Ann. For. Res. 65(1): 9722-9741, 2022
ISSN: 18448135, 20652445

ANNALS OF FOREST RESEARCH
https://www.e-afr.org/

A RAPID COSINE SWARM OPTIMIZATION (RSCSO) – EXTREME LEARNING MACHINE (ELM) FOR AN AUTOMATED BRAIN TUMOR DIAGNOSIS SYSTEM

Sayeedakhanum Pathan[1], Dr.Savadam Balaji[2]
[1,2]Department of Computer Science Engineering, Koneru Lakshmaiah Education Foundation Hyderabad, Telanganasss, 500075, India
[1]Department of Computer Science Engineering, Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering &Technology Hyderabad, Telanganasss, 500090, India
Email: pathan.sayeeda@klh.edu.in[1],balajis@klh.edu.in[2]

Abstract— For detecting tumor and non-tumor cells in the brain and evaluating cell levels, an efficient classification and segmentation of brain tumors is the intriguing aspect of the categories. Based on their experiences, the classification and segmentation of brain tumors were developed by many researchers in the medical field. Yet, traditional works have the critical problems of over-segmentation, overfitting, high time consumption, and error rate. Therefore, the proposed work motivates to development of an automated and highly efficient diagnosis framework for brain tumor detection and segmentation. Here, an iterative preprocessing algorithm is used first to improve the contrast and quality and reduce the noise of input brain MRI. Next, the statistical and texture features are retrieved from the preprocessed image to streamline the classification process. Consequently, the Rapid Sine Cosine Swarm Optimization (RSCSO) mechanism is used to decrease the dimensionality of features to speed up training and improve classification accuracy. Then, an Extreme Learning Machine (ELM) algorithm is employed to precisely forecast the photos of the healthy and tumor-affected tissues. Finally, an Auto Encoder-based segmentation process is used to accurately locate and crop the tumor-affected region from the aberrant images. During performance analysis, the proposed RSCSO-ELM mechanism's results are validated and compared using different measures and datasets.

Index Terms— Brain Tumor, Computed Aided Diagnosis (CAD), Magnetic Resonance Imaging (MRI), Iterative Preprocessing, Statistical & Texture Features, Rapid Sine Cosine Swarm Optimization (RSCSO), Extreme Learning Machine (ELM), and Auto-Encoder.

INTRODUCTION

By the recent statistical report of the World Health Organization (WHO), brain tumors [1, 2] are among the most common causes of cancer-related fatalities worldwide. Although it's not always possible, early detection of a brain tumor can prevent death and help with timely treatment. Gliomas are the primary brain tumors [3] in the central nervous system that are most threatening. The radiologist uses many different medical imaging procedures to locate the tumor. The Magnetic Resonance Imaging (MRI) [4, 5] is preferred for brain tumors because of its safety among the different methods available. The radiologist manually recognizes brain tumors as part of daily practice. The tumor categorization process is labor-intensive and dependent on the radiologist's knowledge and experience. As the number of patients grows, a greater volume of data must be routinely processed, increasing the cost and unreliability of readings based solely on visual

interpretation. Moreover, compared to binary classification, the pathological categorization of brain tumors presents more difficulties. The considerable diversity in shape, size, and intensity for the same tumor type [6] and the similar appearances for different disease types are some of the variables that contribute to the related issues. An incorrect brain tumor diagnosis [7] can have catastrophic consequences and reduce the patient's probability of survival. Designing an automated image processing systems is becoming increasingly popular as a way to overcome the limitations of manual diagnosis. Traditional approaches cannot effectively manage the substantial growth in data volume in the medical sector. The storage and interpretation of big medical data constitute ongoing difficulties in medical image analysis.

Many academics have suggested a variety of ways to enhance the CAD system that can categorize some tumors in brain MRI images. Typical processes in traditional machine learning techniques used in classification include preprocessing, feature extraction, segmentation, feature selection and classification. For a CAD system [8-10] to function well, feature extraction is essential. It is a difficult task that necessitates prior expertise in the problem domain because the classification accuracy depends on the successfully obtained valuable features. The different types of feature extraction models used to categorize the class of tumor are spatial domain features, wavelet and frequency features, and contextual and hybrid features. Developing a workable diagnostics tool [11] for tumor classification and segmentation from MRI images is essential to acquire an accurate diagnosis and avoid medical procedure and subjectivity. The emergence of new technologies, particularly machine learning and artificial intelligence [12], has significantly impacted the medical sector since it has given medical departments - including medical imaging - an essential support tool. Various machine learning algorithms [13] are used for segmentation and classification, which interprets the MRI images and support the radiologist's choice. Despite having a lot of potential, the supervised approach to classifying a brain tumor requires special training to extract the best characteristics and feature selection algorithms. Unsupervised techniques have drawn attention from researchers recently, not just for their excellent results but also because of the automatically created features that lower the error rate. Recent advancements have made Deep Learning (DL)-based models [14] one of the essential techniques for medical image analysis, including reconstruction, segmentation, and classification. However, the traditional works limit with the following problems [15-18]: over segmentation, over fitting, high classification error and high time consumption. Therefore, this research work aims to introduce a computationally efficient and competent detection framework for brain tumor diagnosis. The major objectives of this work are listed below:

To increase the quality and contrast of the input brain MRI, an iterative thresholding based preprocessing methodology is implemented, which eliminates the noisy pixels for improving the segmentation accuracy.

To simplify the process of classification, the statistical and texture features are extracted from the preprocessed image.

To reduce the dimensionality of features for increasing the training speed and accuracy of classification, a Rapid Sine Cosine Swarm Optimization (RSCSO) mechanism is deployed.

To accurately predict the healthy and tumor affected images, an Extreme Learning Machine (ELM) algorithm is used.

To exactly crop the tumor affected region from the abnormal images, an Auto Encoder based segmentation mechanism is used.

The remaining parts of this paper are categorized into the followings: Section 2 discusses the conventional medical image techniques for feature extraction, segmentation, optimization, and classification to identify and classify MRI brain tumors. Additionally, based on their detection procedure, it looks into the issues and difficulties the existing works have to deal with. With its overall approach and concise illustrations, Section 3 provides a detailed discussion of the suggested framework for tumor detection. Utilizing several MRI datasets and performance measures, Section 4 compares and evaluates the findings of the proposed technique. Section 5 summarizes the entire work with findings, implications, and future scope.

Related Works

This section presents the literature review of the traditional medical image processing mechanisms used for developing an automated brain tumor detection framework. Also, it scrutinizes the benefits and problems of the works according to their detection efficiency and classification performance.

