

Extreme Learning Bat Algorithm in Brain Tumor Classification

G. R. Sreekanth¹, Adel Fahad Alrasheedi², K. Venkatachalam³, Mohamed Abouhawwash^{4,5,*} and S. S. Askar²

¹Department of Computer Science and Engineering, Kongu Engineering College, Erode, 638060, India

²Department of Statistics and Operations Research, College of Science, King Saud University, Riyadh, 11451, Saudi Arabia

³Department of Applied Cybernetics, Faculty of Science, University of Hradec Králové, Hradec Králové, 50003, Czech Republic

⁴Department of Mathematics, Faculty of Science, Mansoura University, Mansoura, 35516, Egypt

⁵Department of Computational Mathematics, Science, and Engineering (CMSE), Michigan State University, East Lansing, MI, 48824, USA

*Corresponding Author: Mohamed Abouhawwash. Email: abouhaww@msu.edu

Received: 21 October 2021; Accepted: 10 January 2022

Abstract: Brain tumor is considered as an unusual cell that presents and grows in the brain. Similarly, it may lead to cancerous or non-cancerous. So, to improve the survival rate of the patient and to give the best treatment at the earliest, it's very necessary for early prediction of tumor. Accurate classification of tumor in the brain is important for improving the diagnosis. In accordance with that, various research programs are invited for the better treatment of the patients. Machine Learning (ML) algorithms are applied to help the health associates for the classification of brain tumor and present their diagnosis. This paper focuses primarily on brain tumors of meningioma, Glioma, and pituitary. Moreover, the manual evaluation of Magnetic Resonance Image (MRI) is a difficult process. For accessing MRI brain image in the aspects of its volume, boundaries, detecting tumor size, shape and classification are the challenging tasks. To overcome these difficulties, this paper proposes a novel approach in feature selection using bat algorithm with Extreme Learning Machine (ELM) and for enhancing the accurate classification by Transfer Learning (BA + ELM-TL). Here the data is pre-processed to remove noises; Stationary Wavelet Transforms (SWT) is used to extract the features from the MRI brain image. This paper has collected the dataset from fig share, whole brain atlas and TCGA-GBM data set. Therefore, it is proved that 92.6% is the accuracy of Bat algorithm, 90.4% for Extreme Learning algorithm and 98.87% for BA + ELM-TL.

Keywords: MRI; brain tumor; wavelet transform; bat algorithm; ELM; transfer learning

1 Introduction

In medical field, the development of technology gives prompt diagnosis of MRI brain tumors, and it can be accessed by the tools of Computer Aided Diagnosis (CAD), MRI. Though, it can be identified by humans, it is difficult to monitor the huge volume of data for them. In brain tumor, detection at the early stage is done



This work is licensed under a Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

by expert in radiologist [1]. The diagnostics of brain tumor is dependent on the examination of the tissue, for which biopsy is needed. In order to get precise analysis, a diagnostic tool is required. The classification from MRI images is done using machine learning and artificial intelligence. In the field of medicine, these tools support for various medical branches including medical image processing. Different algorithms in machine learning are used in tumor image classification, and segmentation of image.

For brain tumor classification, this paper has used three well-known types of tumors like meningioma, glioma, and tumors in pituitary. The meningioma tumor arises from the membrane which surrounds the brain and mid part of the nervous system. Next, Glioma is initiated from the brain tissue. Lastly, tumors at Pituitary are similar to lumps that arise inside the skull [2–5]. Automatic computer aided diagnostics tools are used to process the clinical medical data such as detection of tumor, its location, size, and classification. Using MRI for the treatment process generates contrast in image and has non-invasive property [6].

The most important task in understanding the image is segmentation of image and only after that it helps in terms of feature extraction, feature selection, and implication in many real-life medical applications. For example, it can be used in the estimation of tumor size, tumor volume, classification of tissue in the brain image, and location of tumors and image registration. For monitoring clinical image data, the identification of tumor in the brain image is a critical task. However, recently there are numerous automatic tumor detection techniques that are proposed for brain tumor classification using deep learning algorithms.

