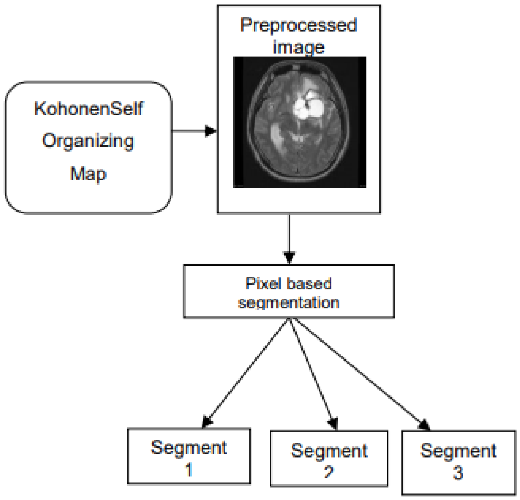

Fig. 2 Block diagram of Kohonen Self Organizing Map Segmentation (KSOMS)

In this EFSOM-GB technique, a Kohonen Self Organizing map is designed. Fig 2 illustrates the block diagram of Kohonen Self Organizing Map Segmentation (KSOMS) to obtain the segmented region based on the pixels of interest.

The pixels of each input images is denoted as$r_{1,}r_2, r_3, \dots r_n$. KSOMS is functioned based on two modes of operations namely training and mapping. In training mode, the input images pixels are trained and the mapping mode is used to automatically organize an input. In KSOMS, the input is represented as image pixels. The KSOMS consists of two layers such as input and Kohonen layers which are also called output layer. The output part consists of components called nodes or neurons.

Fig. 3 illustrates Kohonen Self-Organizing map where the input layer receives the pixels of the input image$r_{1,}r_2, r_3, \dots r_n$. The input is connected to the node or neurons. Each connection has different weights (τ_j). For the clustering process, weights of the neurons (i.e.nodes) are initialized with random integer values.

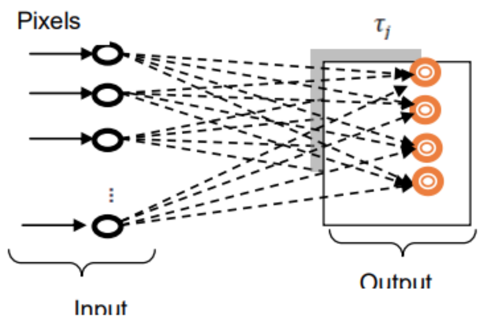

Fig. 3 Kohonen Self-Organizing map

In the Map phase, the input pixels from the input space are mapped into the weight of node in output space through the distance measure. The distance between the input and the weight of the node in output space is calculated as given below,

(4) $$\boldsymbol{D_{ij}} = \sum_{i=1}^{n} \sum_{j=1}^{m} \left| r_i - \tau_j \right|$$

From (4), D_{ij}symbolizes a distance between the image pixels'r_i' and the node weight vectorτ_j. Then best matching neuron is selected as a winner, whose weight is closest to the input pixel. The closest distance is identified as given below,

(5) $$G = \arg min\ D_{ij}$$

where G indicates a function, $\arg min$is an argument of minimum function at which lesser distance of pixels and weight value is identified. The pixels having a similar intensity are grouped and obtain the different regions. In this way, the different segments of images are obtained. After segmenting the input images, the features in the input images are extracted. The segmentation process reduces the tumor detection time by extracting the features from the region of interest part (i.e. lesion) based on pixel intensity value instead of processing the whole images.

The different features namely texture, shape, gray level intensity, and color are extracted. Initially, image texture is used to obtain information about the spatial display of color or intensities in selected segmented of an image. Therefore, the texture is measured through the correlation measure between segmented images.

(6) $$R = \frac{\sum_i \sum_j (r_i - \mu_i)(r_j - \mu_j)(r_i r_j)}{\sigma_i \sigma_j}$$

Where 'R'represents the texture feature of the segmented image, μ_i and $\mu_j$are the mean of the pixelsr_i, r_j, $\sigma_i \sigma_j$ denotes a deviation of the pixelsr_i andr_j. The shape feature is extracted through the contour in which the midpoint of the image is denoted by $(0,0)$. The distance from center to edge of object is estimated to attain shape.

(7) $$Dis = \sqrt{(u_2 - u_1)^2 + (v_2 - v_1)^2}$$

Here,$'D'$ is indicates the distance, the center point of the coordinates is denoted by (u_1, v_1)i.e.$(0,0)$ and coordinates $(u_2, v_2)$is an edge of object. The perfect shape of boundary is obtained. Gray level intensity contrast is calculated as difference among pixels in set of pixels as given below,

(8) $$S_b = \sum_i \sum_j |r_i - r_j|^2$$

From (8), $S_b$indicates a gray level intensity contrast, r_i denotes pixels and $r_j$denotes a neighboring pixel. Finally, the color features are extracted by transferring RGB image as HSV (hue, saturation, value) color spaces as represented below,

(9) $$C = \frac{1}{m} I_p$$

From (9), 'C' specifies the color feature of the image block, I_p denotes pixel intensity, 'm' signifies a total number of pixels in an image.