Ayadi, et al [19] utilized a deep convolutional Neural Network (CNN) mechanism for the detection and class categorization of MRI brain tumor. Typically, an automated CAD model is more essential for developing an efficient medical image disease diagnosis framework. The CNN is one of the most popular deep learning mechanism widely used for brain tumor diagnosis. The suggested CNN architecture includes the operating layers of convolutional layer, non-linearity, batch normalization, pooling, and fully connected. Moreover, this paper uses the Figshare dataset for system implementation and testing. However, the suggested classifier requires high time for training and testing, which increases the complexity of the detection system. Veeramuthu, et al [20] deployed a deep learning based NN classification model for an automated brain tumor detection. Here, the feature based classification, image based classification, and hybridization of both have been used. Kang, et al [21] developed a hybridized deep features based machine learning classification algorithm for brain tumor detection and categorization. Here, the image cropping and resizing operations are performed before feature extraction and classification. Then, the CNN model is used to extract the set of deep features with the use of dense net, inception, and res net layers. After that, an ensemble of 9 different machine learning algorithms are utilized to predict the output result. In addition, thresholding, outer contour extraction, edge point identification, and image cropping were also performed to improve the quality of raw MRI brain image. Due to the inclusion of many techniques, the complexity of detection is highly increased, which could be the major drawback of this model. Raza, et al [22] used a hybrid deep learning mechanism for MRI brain tumor identification and classification. In this system, the CE-MRI dataset is used for implementation and testing. Based on this study, it is analyzed that the CNN is highly suitable for

the brain tumor detection system. However, it has an increased time and computational complexities, which affects the competency of the suggested model.

Diaz-Pernas et al [23] employed a multi-scale CNN mechanism for developing a fully automatic diagnosis system for brain tumor identification and segmentation. Here, the T1-CE MRI image dataset has been utilized to implement and test the suggested diagnosis framework. Moreover, this system includes the operations of scale feature extraction, concatenation, and classification. In addition, the 5-fold cross validation is performed in this study to test the detection efficacy and competence of the multi-scale CNN model. Specifically, it provides the benefits of easy to understand and reduced overfitting. Abd-EI Kader, et al [24] introduced a differential deep CNN technique for constructing an automated brain tumor detection system. Garg, et al [25] developed a hybrid ensemble learning classifier by incorporating the methods of Random Forest (RF), Decision Tree (DT), K-Nearest Neighbor (KNN) for an accurate brain tumor diagnosis. Here, the Otsu thresholding mechanism is applied to segment the foreground and background regions from the MRI input. After that, a combination of Grey Level Co-occurrence Matrix (GLCM), Principal Component Analysis (PCA), and Stationary Wavelet Transform (SWT) techniques are applied to extract the most suitable features for detecting brain tumor. Based on the majority voting scheme, the tumor is predicted as benign or malignant. However, it required to increase the level of accuracy, which is the major drawback of this work.

Khairandish, et al [26] utilized a hybrid CNN-SVM model incorporated with the thresholding segmentation methodology for brain tumor classification. Here, the feature extraction is performed with the help of CNN, and the decision making is carried out using SVM. In addition, the input image preprocessing is performed at the initial stage with the operations of image resizing, skull removal, and filtration. Then, the thresholding based segmentation algorithm is also used to segregate the input into multiple segments, which helps to obtain an increased accuracy. Still, it suffers with the problems of over segmentation, high feature dimensionality, and more time consumption. Bucklak, et al [27] conducted a systematic review to examine the different types of machine learning techniques used for the identification and grading of brain tumor. Also, it discusses about the different types of validation methods used for identifying the most suitable technique to detect the tumor. Sadad, et al [28] suggested an advanced deep learning mechanism for developing a multi-classification model to detect the brain tumor from MRIs. Here, the transfer learning is performed with the operations of freeze and fine tune, which helps to extract the sufficient number of features from the brain MRIs. During preprocessing, the contrast stretching algorithm is used to generate the high resolution images. Furthermore, the data augmentation mechanism also used to reduce the size of training data, hence the time required for training and testing operations are effectively minimized.

Tiwari, et al [29] used a CNN mechanism for developing a brain tumor diagnosis framework with reduced training loss and high accuracy. The authors intend to implement an automated method for designing a multiclass prediction framework to accurately detect the brain tumor. Maqsood, et al [30] employed a fuzzy logic integrated U-Net segmentation model for an accurate prediction and grading of brain tumor. Here, the Dual Tree Complex Wavelet Transform

(DTCWT) technique is applied to extract the sub-band image features for categorizing the tumor class as meningioma and non-meningioma. Moreover, this framework includes the operations of contrast enhancement, wavelet transformation, edge detection, classification, and segmentation. For increasing the contrast of input, the Non-parametric Modified Histogram Equalization (NPMHE) model is utilized that eliminates the spikes from the input MRI. However, the computational complexity of the suggested framework is very high, which affects the reliability and performance of this mechanism.

Table 1. Comparative analysis

Ref	Detection Methods	Benefits	Challenges
[31]	Ensemble classification model	Better prediction accuracy and low error rate.	Less interpretable, and highly expensive in terms of time and space.
[32]	SVM + Kalman filtering model	Works well in high dimensional space, and memory efficient.	Overlapping results, high training time, and not more suitable for huge datasets.
[33]	RF + GLCM	Reduced overfitting, and high robustness.	More computational power, high time consumption, and slow in speed.
[34]	DT + wavelet transformation	More capable to handle both continuous and categorical data. It does not require data scaling.	Poor prediction, and high overfitting.
[35]	Otsu segmentation + CNN	Accurate recognition rate, and weight sharing.	Uneven illumination, and high computational complexity.
[36]	Thresholding + CNN	High processing speed, simple to deploy, and easy to interpret.	Difficult to estimate the threshold value, more sensitive to noise

From this literature review, it is observed that developing a computationally efficient and simple medical image diagnosis framework is highly essential for brain tumor prediction and classification. Therefore, the proposed work motivates to develop a new and proficient imaging techniques for constructing a brain tumor diagnosis framework.