To overcome these issues the proposed work has implemented feature selection using bat algorithm with extreme learning machine technique for accurate MRI classification of brain image using transfer learning. The contributions of the proposed work are given below:

1. To implement an enhanced version of feature selection using Bat algorithm with extreme learning machine via transfer learning.
2. Proposed work (BA + ELM-TL) generates the classification of brain image and establish better performance metric measures using Figshare dataset.

Rest of the research article is written as follows: Section 2 discusses the literature work on various classification of brain image processing and methods. Section 3 shows the algorithm process and general working methodology of proposed work. Section 4 evaluates the implementation and results of the study. Section 5 concludes the work and discusses the result evaluation.

2 Review of Literature

In the medical field, the image analysis and the image processing of brain MRI are the most challenging tasks in producing high quality images for diagnosing the diseases. Brain tumor classification is manually an error prone, and it is a challenging one for the radiologists. Various multimodalities of MRI brain tumors are T1, T2, and Flair that are needed to be determined for texture and shape features of MRI image [7]. Computer Aided Diagnosis (CAD) system is the most popular technique in the diagnosis of MRI brain tumor [8]. In an automated processing of CAD system, the two-stage processes are exhibited. In the first step, it implements the preprocessing algorithm and extracts the features and in the second stage, it classifies the tumor image into a relevant group.

Various machine-learning techniques are used for segmentation and classification of MRI image that helps the neuro-oncologists for providing efficient treatment of brain tumor. In the classification of brain tumors, four types of sarcoma, tumor-free, metastasis and glioblastoma tumors are used and by the use of DNN, it produces 96.97% of accuracy [9]. In the literature, various modifications of pre-trained network were used for analysis of image, segmentation, and classification of brain images. Various techniques have been implemented in the brain tumor medical databases [10,11].

Classification of brain tumor using regions in the image augmentation process such as ring-form image partition and dilation of image help in the accurate classification. This approach got accuracy of 91.28% [12]. Statistical features are separated from the MRI brain image with the help of filters namely, Gabor and Discrete-Wavelet Transforms (DWT). Further Multi-Layer Perceptron (MLP) classifier algorithm is applied in training the model using statistical features. Dataset of Figsh is used and trained the model on the basis of 70:30 as training and validation set of images [13].

Bat algorithm was presented in Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) and evaluated using benchmark functions [14]. This BA was outperformed in solving the problem of optimization like clustering, motor wheel optimization, constrained optimization, and global engineering optimization [15–20]. BA algorithm is more complicated in assigning the bat as agent with parameters of loudness, pulse rate, position, frequencies, and velocity [21]. Tab. 1 shows the existing algorithm.

Table 1: Survey on existing algorithm

Author	Data set	Method
Ramesh et al. (2021) [22]	BRATS2012, BRATS2013, BRATS2014, BRATS2015	Deep wavelet auto-encoder model
Amin et al. (2021) [23]	MRI scan data	Deep learning, VGG16
Nayak et al. (2020) [24]	Harvard, RIDER	Three variants of SVM
Badža et al. (2020) [25]	MD-1 and MD-2	Deep stacked autoencoder
Khan et al. (2020) [26]	Nanfang Hospital and General Hospital, Tianjin Medical University, China from 2005 to 2010	CNN
Mallick et al. (2020) [27]	BraTs2015, BraTs2017, and BraTs2018	(CNN) models, namely VGG16 and VGG19-ELM
Seetha et al. (2019) [28]	RIDER Neuro MRI-1086100996	Deep learning-based wavelet with auto encoder in deep neural network
Sajjad et al. (2018) [29]	BRATS 2015	CNN

3 Proposed Methodology for Classifying Brain Tumor

The process of classifying the brain tumors images is an essential one for the purpose of diagnosis. This proposed work BA + ELM-TL improves the performance of classification, requires less time complexity, high processing speed. It is computer based assisted for the classification of brain tumor and its diagnosis. This work needs three phases such as 1. Pre-processing, 2. Feature Extraction, 3. Feature Selection. Fig. 1 shows the architecture of the proposed work.

Proposed algorithm extracts the features from the MRI brain image using stationary wavelet algorithm and for feature selection using BAT with ELM algorithm in order to produce the output promptly. Therefore, transfer learning is adopted for providing fine tuning classification of tumor images.