\\ Algorithm 2: Kohonen Self Organizing Map Segmentation

input: Preprocessed MRI brain images$I_1, I_2, I_3 \ldots.. I_m$
Output: Segmented image

Begin
 For each preprocessed image (I_i)
 Select pixels $r_1, r_2, r_3, \ldots . r_n$ in given image
 Set synaptic weights τ_j to the output node
 for each pixelr_i
  for each node weight τ_j
 Compute distance D_{ij}
  Find minimum distance $argminD_{ij}$
 Group the similar pixels having a minimum distance
  end for
 end for
 9Extract the texture, shape, gray level intensity and color features
End for
End

The step-by-step process of segmentation and feature extraction is clearly described in algorithm 2. First, the preprocessed MRI image is taken for the segmentation process. The pixel-based segmentation of input MRI image is applied to partition the given image as diverse segments and obtain region of interest part. The distance similarity is measured between the input pixels and the weight of the neuron at the output layer. Similar pixels' values are grouped and obtain different segments. Followed by, the different features are extracted.

2.3 Intensified Gradient Boosting Classification based tumor detection

Final step of EFSOM-GB is a classification to perform accurate tumor detection. The classification process is carried out using the Intensified Gradient Boosting technique based on the extracted features.

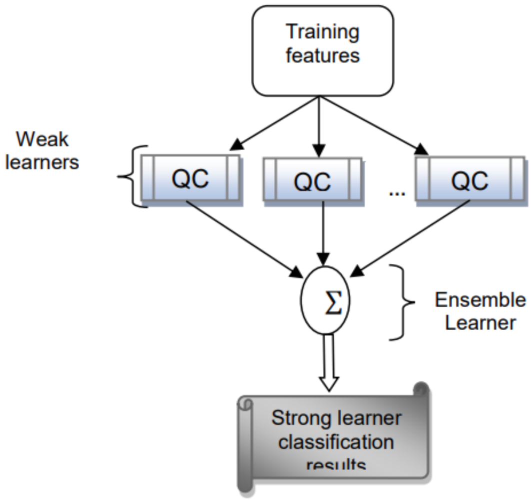

Fig. 4 Structural design of Intensified Gradient Boosting classification

Intensified Gradient Boosting is an ensemble machine learning technique comprising 'n' number of weak learners (i.e., Quadratic classifier) to categorize MRI image as various classes namely normal or tumor. A weak learner is a base classifier which offers less precise classification results. Ensemble technique provides strong classification results by combining the weak learners' outcome. The weak learner's outcome is combined to offer strong classification results for tumor detection with higher accuracy. In the ensemble learning, intensify is referred to create a much stronger classifier for tumor detection with a lesser error rate. The structural designs of the ensemble boosting classifiers are illustrated in Fig. 4.

Gradient boost ensemble classifier comprises the training sets $\{x_i, y_i\}$ where x_i is an input i.e. extracted features, and $y_i$symbolizes final ensemble tumor classification outcomes. Proposed boosting ensemble classifier builds empty set of 'm' weak classifiers $\mathrm{QC1}, \mathrm{QC2}, \mathrm{QC3} \ldots, \mathrm{QCn}$ with extracted features. Proposed ensemble technique utilizes weak classifiers as a quadratic classifier to categorize the images as normal or tumor. A quadratic classifier is a statistical classifier that takes a decision and categorizes the given input into two or more different classes. Let us consider the learned features and define the two classes namely $\{0,1\}$ and the each class are defined asm_1,m_2 respectively. After that, the likelihood ratio test is performed between the features and mean value

(10) $$\varphi(m, v | F_i) = \frac{1}{\sqrt{2\pi v^2}} e^{\left(-\frac{(F_i - m_i)}{2v^2}\right)}$$

Here,φ likelihood ratio test is performed between the selected feature F_i and mean value 'm_i', deviation 'v'. The likelihood ratio test between each class means and features are measured and obtain the classification outcomes. The feature which is close to the class means 'm_1' and then the image is classified as a tumor. Otherwise, the feature which is not close to the class means 'm_2' and then the image is classified as normal. In this way, the quadratic classifier classifies the given input image into two different classes.