Research Methodology

This section provides the complete explanation for the proposed brain tumor diagnosis system with its appropriate work flow and illustrations. The original contribution of this paper is to develop an automated and computationally effective detection framework for the identification of brain tumor from MRIs. For this purpose, an effective image processing methodologies are developed in this paper. Here, various MRI brain image datasets have been used for system

implementation and testing. Initially, the raw input MRI is preprocessed by using an iterative thresholding technique, which increases the quality and contrast of the image before classification. Then, the statistical and texture features are extracted from the preprocessed image for accurately detecting the tumor affected region. As a result, the Rapid Sine Cosine Swarm Optimization (RSCSO) technique is used to select the best features for lowering the dimensionality of the feature set and also contributes to minimizing the classifier's training time. An Extreme Learning Machine (ELM) algorithm classifies tumor-free photos and those afflicted by tumors using the optimal characteristics. The tumor section is precisely cropped using an auto-encoder-based segmentation algorithm if the identified MRIs are tumor-affected. Reduced overfitting, low processing time, good accuracy, and prevented over-segmentation are the main advantages of the proposed RSCSO-ELM system. Fig. 1 depicts the workflow of the suggested brain tumor detection system, which entails the following actions:

- Iterative thresholding based image preprocessing
- RSCSO based feature selection
- ELM classification
- Auto-Encoder segmentation

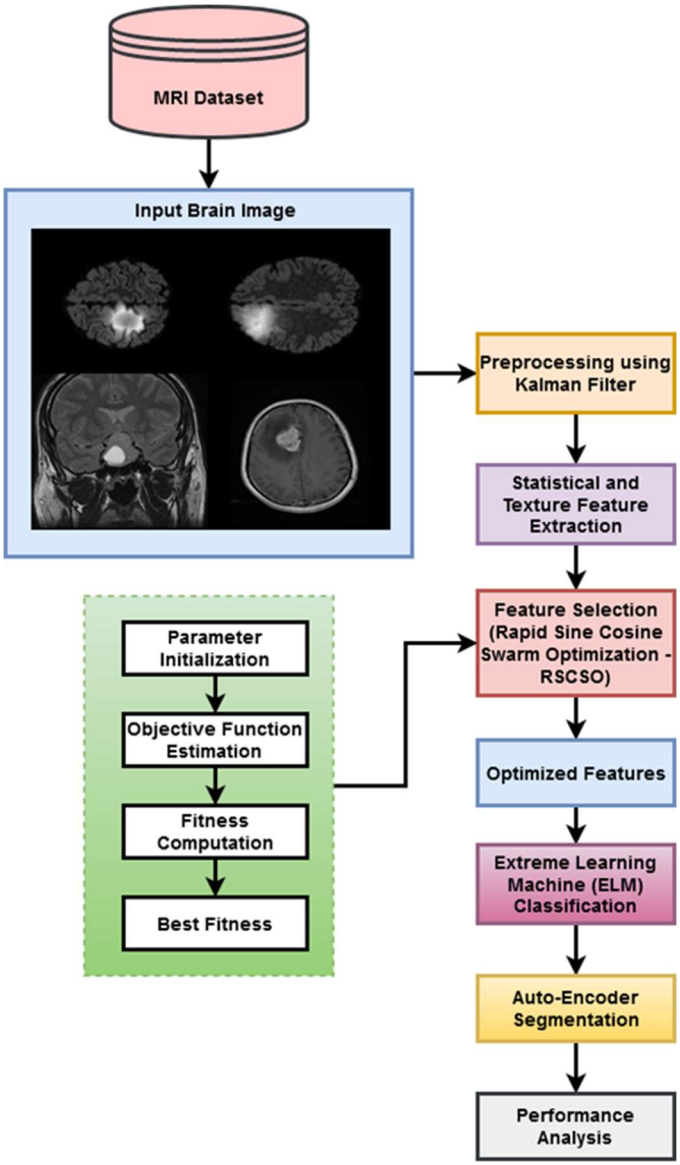

Fig 1. Workflow of RSCSO-ELM brain tumor detection system

Iterative Thresholding based Preprocessing

When compared to CT, MRI is a valuable imaging technique for finding brain tumors because it provides clear, high-contrast images while being entirely safe. T1- and T2-weighted sequences are typical in brain MRI, and it is possible to diagnose brain cancers with T2-weighted brain MRI because abnormal lesions appear brighter than the normal tissues around them[44]. Therefore, T2-weighted brain sequences are typically used as a data set to diagnose brain tumors. The adaptive threshold method is used in this system for background removal. The iterative process used to determine the threshold's primary execution steps is as follows:

1. The initial threshold is determined at first with the minimum BI_{mn} and maximum BI_{mx} values of the image as shown in below:

$$Th_s = \frac{BI_{mx}+BI_{mn}}{2} \quad (1)$$

2. Based on the estimated threshold, the image is split into two parts as represented in below:

$$P1 = \{BI\ (i,j) | BI(i,j) > Th_s\}$$
$$P2 = \{BI(x,y) | BI(x,y) \leq Th_s\} \quad (2)$$

3. Then, gray averages such as $P1_m$ and $P2_m$ in each sub portion is estimated for determining the changes in thresholds as illustrated in below:

$$Th_s = \frac{P1_m + P2_m}{2} \quad (3)$$

Where, $P1_m$ and $P2_m$ are the mean values of two sub portions.

After background removal, the non-local mean filtering technique is used to enhance the contrast and remove the noise. In this model, the Gaussian weighted average value is computed to get the output value by using the following equation:

$$O(i,j) = \sum_{j \in BI} \omega(i,j) \times BI(i) \quad (4)$$

$$\delta(i,j) = \frac{e^{-\frac{||\omega(y_i) - \omega(y_j)||_2^2}{a^2}}}{Nomalized\ factor} \quad (5)$$

$$Nomalized\ factor = \sum_j F_j \quad (6)$$

$$F_j = e^{-\frac{||\omega(y_i) - \omega(y_j)||_2^2}{a^2}} \quad (7)$$

In addition, the histogram equalization is also applied to highly improve the contrast of the brain image. During this process, the mean and standard deviation of the sub images are estimated. The brightness and MRI features of a tumor and a skull have some similarities; hence, the skull may impact image classification to some extent. The skull can be removed by the location information to lessen the impact on tumor classification because it only exists on the outside border of the brain. Hence, the skull removal is performed to increase the efficiency and accuracy of segmentation. Moreover, this preprocessing helps to avoid image over segmentation and misclassification rate.