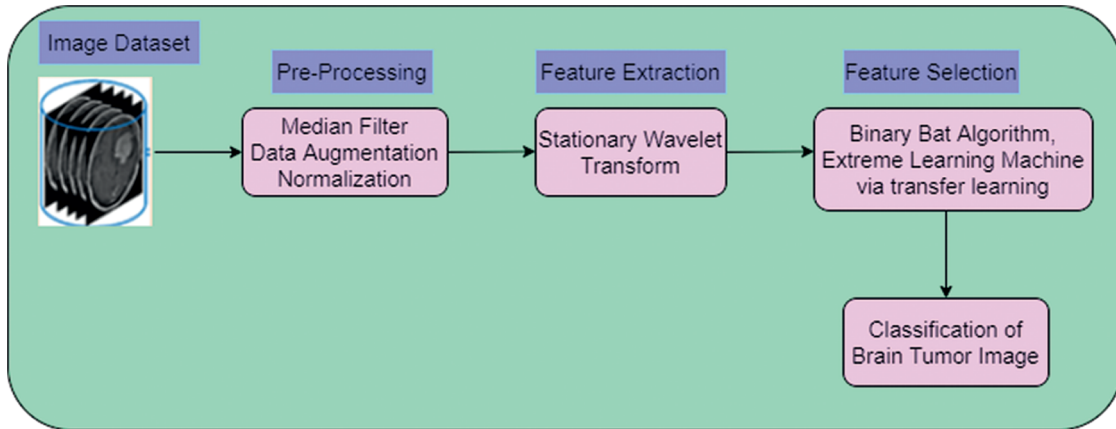


Figure 1: Architecture of proposed work

3.1 Pre-Processing

To improve the MRI image quality and to enhance the parameters of MRI image, which is used for further processing by medical experts, pre-processing stage is needed, Fig. 2.

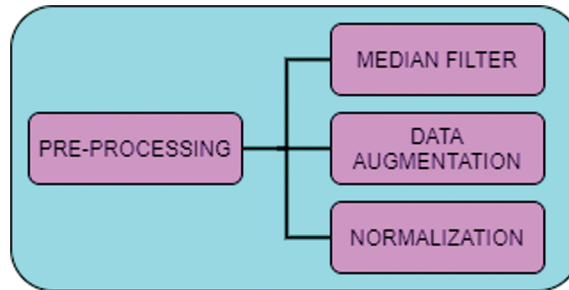


Figure 2: Stages in pre-processing

The stages involve in the pre-processing are:

Stage 1: Applying median filter in the development of brain image.

Stage 2: Data Augmentation

Stage 3: Normalization of the image using Min-Max Normalization Technique.

Fig. 2 shows the different stages of pre-processing.

3.1.1 Enhancing the Brain Tumor Image Using Median Filter

Scan the whole MRI brain image using 4×4 window size and calculate the median value for the image and the central pixel value is to be replaced by its median value. See Eq. (1).

$$img[p, q] = median\{img - med [i, j], (i, j) \in P\} \quad (1)$$

where P represents a neighborhood pixel value defined by the user and the centered around location $[m, n]$ in the image.

3.1.2 Data Augmentation

To get better quality of classification, MRI image data augmentation is applied. It involves transformation of MRI image by performing rotation and flipping operation. The study involves rotation of image using 90 degree and also the image is flipped horizontally [30].

3.1.3 Normalization of the Image Using Min-Max Normalization Technique

To normalize the input, MRI image of size 512×512 pixels is used and the value of intensity between 0, and 1 is evaluated using Eq. (2)

$$p_i = \frac{(q_i - \min(q))}{(\max(q) - \min(q))} \quad (2)$$

Here, p_i is the normalized intensity value of position of image $q_i (1 = 1, 2, \dots, n)$ and intensity values of maximum and minimum are represented as $\max(q)$ and $\min(q)$. After applying the normalization, the size of the image gets resized into 256×256 pixels.

3.2 Feature Extraction Using Stationary Wavelet Transform

In this proposed work, feature extraction of the image is used by Stationary Wavelet Transform (SWT). Here the input signal of the image is convolved with low pass filter value of low[img] and high pass filter value of high[img] and the coefficient number is twice with the input signal of the image in different sub-bands. Fig. 3 shows the single level sub-band technique of input brain image.