The results of weak classifiers have some training errors and thereby providing less accurate. Therefore, the sum of weak classifiers are combined and to make a strong classification as given below,

(11) $\mathrm{y_i} = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{QC_i}$

y_i represents the strong classification result through the linear combination of the base classifiers $\sum_{i=1}^{m} QC_i$. Followed by, the weights are initialized to each weak classifier is expressed as follows,

(12) $y_i = \sum_{i=1}^{m} QC_i \ \vartheta$

Where ϑ indicates a weight which is the integer number to validate the classification performance of weak classifiers. Then the weak classifier has some training loss

(13) $\mathrm{y_i} = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{QC_i} + \mathrm{L_T}$

L_T indicates a training loss of weak classifier 'QC_i'.From (14), the squared error loss is mathematically estimated as given below,

(14) $L_T = (A_e - P_E)^2$

Where, 'A_e' denotes an actual error, $P_E$signifies the predicted error. According to the weight value, the weight of each weak classifier gets updated. In other words, the weak classifier has lesser training loss and the weight is reduced from the initial value. Otherwise, the weight is increased from the initial value. Here, the proposed ensemble technique utilizes gradient descent step-size to discover best weak classifier with lesser training loss than other.

(15) $G_{step} = arg\ min\ L_T\ (QC_i)$

In (15), G_{step}symbolizes a gradient descent step-size function, $arg\ min$symbolizes the argument of the minimum function, L_T indicates a training loss of weak classifier QC_i . As a result, the weak classifier has minimum training loss is taken as final classification results. This process has higher tumor detection accuracy with a lesser error rate.

\\ Algorithm3: Intensified Gradient Boosting Classification based tumor detection

Input: Preprocessed MRI brain images$I_1, I_2, I_3 \ldots\ldots I_m$, Extracted features 'F_i'
Output: tumor classification

Begin
For each extracted feature 'F_i'
Construct a set of weak classifiers
$\mathrm{QC1}, \mathrm{QC2}, \mathrm{QC3} \ldots., \mathrm{QCn}$
Initialize two classes and mean value 'm_1', 'm_2'
For each mean m_i
For eachF_i
Measure the likelihood ratio test '$\varphi(m, v|F_i)$'
Categorize the images into two classes'normal'
`or 'tumor'
End for
End for
End for
Combine the weak classifiers '$y_i = \sum_{i=1}^{m} QC_i$'
For each QC_i
Initialize the weight 'ϑ'
Measure training loss 'L_T'
Update the weight '$\nabla\vartheta$'
Find $arg\ min\ L_T\ (QC_i)$
Obtain strong classification results
End for
End

The algorithm 3 describes the different processing steps of tumor classification. The extracted features from the given input image are given to the ensemble classifier. The ensemble technique analyzes the given input features and classifies the given input image into a normal or tumor based on the likelihood ratio test. The weak learner's results are combined and make a strong classification. After combing the weak classification result, the weights are initialized.

Then, training loss is measured based on actual and predicted classification outcomes. According to training loss, the weight gets adjusted. Followed by, the weak learner with the smallest training loss is selected as the best classification results.

Experimental Evaluation

The performance of proposed EFSOM-GB technique and existing PCA-NGIST with RELM [8], SR-FCM-CNN [17]), DWA-DNN [16], and Existing CNN are implemented using MATLAB R2023a Software for detecting the brain tumor at an earlier stage. The execution is carried out using Windows 11 Operating system, core i5-4130 4.60GHZ Processor, 8GB DDR4 RAM, 1TB (1000 GB) Hard disk, ASRock B760M-ITX/D4 Motherboard. The results of proposed and existing methods are analyzed by using the brain MRI images collected from the database https://radiopaedia.org/articles/medulloblastoma?lang=us.

The database consists of more than 25,500 patients MRI images with different sizes. In the implementation process, majority of the images i.e., 80% images from the given database is used for training and remaining 20% images are used for testing. The input MRI image is first preprocessed using an enhanced frost filter to remove the noise artifacts and obtain the quality enhanced images. Secondly, the input preprocessed images are segmented into different parts based on the pixel intensity. Then the texture, color, shape, intensity features are obtained from segmented images. Finally, intensified gradient boost ensemble classification technique scrutinizes extracted features and classifies the images into normal or tumor. Qualitative and quantitative analyses are discussed in performance results. Firstly, the analysis of the Qualitative results is explained followed by the statistical analysis with different metrics are discussed.

Results and Discussion

Our study on the EFSOM-GB technique for identifying tumor regions in MRI images holds promising real-time clinical implications that can significantly impact the diagnosis and treatment of diseases, particularly in the field of medical imaging. One of the foremost implications of our method is its potential to enhance diagnostic accuracy. By reducing noise and improving the precision of tumor identification, clinicians can expect more reliable and consistent MRI-based diagnoses.