Rapid Sine Cosine Swarm Optimization (RSCSO) for Feature Selection

After preprocessing, the statistical and texture features are extracted from the preprocessed brain image. The purpose of feature extraction to exactly locate the tumor region from the given MRI image. Generally, the sine cosine optimization is a kind of population based algorithm, which is widely used for solving complex problems. Similar to the other stochastic algorithms, it also has the major operations of exploration and exploitation. By using the sine-cosine functions, various regions of the searching space are explored in this model. Then, the RSCSO algorithm is applied to reduce the dimensionality of features by selecting the most relevant and optimal features. Due to the increased convergence rate and reduced computational complexity, the RSCSO algorithm is deployed in this detection framework. Here, the learning parameter is updated with the new velocity and position models as represented in below:

$$\alpha_i(k+1) = \delta \times \alpha_i(k) + L_P t_1 \left(G_i^{best} - c_i(k)\right) + G_P t_2 \left(G_i^{best} - c_i(k)\right)$$
(8)

$$c_i(k+1) = c_i(k) + \alpha_i(k+1) \quad (9)$$

Where, α_i indicates the position, k number of particles, δ is the inertia coefficient, L_P denotes the weight coefficient of local position, G_P is the weight coefficient of global position, t_1, t_2 are the random numbers, c_i is the position, and G_i^best represents the current best solution. Consequently, the position equation is updated by using the following model:

$$C_i^{k+1} = \begin{cases} C_i^k + r_1 \times \sin(r_2) \times \left|r_3 G^{best} - C_i^k\right|, & r_4 < 0.5 \\ C_i^k + r_1 \times \cos(r_2) \times \left|r_3 G^{best} - C_i^k\right|, & r_4 \geq 0.5 \end{cases} \quad (10)$$

Where, C_i^(k+1) is the updated position, r_1, r_2, r_3, and r_4 are the random numbers. Based on this process, the best optimal solution is identified and returned as the output of this algorithm. Then, the obtained solution can be used to choose the relevant features for classifier training and testing processes.

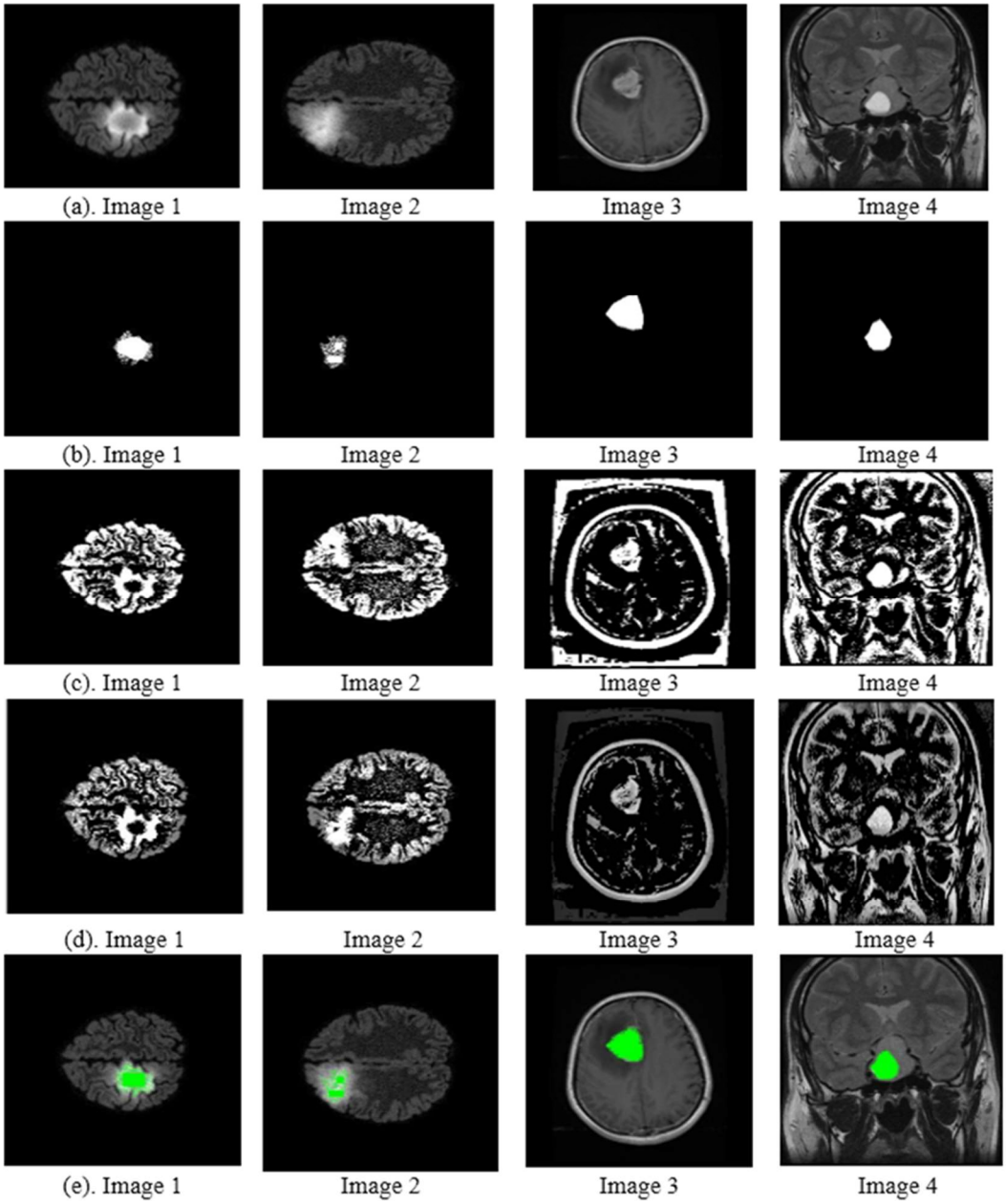

Fig 2 (a). Input brain MRIs, (b). Ground truth, (c). Binary region
(d). Clustered region, and (e). Segmented portions

Extreme Learning Machine (ELM) Classification

After feature selection, an ELM classification methodology is used to predict the given MRI brain image as whether healthy or tumor-affected. The ELM is a single hidden layered feed forward neural network, where the output weights are derived analytically and the input weights are determined arbitrarily. The training process is quick thanks to the model that is learned through output hidden weights. In this model, the training samples { 〖(H_i, 〖tar〗 _j)}j〗 _(j=1)^N is

considered with x classes, N number of samples, hidden nodes g, and activation function ρ(h). It is mathematically represented by using the following equation:

$$\sum_{i=1}^{g} \omega_i \rho_i(h_j) = \sum_{i=1}^{g} \omega_i \rho(\tau_i \times h_j + \beta_i) = OP_j \qquad (11)$$

Where, j = 1, 2, … N, $h_j = [h_{j1}, h_{j2}, h_{j3} \dots h_{jn}]^S$, $tar_j = [tar_{j1}, tar_{j2} \dots tar_{jn}]^S$, weight value $\tau_i = [\tau_{i1}, \tau_{i2} \dots \tau_{in}]^S$, β_i indicates the bias value, and OP_j denotes the output value. Moreover, One against all coding is used with ELM to transmit numerous discriminations to various output functions of regression. Prior to assigning anticipated labels using the actual output index, the actual sample of each output is calculated. When the pseudo-inverse is statistically unstable, the regularized least-squares method is employed to find the best solution. Then, the identity matrix is computed based on the regularization parameter, which is used to predict the classified label. The key benefits of using this mechanism are increased training speed, minimal time consumption, high classification accuracy, and simple to implement.