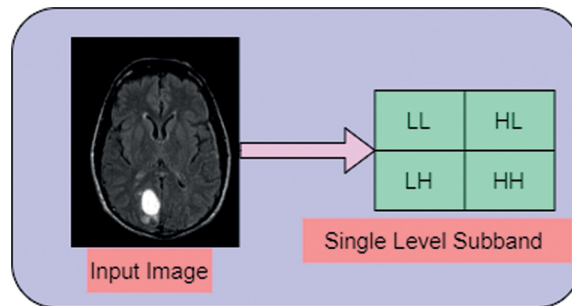


Figure 3: Single-level sub-band technique

In Fig. 3, Sub-band LL represents the horizontal and vertical low frequency components of the MRI brain image. Sub-band HH represents the horizontal and vertical high frequency components of the MRI brain image. Sub-band LH represents the horizontal low and vertical high frequency components of MRI brain image. Sub-band HL represents the horizontal high and vertical low frequency components of MRI brain image. Fig. 4 shows the level as single and stationary based wavelet transform decomposing the image into four sub-bands.

In Fig. 4, the MRI image $Img(x, y)$ is splitted into four separate sub bands as 1) LowLow (LL), 2) LowHigh (LH), 3) HighLow (HL), and 4) HighHigh (HH) which represents approximately low resolution, and has information regarding horizontal, vertical, and diagonals of input image which produce the same $x \times y$ resolution. For extracting the features of input, brains image in i^{th} level is given in Eq. (3):

$$\begin{aligned}
LowLow_{i+1} &= (m, n) = \sum_x \sum_y low_x^i low_y^i LL_i(m+x, n+y), \\
LowHigh_{i+1} &= (m, n) = \sum_x \sum_y high_x^i low_y^i LL_i(m+x, n+y), \\
HighLow_{i+1} &= (m, n) = \sum_x \sum_y low_x^i high_y^i LL_i(m+x, n+y), \\
HighHigh_{i+1} &= (m, n) = \sum_x \sum_y high_x^i High_y^i LL_i(m+x, n+y),
\end{aligned} \tag{3}$$

where $x = 1, 2, \dots, m$, $y = 1, 2, \dots, n$, and LL, LH, HL, and HH represent horizontal, vertical, and diagonal sub bands, respectively.

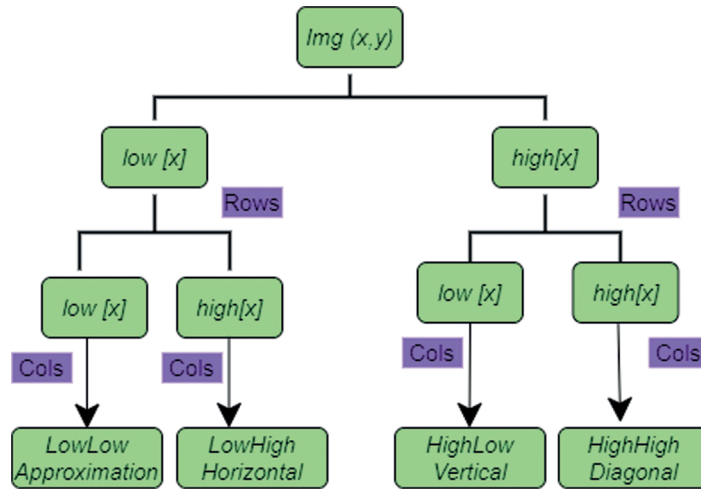


Figure 4: Single level of stationary based decomposition using wavelet transform

3.3 Feature Selection

The MRI brain images are available in various multi-modals. The selection of best features is essential in the classification of image. This proposed work implements Bat Algorithm with Extreme Learning via Transfer Learning (BA + ELM-TL).