The clinical implications of the EFSOM-GB technique are substantial and offer a new dimension to medical imaging. However, it is important to acknowledge that further research and validation are necessary before widespread clinical adoption. The use of advanced medical imaging techniques like ours raises ethical and regulatory considerations, including patient consent, data privacy, and compliance with healthcare regulations. Addressing these concerns is critical for responsible deployment. While our study focuses on tumor identification in MRI images, the techniques employed can potentially be adapted to other medical imaging modalities and disease types. Exploring these broader applications can further expand the clinical impact Initially, the input MRI image is collected from the database https://radiopaedia.org/articles/medulloblastoma?lang=us.

Then the Kohonen Self Organizing Map Segmentation is performed and extracts the features such as texture, shape, color and gray level intensity. Finally, the tumor detection is obtained using intensified gradient boost classification technique.

For the discussion of the quantitative results, 150 MRI images are obtained from database. The performance of EFSOM-GB technique and four conventional methods, PCA-NGIST with RELM [8], SR-FCM-CNN [17], DWA-DNN [16], and Existing CNN are evaluated with four metrics. Peak signal-to-noise ratio is measured as fraction of Maximum possible pixel to mean square error.$ms_{er}$is computed as difference among size of original MRI brain image and preprocessed image size.

(16) $\boldsymbol{R_{PS}} = 10 * \log_{10}\left(\frac{M^2}{ms_{er}}\right)$

(17) $ms_{er} = [Size_d - Size_o]^2$

From (16), R_{PS} denotes a peak signal to noise ratio, 'M' denotes a maximum possible pixel value (255), $ms_{er}$is the mean square error. From (17) ,$Size_d$be the denoised image size,$Size_o$signifies the original image size. R_{PS} measurement is done in decibel (dB).

Fig 5 illustrates the qualitative results of the EFSOM-GB technique. The original input MRI image is taken from the Database. Then the enhanced frost filtering-based image denoising is performed and obtains a quality enhanced image. Table 1 describes the results of peak signal to noise ratio with different sizes of MRI images.

For each size of the input MRI image, the various peak signals to noise ratio results are obtained for each method. The different sizes of input MRI image are taken as input to estimate the mean square error and peak signal to noise. The obtained outcomes confirm the improvement of EFSOM-GB when compared to other existing works. This is proved through the statistical estimation. Let us consider the $12.5KB$ size of the MRI image.

Table 1.Peak signal to noise ratio

Size of MRI image	Peak signal to noise ratio (dB)				
	EFSOM-GB **(proposed)**	PCA-NGIST with RELM	SR-FCM-CNN	DWA-DNN	CNN
12.5KB	54.15	49.04	50.06	48.13	47.3
14.7KB	51.22	47.30	48.13	46.54	45.85
11.9KB	56.08	51.22	52.56	50.06	49.04
13.0KB	58.58	52.56	54.15	51.22	50.06
29.3KB	52.56	47.30	49.04	46.54	45.85
13.4KB	54.15	49.04	50.06	48.13	47.3
14.5KB	56.08	51.22	52.56	50.06	49.04
30.5KB	46.54	43.02	44.04	42.55	42.11
41.8KB	49.04	45.85	47.30	44.6	44.04
40.5KB	50.06	45.85	48.13	45.2	44.6

The Enhanced Frost Filter removes noisy artifacts in MRI image. Then the denoised image size is $12KB$. Based on the original and denoised image size, the obtained mean squarer error is 0.25. With the obtained error value, the peak signal to noise ratio of EFSOM-GB is $54.15\ dB$. Similarly, the mean squarer error of PCA-NGIST with RELM [8], SR-FCM-CNN [17] DWA-DNN [16], and Existing CNN is 0.81,0.64,1 and 1.21 peak signal to noise ratio is$49.04\ dB$, $50.06\ dB$$48.13\ dB$, and $47.3\ dB$ respectively. Likewise, ten various results are obtained for each method. The average peak signal to noise ratio of the EFSOM-GB technique is enhanced the by 10% as compared to PCA-NGIST with RELM [8], 6% as compared to SR-FCM-CNN [17], 12% as compared to DWA-DNN [16], and 14% as compared to Existing CNN.