Auto Encoder Segmentation

If the predicted image is abnormal or tumor-affected, the auto-encoder segmentation mechanism is applied to exactly crop the tumor-affected portion. Accurate tumor segmentation is one of the most crucial stages in computer-assisted brain tumor detection and surgical planning. Due to the varying professional backgrounds of the doctors, it is not only time-consuming but also yields varied segmentation results. Aside from that, segmenting a brain tumor is still a difficult task because of the tumor's various forms and its nearby organs' grey-level similarity. Despite being frequently used in clinical diagnosis and treatment, subjective segmentations must be more accurate and dependable. It is highly anticipated that a brain tumor segmentation system will be automatic and objective. Hence, this work uses a highly efficient auto-encoder mechanism for an accurate brain tumor segmentation with reduced time consumption. One sort of artificial neural network called an auto-encoder has three layers: the input layer, the output layer, and the hidden layer. Each layer is trained to reduce the cross-entropy of a reconstruction. The main benefit of using this segmentation technique is to reduce the average reconstruction error by training the initial layer. Fig 2 represents the input, ground truth, binary region, clustered region, and segmented portions of brain MRI image.

Results and Discussion

This section validates and tests the results of proposed tumor detection mechanism by using various datasets and evaluation measures. Table 2 presents the clear description for the datasets used in this study.

Table 2. Dataset details

Reference	Dataset
[37]	BRATS 2012 to 2018
[38]	TCIA – MRI/CT scan reports
[39]	OASIS – Structural MRIs

[40]	IBSR – Raw MRIs with GM, WM, and CSF
[41]	Kaggle repository

Moreover, the different types of parameters are used to validate and compare the results of RSCSO-ELM mechanism, which includes the followings:
Accuracy: According to image classification, the accuracy is a percentage that represents the number of pixels that have been correctly classified in proportion to the number of image pixels. It assesses every single properly placed pixel in an image, and is estimated by using the following equation:

$$Accuracy = \frac{Tr_{Pos}+Tr_{Neg}}{Tr_{Pos}+Tr_{Neg}+Fa_{Pos}+Fa_{Neg}} \quad (12)$$

Sensitivity: The proportion of true positives that are accurately identified is measured by sensitivity (also known as the true positive rate or recall). It is computed by using the following equation:

$$Sensitivity = \frac{Tr_{Pos}}{Tr_{Pos}+F_{\ Neg}} \quad (13)$$

Specificity: The percentage of actual negatives that are accurately detected is determined by specificity (also known as true negative rate). It is computed as follows:

$$Specificity = \frac{Tr_{Neg}}{Tr_{Neg}+Fa_{Pos}} \quad (14)$$

Positive Predictive Value: The true positive (TP) indicator displays the likelihood of correctly categorized pixels in addition to accuracy, which is computed as shown in below:

$$PPV = \frac{Tr_{Pos}}{Tr_{Pos}+F_{\ Pos}} \quad (17)$$

F1-Score: It is represented by the average of recall and precision. As a result, this rate takes both FP and FN into consideration. Although, F1 is far more effective than accuracy, especially if it is an asymmetric class distribution, and is estimated as follows:

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision+Recal} \quad (18)$$

Where, Tr_{Pos} denotes true positives, Tr_{Neg} indicates true negatives, Fa_{Pos} represents false positives, and Fa_{Neg} represents false negatives. Table 3 and Fig 3 compares the accuracy of various classification approaches used for brain tumor identification and classification. Despite being a sizable share of accurately predicted perceptions relative to all perceptions, it is an important natural performance estimation.
One of the key parameters in result analysis is accuracy. The proposed RSCSO-ELM provides an increased accuracy, when compared to the other classification approaches.

Table 3. Comparison based on accuracy

Methods	***Accuracy (%)***
PT-CNN	99.04
LBP – SVMKNN	95.56
CNN	96
GA-CNN	94.26
GWO + MSVM	95.23
BWT + SVM	95
CNN	84
Deep CNN	99.67
Proposed	99.8

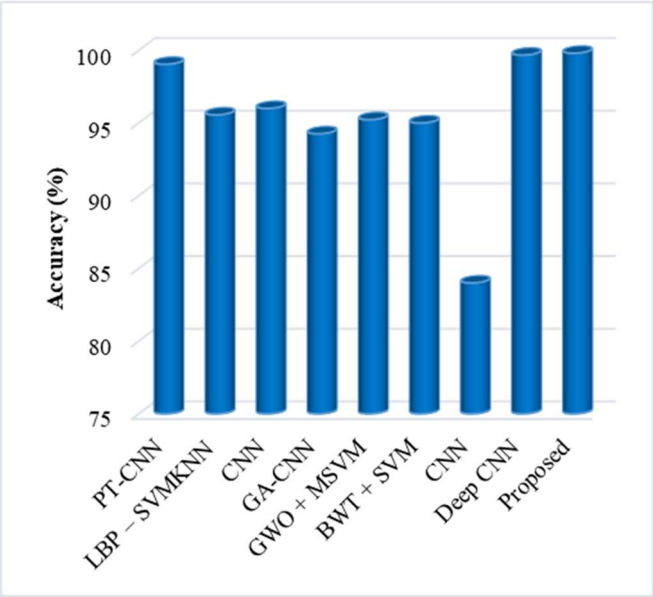

Fig 3. Accuracy of various classification methods

Table 4 and Fig 4 presents the overall performance analysis of the traditional [25] and proposed brain tumor detection methodologies based on the parameters of accuracy, precision, sensitivity, f1-score and specificity. Based on the results, it is observed that the RSCSO-ELM mechanism has produced the best results in terms of all suggested parameters, as can be observed from the analysis of all the outcome parameters.