3.3.1 Bat Algorithm (BA)

It is based on the concept of Particle Swarm Optimization (PSO). Bats are mammals and it is capable of flying in sustainability. Echolocation is used so as to find food in microbats which avoid obstacles, locate the position in dark night. It updates their position and velocity in multidimensional searching space. Each microbat represents the echolocation of its pulse emission rate, a wavelength and frequency. Frequency of each microbat is defined as in Eq. (4):

$$frq_i = frq_{min} + \mu(frq_{max} - frq_{min})\beta \quad \beta \in [0, 1] \tag{4}$$

where, frq_i is frequency between the range of frq_{min} and frq_{max} . And the velocity of each microbat for j^{th} iteration is given in Eq. (5):

$$vel_i(j) = vel_i(j-1) + frq_i(x_i(j) - x^{OPTI}(j)) \tag{5}$$

where, $vel_i(j)$ is velocity of microbat in j^{th} iteration and x^{OPTI} is the optimized solution in step j. Position calculation of each microbat in the j^{th} iteration is given in Eq. (6):

$$x_i(j) = x_i(j - 1) + vel_i(j) \tag{6}$$

where, $x_i(j)$ is the position of microbat in the j^{th} iteration.

Tab. 2 shows the different notations that are used. Algorithm 1 describes the Bat Algorithm (BA) which is used for selecting the features of MRI brain image. The steps involved in the Bat Algorithm is given below:

Algorithm 1: Bat Algorithm for Feature Selection

Input: Features of MRI Brain image

Output: Classifying Brain Tumor based on selected features.

Step 1: Initialize the parameter values as in the symbolic notation.

Step 2: Best position is updated ($best^*$), pulse of the frequency ($freq_i$), i^{th} bat's position (x_i), i^{th} bat's velocity (vel_i) using Eqs. (4)–(6). And β generates range randomly of [0, 1].

Step 3: If random number $> prate_i$; generates new solution for bat using

$$best_{new} = best_{old} + \epsilon loud^t \tag{7}$$

where, ϵ is random number between [-1, 1] and $loud^t$ is at time t average loudness of all bats.

Step 4: If random number $\beta < loud_i$, $fit(x_i) < fit(x^*)$ is a new solution.

Step 5: Updating the values of $loud_i$ and $prate_i$ using

$$loud_i^{t+1} = \alpha loud_i^t \tag{8}$$

$$prate_i^t = prate_i^0 [1 - e^{-\gamma t}] \tag{9}$$

where $loud_i^{t+1}$ and $loud_i^t$ are loudness in the time interval of t and $t + 1$. Similarly, for $prate_i^0$ is the initial rate of pulse and $prate_i^t$ is the rate of pulse at time t. α is a constant range of 0 to 1. γ is a constant parameter and $\gamma > 0$. At a time $t \rightarrow \infty$, $prate_i^t \rightarrow prate_i^0$ and $loud_i^t \rightarrow 0$.

Step 6: Based on the fitness value $fit(x)$ sort bat and the best solution ($best^*$) is evaluated currently.

Step 7: Go to Step 2 until it reaches the maximum iterations.

Table 2: Symbolic notations

Symbols	Notations
P	Population size of bat
Max	Number of maximum iterations
Bat	Number of total bats in the rage of [1,...P]
$best^*$	The best current solution (location)
x_i	i^{th} bat's position
vel_i	i^{th} bat's velocity
$freq_i$	i^{th} bat frequency and range between $freq_{min}$ and $freq_{max}$.
$fit(x)$	Function of fitness

(Continued)

Table 2 (continued)	
Symbols	Notations
$prate_i$	i^{th} bat pulse rate
$loud_i$	i^{th} bat loudness
α	Constant parameter for updating loudness $loud_i$ in the range of [0,1]
γ	Constant parameter for updating pulse rate $prate_i$ in the range of [0,1]

Algorithm 1 describes how tumor detection in the brain image is done by random choice of the pixel image with velocity at position, wavelength, frequency, and loudness to detect pixels of tumor tissue in the MRI brain image. By the adjustment of the wavelength value of the pixel and the closest pixel value of tumor can be checked out from the image. See Eqs. (7)–(9).

3.3.2 Extreme Learning Machine (ELM)

The aim of feature selection using ELM is used to reduce the feature redundancy and choose only robust exact features classification. And also, ELM is used to minimize the predictors and faster in execution. The working principle is given in Algorithm 2. Tab. 3 shows different notations that are used

Algorithm 1 presents the working principal of the proposed work:

Algorithm 2: Extreme Learning Machine Algorithm for Feature Selection

Input: Original features of the image η_i $i = 1, 2, \dots$

Output: Selected features of the brain image

Step 1: Initialize the parameters as in symbolic notation.