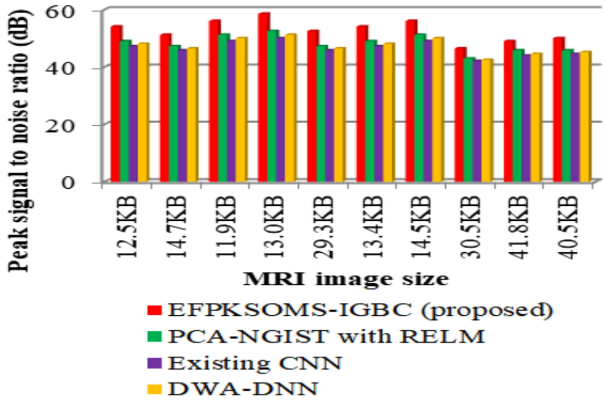

Fig 5 Comparative analysis of peak signal to noise ratio

Tumor detection accuracy is defined as the tumor is correctly identified from the given input MRI images. The accuracy computation is mathematically expressed as given below,

(18) $AC_{td} = \left(\frac{I_{cd}}{I_n}\right) * 100$

From (18), AC_{td}designates the tumor detection accuracy, I_{cd} indicates a number of images are correctly classified as tumor or normal,$I_n$indicates total number of tumor images. AC_{td} is measured in percentage (%).

Table 2 Tumor detection accuracy

Number of images	**Tumor detection accuracy (%)**				
	EFSOM-GB **(proposed)**	PCA-NGIST with RELM	SR-FCM-CNN	DWA-DNN	CNN
15	87	75	78	72	70
30	90	77	80	76	74
45	93	81	83	79	77
60	93	84	86	83	79
75	92	82	84	85	83
90	91	79	81	84	82
105	90	76	80	83	80
120	91	78	82	85	83
135	92	79	78	83	81
150	95	82	83	86	84

Table 2 reports the experimental results of tumor detection accuracy. The different accuracy results are obtained for each run based on the different number of input counts. Among four classification methods, the EFSOM-GB outperforms well interms of achieving the higher accuracy. This is implied from the sample calculation for '15' MRI images. With '15' MRI images, '13' MRI images were successfully classified as a tumor or normal and the accuracy is 87% using EFSOM-GB technique, '11', '12', '11', and '10' images were successfully classified and their classification accuracy is75%, 78%,72%, and 70%using PCA-NGIST with RELM [8], SR-FCM-CNN [17], DWA-DNN [16], and Existing CNN respectively. Similarly, the various accuracy results are obtained for each classification method. The average comparison results prove that the tumor detection accuracy is enhanced using EFSOM-GB technique by 8%, 5%, 12%, and16%as compared to PCA-NGIST with RELM [8] SR-FCM-CNN [17], DWA-DNN [16], and Existing CNN

The tumor detection accuracy is obtained based on the number of images. The Fig. 7 portrays the accuracy of

EFSOM-GB is higher than the other four existing methods. The significant reason for that improvement is achieved by the application of an intensified gradient boost classification technique. The boosting technique uses the set of a quadratic classifier to classify the given input images based on the likelihood ratio. The classified results combined into make a strong one to obtain the accurate disease classification. Depends on classification outcomes, the tumor disease are detected resulting it increases the accuracy.

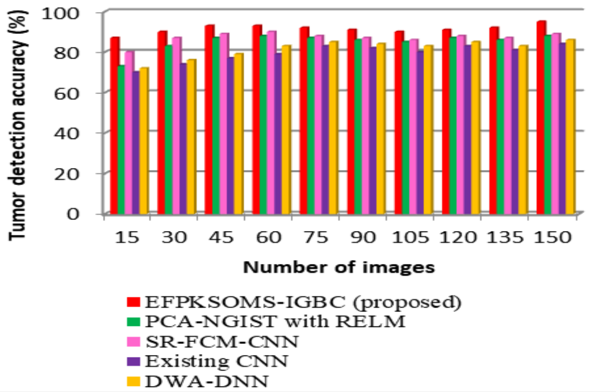

Fig 7 Comparative analysis of tumor detection accuracy

This helps for the EFSOM-GB technique to increases the ratio of a number of MRI images correctly classified and to provide better result when compared to other existing works.

Error rate during the classification is measured as the ratios of the MRI images are incorrectly detected as a tumor or normal to total number of images. Error rate is measured using the following expression,

(19) $$R_{er} = \left(\frac{I_{md}}{I_n}\right) * 100$$

Where R_{er} denotes an error rate, I_{md} indicates a number of images incorrectly or mistakenly identified. Therefore, theerror rate is measured in percentage (%).

Table 3 describes the performance results of the error rate using four methods EFSOM-GB technique, PCA-NGIST with RELM [8], SR-FCM-CNN [17], DWA-DNN [16], and Existing CNN. The above-reported results demonstrate that the error rate during the image classification is reduced than the other two existing methods. Let us consider the '15' images, 2 images are incorrectly classified and the error rate of the EFSOM-GB technique is 13%.By applying the PCA-NGIST with RELM [8], SR-FCM-CNN[17], DWA-DNN [16], and Existing CNN, 10, 7, 4, and 5 images are incorrectly classified and their error rates are 27%,20%, 20%, and 20%.