Table 4. Overall performance comparative analysis

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)	Specificity (%)
KNN + RF + DT	97.305	97.73	97.04	97.41	97.60
SVM + RBF	93.038	92.38	93.82	94.79	92.26

Kernel + Linear Polynomial	85.56	85.20	86.07	85.41	85.05
NB	81.33	81.68	80.83	81.62	81.85
DT	93.157	93.58	92.80	95.45	93.51
NN	93	92.57	93.27	95.30	92.76
KNN	94.765	94.92	94.30	94.60	95.23
Proposed	99.2	98.9	99.1	98.9	99

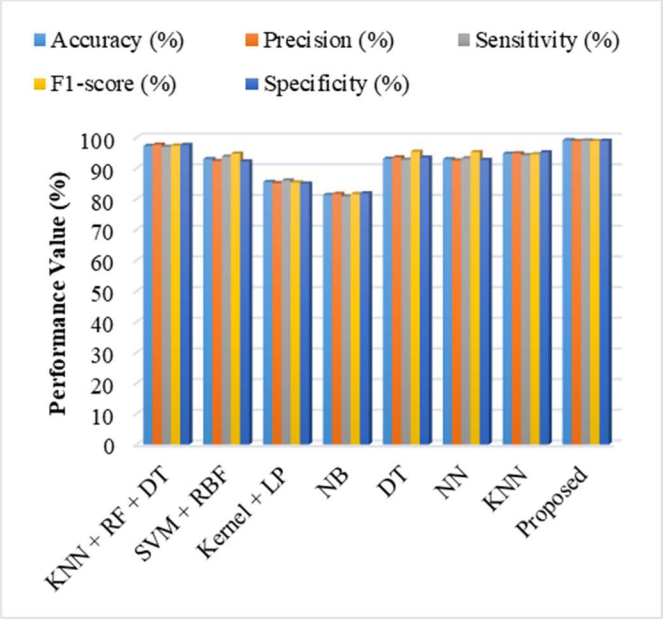

Fig 4. Comparative evaluation

Table 5 and Fig 5 validates the FPR, FNR, accuracy of the existing [42] and proposed brain tumor classification approaches, and these parameters are estimated to assess the detection accuracy and efficacy of the suggested approaches. Moreover, Table 6 and Fig 6 compares the sensitivity and specificity of the disease prediction approaches. Correctly identifying the percentage of true positives serves as a gauge of sensitivity. It is used to identify the positive outcomes by a test's capacity, where the ground truth values are used to determine the sensitivity. According to that analysis, our suggested method has high sensitivity and specificity values than the existing methods.

Table 5. Accuracy analysis

Methods	***FPR***	***FNR***	***Accuracy***
ACM	1.84%	7.51%	90.65%
Fuzzy connectedness	2.95%	5.02%	92.04%
KNN	2.75%	7.51%	93.50%
Adaboost	3.15%	6.07%	90.05%
ANN	2.70%	1.03%	94%
Proposed	0.99%	0.98%	99.2%

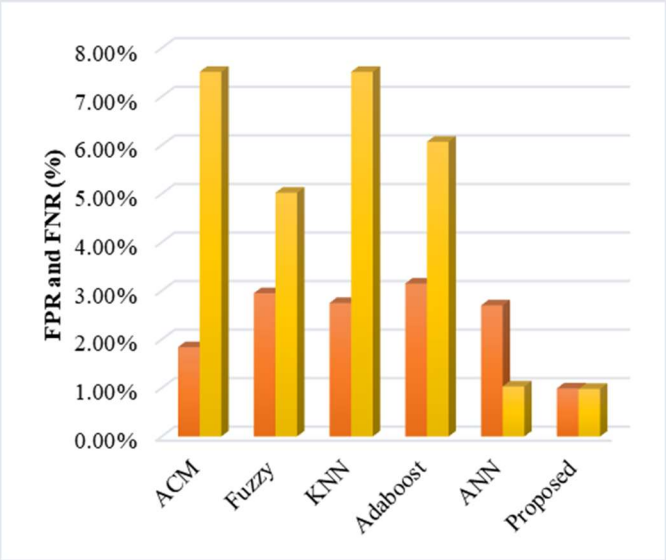

Fig 5. FPR and FNR

Table 6. Comparison based sensitivity and specificity

Methods	*Sensitivity*	*Specificity*
BNN	76.19	82.3
RBNN	85	72
SMO	92	90
MLPNN	80.4	78.3
SVM	84.3	81.8
ANN	52.90	93
Proposed	98.5	98.9

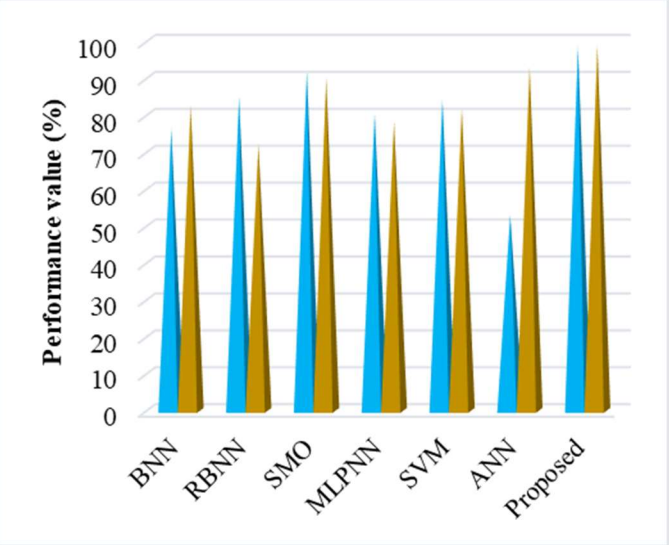

Fig 6. Sensitivity and specificity analysis

Table 7 and Fig 7 compares the segmentation time and error rate of the traditional [43], and proposed classification approaches. When compared to other methods, our suggested method,

RSCSO-ELM, required extremely less time to segment and classify the tumor. As a result, the proposed method is less time-consuming than existing ones, because the RSCSO-ELM technique has a low computational burden. Due to the proper feature extraction and selection operations, the error rate of the proposed classifier is efficiently reduced. Table 8 and Fig 8 presents the performance analysis of the proposed RSCSO-ELM model in terms of sensitivity, specificity, and accuracy.