$sf(i) = \eta_i$ and $i = 1, 2, 3, \dots, n$

$\alpha_{-1} = 0$ and $\alpha_{-0} = 1$

Step 2: For $1 = 1$ to p Do

$$bi_i = \frac{\alpha_{i-2} - 1}{\alpha_{i-1}} \quad (10)$$

$$Ac^i = sf(i) + bi_i(sf(i) - sf(i-1)) \quad (11)$$

Step 3: Update the values of $sf(i+1)$.

Step 4: Find the least value of regularization parameter LR among $(LR_{i-1}, 2 LR_{i-1}, 3LR_{i-1}, \dots)$

Step 5: $f(sf(i) \leq g(LR_i, Up^i) sf(i+1))$

Step 6: Substitute the value of LR in ELM classifier

Step 7: Evaluate minimum squared error rate (MSER) using

$$MSER = \frac{i}{n} \sum_{i=1}^m (LR_i - \widehat{LR}_i)^2 \quad (12)$$

Step 8: IF $MSER \geq 0.1$ update LR_{i+1} value.

Step 9: End For

Table 3: Symbolic notations

Symbols	Notations
η	Original features of brain image
$sf(i)$	Selected features of the brain image
LR :	Regularization parameter
$sp(i)$	Selected parameter
Ac^i	Affine combination of selected feature $sf(i)$ and $sf(i-1)$

Algorithm 2 is implemented and LR_i is observed in the features of brain image, and \widehat{LR}_i denotes the predicted features of brain image. For each time, Minimum Squared Error Rate (MSER) is computed as greater than or equal to 0.1 and updates brain image features. This iteration is repeated until the features are selected for the classification of the brain image. See Eqs. (10)–(12).

3.3.3 Feature Selection Using Bat with Extreme Learning Machine via Transfer Learning (BA + ELM-TL)

In the BRATS data set, training the model of VGG 19 using the same parameter values of Bat and ELM algorithm via Transfer Learning (TL) [31] is done. During the training process, read the input brain data set and evaluate the training in the ratio of 80:20 and each brain image label is defined. Then assign the training of input and output layer model. For VGG19 model, input convolution layer is applied using 64 filters with a size of $3 \times 3 \times 64$ and the output is FC8. Afterwards, implement the activation function in the CNN model for the selected features of the brain image and train the model. The algorithm for BA + ELM-TL is given below:

Algorithm 3: BA + ELM-TL via Deep Transfer Learning (Proposed)

Input: Selected features of MRI brain image

Output: Classifying the brain tumor depending on selected features.

Step 1: Initialize the parameters using step 1 in Algorithm 1

Step 2: Generate total number of bats (bat_{max})

Step 3: Evaluate fitness value for all bats

Step 4: Find the current best bat ($best^*$)

Step 5: For $I = 1$ to bat_{max}

Step 6: Evaluate frequency and velocity using Eqs. (4) & (5).

Step 7: if ($vel_i > vel_{max}$) then

Step 8: $vel_i = vel_{max}$

Step 9: End-if

Step 10: if ($vel_i < vel_{min}$) then

Step 11: $vel_i = vel_{min}$

Step 12: End-if

Step 13: Update the locations using Eq. (11).

Step 14: Find the least value of regularization parameter LR among ($LR_{i-1}, 2 LR_{i-1}, 3LR_{i-1}, \dots$)

Step 15: $f(sf(i)) \leq g(LR_i, Up^i) sf(i+1)$

Step 16: Evaluate minimum squared error rate (MSER) using Eq. (12).

(Continued)

Algorithm 3: (continued)

Step 17: IF $MSE \geq 0.1$ update LR_{t+1} value.