Table 3 Error rate

Number of images	**Error rate (%)**				
	EFSOM-GB **(proposed)**	PCA-NGIST with RELM	SR-FCM-CNN	DWA-DNN	CNN
15	13	25	22	28	30
30	10	23	20	24	26
45	7	19	17	21	23
60	7	16	14	17	21
75	8	18	16	15	17
90	9	21	19	16	18
105	10	24	20	17	20
120	9	22	18	15	17
135	8	21	22	17	19
150	5	18	17	14	16

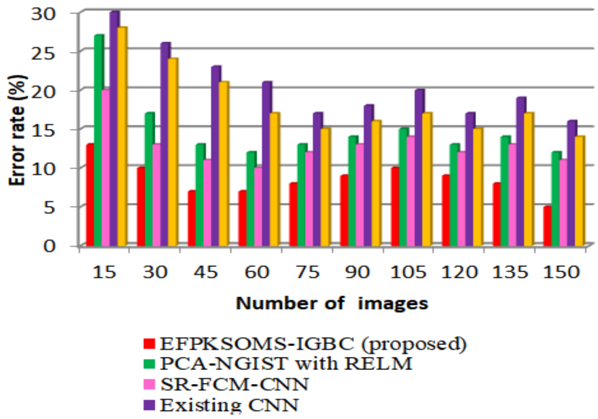

Fig 8 Comparative analysis of error rate

The statistical result proves that the error rate of the EFSOM-GB technique is considerably reduced. The average error rate of ten values confirms that the EFSOM-GB technique minimizes the error rate by 42% when compared to PCA-NGIST with RELM [8], 36% when compared to SR-FCM-CNN [17],53% when compared DWA-DNN [16], and 58% when compared to Existing CNN. Fig 8 portrays the comparative analysis of error rate using four methods along with different MRI images. The graphical plot indicates that the error rate of three methods EFSOM-GB technique, PCA-NGIST with RELM [8], SR-FCM-CNN [17], DWA-DNN [16], and Existing CNN are represented by three different colors namely red, green, pink, violet, and yellow. The ensemble technique combines the weak classifier results. For each weak classifier, training loss is measured to find accurate results. The ensemble technique discovers weak learner with lesser training loss. This process of EFSOM-GB technique reduces the error rate in tumor detection.

Table 4 and Fig 9 designate comparative analysis of tumor detection time along with various input MRI images. While increasing the number of images, tumor detection time also increased. When considering 15 images, the EFSOM-GB technique consumes $16ms$ of time for detecting tumors or normal.

By applying a similar count of 15 images, the tumor detection time of PCA-NGIST with RELM [8], SR-FCM-CNN [17], DWA-DNN [16], and Existing CNN, is obtained by $20ms$, $18ms$, $23ms$ and $25ms$respectively. With these results, it is inferred that the tumor detection time to be reduced using the EFSOM-GB technique when compared to PCA-NGIST with RELM [8], SR-FCM-CNN [17], DWA-DNN [16], Existing CNN. The reason is for lower detection time to apply the Kohonen self-organizing map segmentation and feature extraction. Segmentation is carried out to separate the input MRI image into different parts based on the pixel intensity. Based on the segmented result, the lesion area in the input images is segmented. From the identified region, the texture, shape, gray level intensity, and color features are extracted to perform feature extraction from the input segmented image. Based on extracted features, the tumor detection is accurately performed with the minimum amount of time. This helps for the EFSOM-GB technique to offer good outcome as compared to other existing works with minimum time. This process of EFSOM-GB technique decreases the amount of time taken by the algorithm. The average tumor detection time of the EFSOM-GB technique is reduced by 15%, 8%, 20%, 24% when compared to PCA-NGIST with RELM [8], SR-FCM-CNN [17], DWA-DNN [16], Existing CNN.

Table 4 tumor detection time

Number of images	Tumor detection time (ms)				
	EFSOM-GB (proposed)	PCA-NGIST with RELM	SR-FCM-CNN	DWA-DNN	CNN
15	16	20	18	23	25
30	19	24	21	26	27
45	21	25	23	28	30
60	23	29	26	31	33
75	28	32	30	34	36
90	30	34	32	36	37
105	31	37	34	38	40
120	35	40	37	41	43
135	36	41	39	43	44
150	39	43	41	44	45

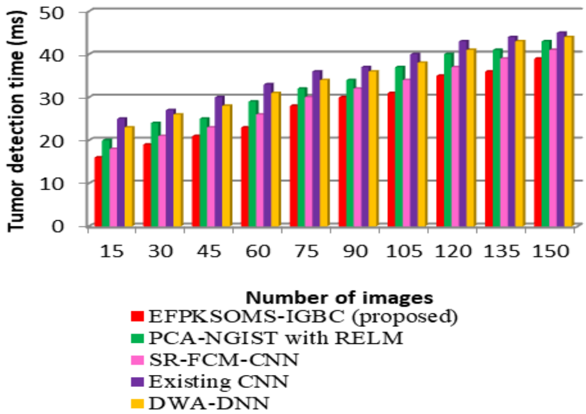

Fig 9 Comparative analysis of tumor detection time

.