Table 7. Segmentation time and error rate

Techniques	*Segmentation time (ms)*	*Error rate (%)*
GAN	25	27
LBP	22	26
D-SCAN	20	22.5
FE	18	21
FCM-RBNN	15	16
Proposed	8	7

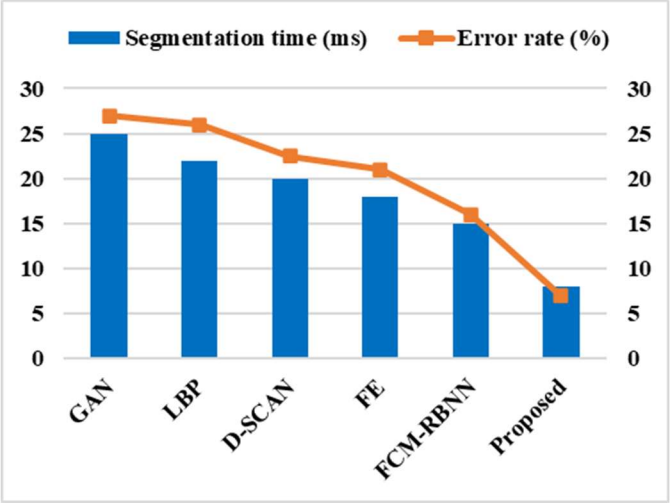

Fig 7. Time complexity and error rate

Table 8. Performance analysis of the proposed RSCSO-ELM

Input images	Sensitivity	Specificity	Accuracy
1	99.2	99.7	99.7
2	99	99.3	99.3
3	98.18	97.85	97.85
4	93.40	98.85	98.70
5	99.7	99.4	99.4
6	97.7	99.4	99.3

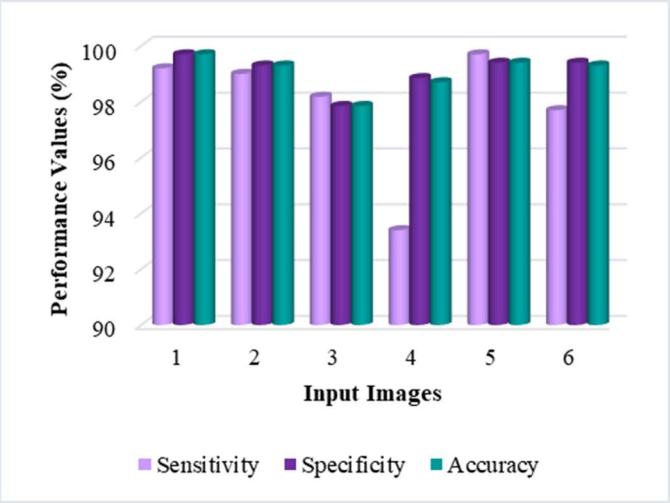

Fig 8. Performance evaluation of the RSCSO-ELM model

Conclusion

The classification of brain tumors is one of the most important areas of research in the medical sciences. For the classification of different types of tumors, various methods have been offered. These techniques delivered a performance in classification accuracy that is satisfactory. However, the issue of tumor classification is still unresolved and requires proper attention. An effective framework can help to further improve categorization accuracy. The major goal of this research project is to develop a brain tumor classification model with low complexity and high classification accuracy. The suggested model initially improves the image's visual quality using an iterative preprocessing algorithm. After that, the texture and statistical features are extracted from the preprocessed image for simplifying the operations of classifier. Consequently, the RSCSO mechanism is deployed to reduce the dimensionality of features by choosing the most relevant features based on the global optimal solution. Then, the ELM is used to classify the given MRI is whether healthy or abnormal. If the predicted image is abnormal, the auto encoder segmentation algorithm is applied to accurately crop the tumor affected region with increased segmentation accuracy. During evaluation, the performance and results of the proposed RSCSO-ELM techniques are validated and compared by using various operators. Finally, the estimated results state that the proposed RSCSO-ELM model outperforms other algorithms with high performance prediction results.

In future, the present can be enhanced by implementing a U-Net segmentation based deep learning classifier for brain tumor identification and class categorization.

References

[1] A. Gurunathan and B. Krishnan, "A Hybrid CNN-GLCM Classifier For Detection And Grade Classification Of Brain Tumor," Brain Imaging and Behavior, vol. 16, pp. 1410-1427, 2022.

[2] G. U. Kaya and T. O. Onur, "A Comparative Study for Brain Tumor Detection Using Segmentation Based on Soft Computing and Thresholding Methods," Journal of Electrical Engineering, Electronics, Control and Computer Science, vol. 8, pp. 21-32, 2021.

[3] A. Ramesh Kumar and H. Kuttiappan, "Detection of brain tumor size using modified deep learning and multilevel thresholding utilizing modified dragonfly optimization algorithm," Concurrency and Computation: Practice and Experience, vol. 34, p. e7016, 2022.

[4] N. Nagar, N. Pandey, and A. Agwekar, "Brain Tumour Detection and Classffication Using CNN," International Journal of Engineering and Applied Physics, vol. 2, pp. 472-479, 2022.

[5] S. Ayub, Kannan, S Shitharth, R. Jagadeesh, R. Alsini, T. Hasanin, et al., "LSTM-Based RNN Framework to Remove Motion Artifacts in Dynamic Multicontrast MR Images with Registration Model," Wireless Communications and Mobile Computing, vol. 2022, 2022.

[6] D. M. Toufiq, A. M. Sagheer, and H. Veisi, "Brain Tumor Segmentation from Magnetic Resonance Image using Optimized Thresholded Difference Algorithm and Rough Set," 2022.

[7] A. Jain, A. Malviya, D. Bajaj, R. Bhavsar, and A. Savyanavar, "Brain Tumor Detection using MLops and Hybrid Multi-Cloud," in 2022 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS), 2022, pp. 1-6.

[8] T. A. Soomro, L. Zheng, A. J. Afifi, A. Ali, S. Soomro, M. Yin, et al., "Image segmentation for MR brain tumor detection using machine learning: A Review," IEEE Reviews in Biomedical Engineering, 2022.

[9] N. Molachan, K. Manoj, and D. A. S. Dhas, "Brain Tumor Detection that uses CNN in MRI," in 2021 Asian Conference on Innovation in Technology (ASIANCON), 2021, pp. 1-7.

[10] D. V. Gore, A. K. Sinha, and V. Deshpande, "Automatic CAD System for Brain Diseases Classification Using CNN-LSTM Model," in Emerging Technologies in Data Mining and Information Security, ed: Springer, 2023, pp. 623-634.

[11] S. Pandey, "Brain tumor detection using CNN," Turkish Journal of Computer and Mathematics Education (TURCOMAT), vol. 12, pp. 4597-4603, 2021.

[12] P. Shetty, S. Singh, R. Jambhulkar, K. Sheth, and D. Ujlambkar, "Detection of brain tumor using CNN and ML," IJAR, vol. 7, pp. 308-313, 2021.

[13] A. Sharma, "A survey of the identification strategies of brain tumors for MR images," Turkish Journal of Computer and Mathematics Education (TURCOMAT), vol. 12, pp. 6172-6178, 2021.

[14] T. Liu, Z. Yuan, L. Wu, and B. Badami, "Optimal brain tumor diagnosis based on deep learning and balanced sparrow search algorithm," International Journal of Imaging Systems and Technology, vol. 31, pp. 1921-1935, 2021.