Conclusion

In this paper, EFSOM-GB technique is introduced to detect the brain tumor with different such as image denoising, segmentation, feature extraction, and classification. The EFSOM-GB technique initiates the noise removal process to obtain a quality enhanced image for accurate segmentation and classification. Then the Kohonen self-organizing map technique is applied to perform pixel-based segmentation and significant features are extracted from the segmented region for minimizing the time consumption of tumor detection. Finally, the ensemble technique detects the tumor with higher accuracy and a lesser error rate. The comprehensive experimental evaluation is conducted with an MRI brain image database. The qualitative and quantitative analysis is accomplished and the results verified the advantages of our quantitative and are better in terms of higher tumor detection accuracy and lesser time and error rate when compared to other related works. One of the notable strengths of our proposed method is its significantly improved accuracy in identifying tumor regions from MRI images. This is due to the enhanced frost filtering with window filtering technique, which effectively minimizes classification errors .We observed a reduction in processing time, a critical aspect in medical image analysis. The implementation of Kohonen Self Organizing Map for extracting features such as texture, color, shape, and intensity , reduced the tumor detection time. The gradient descent step-size determines best classifier outcomes with minimum training loss. The proposed method's ability to mitigate noise in feature extraction played a pivotal role in bolstering its performance. One of the limitations of the proposed study is the reliance on a specific dataset. Although we obtained promising results, it is essential to acknowledge the potential bias or overfitting associated with a single dataset. Future research could benefit from testing the method on diverse datasets to assess its generalizability. Like many machine learning techniques, our method is sensitive to parameter settings. While we optimized these parameters for the current dataset, further research may explore automated parameter tuning methods to enhance robustness.

Our study relied on a specific dataset, which may not fully capture the diversity of clinical scenarios and patient populations. Future research should aim to incorporate larger and more diverse datasets from various healthcare institutions to enhance the method's generalizability. Since our method is sensitive to parameter settings, suboptimal parameter choices could affect performance. Automated parameter tuning algorithms or robust parameter optimization strategies should be explored to reduce sensitivity and improve the method's robustness.

Authors:
1. Simy Mary Kurian, Amal Jyothi College of Engineering, Kerala, India, simymarykurian@amaljyothi.ac.in
2. Sujitha Juliet, Karunya Institute of Technology and Sciences, Tamilnadu, India, sujitha@karunya.edu

REFERENCES

[1] Abdulraqeb AR, Al-Haidri1 WB, Sushkova LT, Abounassif MM, Parameaswari PJ, Muteb MA An Automated Method for Segmenting Brain Tumors on MRI Images. Biomedical Engineering, Springer 51 (2017), 97–101.DOI 10.1007/s10527-017-9692-9
[2] Anaraki AK, Ayati M, Kazemi F,Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms.Biocybernetics and Biomedical Engineering. Elsevier 39 (2018),63-74.https :// doi .org /10.1016/j.bbe.2018.10.004
[3] Badža MM, Barjaktarovic MC Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network.AppliedScience.10(2020), 1-13. https://**doi**.org/ 10.3390/app10061999.
[4] C. Jonitta Meryl, K. Dharshini, D. Sujitha Juliet, J. Akila Rosy and S. S. Jacob, "Deep Learning based Facial Expression Recognition for Psychological Health Analysis," ,IEEE xplore 2020,pp. 1155-1158, doi: 10.1109/ICCSP48568.2020.9182094.
[5] Bahadure NB, Ray AK, Thethi HP ,Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM. International Journal of Biomedical Imaging, Hindawi 2017:1-12.
https://**doi**.org/ 10.1155/2017/9749108
[6] Bai X, Zhang Y, Liu H, Ch Z,Similarity Measure-Based Possibilistic FCM With Label Information for Brain MRI Segmentation. IEEE Transactions on Cybernetics 49 (2019) 2618–2630.https://**doi**.org/.10.1109/TCYB.2018.2830977
[7] Çinar A, Yildirim M ,Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture. Medical Hypotheses, Elsevier, (2020) 139: 1-8.
https://doi.org/ 10.1016/j.mehy.2020.109684.
[8] Ge T, Mu N, Zhan T, Chen Z, Gao W, Mu SC,Brain Lesion Segmentation Based on Joint Constraints of Low-Rank Representation and Sparse Representation. Computational Intelligence and Neuroscience, Hindawi 2019:1-11.https://doi.org/10.1155/2019/9378014
[9] Gumaei A, Hassan MH, Hassan Md. R, Alelaiwi A, Giancarlo F) A Hybrid Feature Extraction Method with Regularized Extreme Learning Machine for Brain Tumor Classification(2019). IEEE Access7:36266 -6273.
https://doi.org/10.1109/ACCESS.2019.2904145.
[10] Hu K, Gan Q,Zhang Y,Deng S,Xiao F,Huang W,Cao C Gao X ,BrainTumor Segmentation Using Multi-Cascaded Convolutional Neural Networks and Conditional Random Field. IEEE Access 7 (2019):2615–92629.http://doi.ordg/10.1109/ACCESS.2019.2927433
[11]Johnpeter JH, Thirumurugan, Ponnuchamy , Computer aided automated detection and classification of brain tumors using