[15] S. K. HS and K. Karibasappa, "An effective hybrid deep learning with adaptive search and rescue for brain tumor detection," Multimedia Tools and Applications, vol. 81, pp. 17669-17701, 2022.

[16] S. S. More, M. A. Mange, M. S. Sankhe, and S. S. Sahu, "Convolutional Neural Network based Brain Tumor Detection," in 2021 5th International conference on intelligent computing and control systems (ICICCS), 2021, pp. 1532-1538.

[17] S. Gull and S. Akbar, "Artificial intelligence in brain tumor detection through MRI scans: advancements and challenges," Artificial Intelligence and Internet of Things, pp. 241-276, 2021.

[18] S. Selvarajan, H. Manoharan, T. Hasanin, R. Alsini, M. Uddin, M. Shorfuzzaman, et al., "Biomedical Signals for Healthcare Using Hadoop Infrastructure with Artificial Intelligence and Fuzzy Logic Interpretation," Applied Sciences, vol. 12, p. 5097, 2022.

[19] W. Ayadi, W. Elhamzi, I. Charfi, and M. Atri, "Deep CNN for brain tumor classification," Neural Processing Letters, vol. 53, pp. 671-700, 2021.

[20] A. Veeramuthu, S. Meenakshi, G. Mathivanan, K. Kotecha, J. R. Saini, V. Vijayakumar, et al., "MRI brain tumor image classification using a combined feature and image-based classifier," Frontiers in Psychology, vol. 13, 2022.

[21] J. Kang, Z. Ullah, and J. Gwak, "Mri-based brain tumor classification using ensemble of deep features and machine learning classifiers," Sensors, vol. 21, p. 2222, 2021.

[22] A. Raza, H. Ayub, J. A. Khan, I. Ahmad, A. S. Salama, Y. I. Daradkeh, et al., "A hybrid deep learning-based approach for brain tumor classification," Electronics, vol. 11, p. 1146, 2022.

[23] F. J. Díaz-Pernas, M. Martínez-Zarzuela, M. Antón-Rodríguez, and D. González-Ortega, "A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network," in Healthcare, 2021, p. 153.

[24] I. Abd El Kader, G. Xu, Z. Shuai, S. Saminu, I. Javaid, and I. Salim Ahmad, "Differential deep convolutional neural network model for brain tumor classification," Brain Sciences, vol. 11, p. 352, 2021.

[25] G. Garg and R. Garg, "Brain tumor detection and classification based on hybrid ensemble classifier," arXiv preprint arXiv:2101.00216, 2021.

[26] M. Khairandish, M. Sharma, V. Jain, J. Chatterjee, and N. Jhanjhi, "A hybrid CNN-SVM threshold segmentation approach for tumor detection and classification of MRI brain images," IRBM, 2021.

[27] Q. D. Buchlak, N. Esmaili, J.-C. Leveque, C. Bennett, F. Farrokhi, and M. Piccardi, "Machine learning applications to neuroimaging for glioma detection and classification: An artificial intelligence augmented systematic review," Journal of Clinical Neuroscience, vol. 89, pp. 177-198, 2021.

[28] T. Sadad, A. Rehman, A. Munir, T. Saba, U. Tariq, N. Ayesha, et al., "Brain tumor detection and multi-classification using advanced deep learning techniques," Microscopy Research and Technique, vol. 84, pp. 1296-1308, 2021.

[29] P. Tiwari, B. Pant, M. M. Elarabawy, M. Abd-Elnaby, N. Mohd, G. Dhiman, et al., "Cnn based multiclass brain tumor detection using medical imaging," Computational Intelligence and Neuroscience, vol. 2022, 2022.

[30] S. Maqsood, R. Damasevicius, and F. M. Shah, "An efficient approach for the detection of brain tumor using fuzzy logic and U-NET CNN classification," in International Conference on Computational Science and Its Applications, 2021, pp. 105-118.

[31] M. A. Alamir, "A novel acoustic scene classification model using the late fusion of convolutional neural networks and different ensemble classifiers," Applied Acoustics, vol. 175, p. 107829, 2021.

[32] B. Chen, L. Zhang, H. Chen, K. Liang, and X. Chen, "A novel extended Kalman filter with support vector machine based method for the automatic diagnosis and segmentation of brain tumors," Computer Methods and Programs in Biomedicine, vol. 200, p. 105797, 2021.

[33] I. H. Rather, S. Minz, and S. Kumar, "Hybrid Texture-Based Feature Extraction Model for Brain Tumour Classification Using Machine Learning," in Emerging Technologies in Data Mining and Information Security, ed: Springer, 2023, pp. 445-455.

[34] R. Garg and O. P. Sangwan, "Hybrid classifier for brain tumor detection and classification," in Artificial Intelligence and Speech Technology, ed: CRC Press, 2021, pp. 239-245.

[35] V. V. Kumar and P. G. K. Prince, "Magnitude Normalized and OTSU Intensity based Brain Tumor Detection Using Magnetic Resonance Images," IETE Journal of Research, pp. 1-11, 2021.

[36] R. Remya and K. Parimala Geetha, "A Novel Thresholding Approach to Find Out the Brain Tumor Region from MR Images," IETE Journal of Research, pp. 1-9, 2021.

[37] (2020). Multimodal Brain Tumor Segmentation Challenge 2020: Data Available: https://www.med.upenn.edu/cbica/brats2020/data.html

[38] "The Cancer Imaging Archive (TCIA)," 2022.

[39] (2020). Open Access Series of Imaging Studies (OASIS) Available: https://www.oasis-brains.org/

[40] (2016). The Internet Brain Segmentation Repository (IBSR) Available: https://www.nitrc.org/projects/ibsr

[41] (2020). Kaggle Dataset. Available: https://www.kaggle.com/datasets

[42] M. Mudda, R. Manjunath, and N. Krishnamurthy, "Brain tumor classification using enhanced statistical texture features," IETE Journal of Research, vol. 68, pp. 3695-3706, 2022.

[43] A. Dixit and A. Nanda, "An improved whale optimization algorithm-based radial neural network for multi-grade brain tumor classification," The Visual Computer, vol. 38, pp. 3525-3540, 2022.

[44] PATHAN, S., & BALAJI, D. S. (2022). A DETAILED ANALYSIS ON MEDICAL IMAGE PROCESSING TECHNIQUES USED FOR BRAIN TUMOR DETECTION AND CLASSIFICATION. Journal of Theoretical and Applied Information Technology, 100(11).