CANFIS classification method. International Journal of Imaging Systems and Technology 29(2019)):431-438. https://doi.org/10.1002/ima.22318.
[12] Khan MA, Lali IU, Rehman A, IshaqM, Sharif M, Saba T, Zahoor S, Akram T ,Brain tumor detection and classification: A framework of marker-based watershed algorithm and multilevel priority features selection. Microsopic research and technique, Wiley, 82(2019) 6):1–14.DOI: 10.1002/jemt.23238
[13] Kharrat A, Neji M Feature selection based on hybrid optimization for magnetic resonance imaging brain tumor classification and segmentation. Applied Medical Informatics 41(2019) 9-23.
[14]Kumar S, Mankamem DP Optimization driven Deep Convolution Neural Network for brain tumor classification. Biocybernetics and Biomedical Engineering, Elsevier 40 (2020):11901204.https://doi.org/10.1016/j.bbe.2020.05.009
[15]Simy M K ,SujithaJ,Vinodh P V).Brain Tumour Detection by Gamma DeNoised Wavelet Segmented Entropy Classifier.Computers, Materials &Continua.Tec Science Press 69(20212093-2109.10.32604/cmc.2021.018090
[16] Lorenzo PR, Nalepa J, Bobek-Billewicz B, Wawrzyniak P, Mrukwa G, Kawulok M, Ulrych P, Hayball, M.P,Segmenting brain tumors from FLAIR MRI using fully convolutional neural networks. Computer Methods and Programs in Biomedicine 176(2019), 135-148.https://doi.org/10.1016/j.cmpb.2019.05.006
[17] Mallick PK, Ryu SH, Satapathy SK, Mishra S, Nguyen NG, Tiwari P Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep NeuralNetwork. IEEEAccess 7(2019): 46278– 46287 https://doi.org/ 10.1109/ACCESS.2019.2902252
[18] Özyurt F, Sert E, Avc D ,An expert system for brain tumor detection: Fuzzy C-means with superresolution and convolutional neural network with extreme learning machine. Medical Hypotheses, Elsevier 134(2020), 1-8.https://doi.org/10.1016/j.mehy.2019.109433.
[19] Simy M K ,Sujitha J,An automatic and intelligent brain tumor detection using Lee sigma filtered histogram segmentation model.SoftComputing, (2022) ,Springer.https://doi.org/ 10.1007/s00500-022-07457-2
[20] Shree NV, Kumar TNR ,Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network. BrainInformatics, Springer 5(2018), 23-30. https://doi.org/10.1007/s40708-017-0075-5.
[21] Rajan PG, Sundar C ,Brain Tumor Detection and Segmentation by Intensity Adjustment, Journal of Medical Systems, Springer 43(2019), 1-13.
[22] Z hao J, Li D, Kassam Z, Howey J, Chong J, Chen B, Li S Tripartite-GAN:Synthesizing liver contrast-enhanced MRI to improve tumor detection. Medical Image Analysis 63(2020),:1-16. https://doi.org/10.1016/j.media.2020.101667
[23] Sujitha Juliet Devaraj, Emerging paradigms in transform-based medical image compression for telemedicine environment,telemedicine technologies(2019),15-29 https://doi.org/10.1007/s10916-019-1368-4
[24] Ragupathy B, Karunakaran M A fuzzy logic-based meningioma tumor detection in magnetic resonance brain images using CANFIS and U-Net CNN classification, International Journal of Imaging SystemsandTechnology, (2020),1-20.https:// doi.org/ 10.1002/ima.22464
[25] Iwin T J, Sasikala J. D S Juliet, Optimized vessel detection in marine environment using hybrid adaptive cuckoo search algorithm,computers and electrical engineering (2019),482-492.
[26] Simy M K , Sujitha J, An improved deep neural learning classifier for brain tumor detection.IEEE xplore, (2022) , 1085-1091.