Step 18: Generate the best solution using $x_{new} = x_{old} + loud^t$

Step 19: End if

Step 20: if $(loud^t > load_{max})$ then

Step 21: $loud^t = load_{max}$

Step 22: End if

Step 23: if $(loud^t < load_{min})$ then

Step 24: $loud^t = load_{min}$

Step 25: End if

Step 26: Create new solution based on current solution value $x_{curnew} = x_{old} + loud^t$

Step 27: If $x_{curnew} \geq x_{new}$ $fx = x_{curnew}$

Step 28: else

Step 29: $fx = x_{new}$ and random number $\beta < loud_i$ then $fit(x_i) < fit(x^*)$ is a new solution.

Step 30: End IF

Step 31: End For

Step 32: End

The proposed Algorithm 3 shows the selected features of the brain image using ELM. Then from the selected features, optimized classification of brain tumor is found based on multiple fitness value. After that, calculate the fitness value for all pixels in the image. Randomly, generate the neighborhood pixel value and set it as the best. Next, evaluate the frequency and velocity for the best pixel values selected. Depending upon the velocity value, set min or max value. Then, update the location of bat. Each time, MSE value is evaluated and MSE is greater than or equal to 0.1. Next, update the features of the image. So, repeat the process for the maximum iterations. If search is not satisfied, the final iteration features were chosen for classification. At the same time, loudness is represented for a period of time it marks the changes in the features and also performs search for i^{th} bat locally. The range of loudness is from minimum and maximum.

When the bat reaches the best solution, the loudness value gets decreased. The value of loudness and fitness plays an important role in finding the optimized solution.

4 Results & Analysis

For brain tumor classification, three datasets were used in this work. First dataset was from the open source that was the available dataset of fig share [32,33]. The second dataset contained images from the whole brain atlas [34]. Third data set images were collected from Cancer Genome Atlas Glioblastoma Multi-form (TCGA-GBM) dataset. In the first dataset data collected from 3064 T1-weighted, MRI brain images of 233 patients were diagnosed with Glioma, Meningioma, and Pituitary brain tumor types. Among this, it contained 1426 MRI brain images with glioma from 88 patients, 707 MRI brain images for meningioma from 83 patients and 931 MRI brain images of pituitary tumor from 62 patients. The images were available as .mat files and the size of each image was 512×512 [35]. Second data set contained 500 normal brain images. The third data set contained 262 MRI brain images [36].

Tab. 4 shows a comparison of existing and proposed BA + ELM-TL model. Here auto-encoder of Deep Wavelet with Deep Neural Network DWA-DNN technique is used for the classification of MRI brain tumor image classification which has got 92.16% of sensitivity, 94.26% of specificity, and 93.15% of precision. Detection of brain tumor images by Convolutional Neural Network (CNN) techniques had obtained 95% of specificity and 94.81% of precision. VGG16 methodology with Google Net model helped in brain tumor classification images and it had obtained 81.25% of sensitivity, 88.48% of specificity, and 89.66% of precision.

Table 4: Comparison of existing model with BA + ELM-TL

Model	Sensitivity %	Specificity %	Precision %
DAE-JOA [37]	95.4	-	95.6
Google Net & Vgg16 [38]	81.25	88.48	89.66
KNN [39]	46	50	52
DNN [40]	75	80	72
M-CNN [41]	95	93	95.7
CNN-SVM [42]	-	95	92.12
Alex-Net [43]	84.38	92.31	93.1
HOG + LBP + Deep [44]	98.46	96.72	-
RG + MKM + U-NET [45]	90.7	99.7	-

MRI Brain tumor classification using K-Nearest Neighbors (KNN) algorithm had produced 46% of sensitivity, 50% of specificity and 52% of precision. The DNN in brain cancer detection had produced 75% of sensitivity, 80% of specificity, and 72% of precision.

Classification of brain tumors using Modified-Convolutional Neural Network (M-CNN) had produced 95% of sensitivity, 93% of specificity, and 95.7% of precision. MRI image segmentation using Deep Auto-Encoder using Jaya Optimization Algorithm (DAE-JOA) model had performed sensitivity with 95.4%, and precision with 95.6%.

From Tab. 2, it is observed that the results comparison of existing models with the proposed bat algorithm and Extreme Learning Machine via transfer learning (BA + ELM-TL) model has achieved better performance in the aspects of sensitivity, specificity, and precision values.

For the proposed work, stationary wavelet transform is used for feature extraction. The various SWT sub-bands are HL, LH, LH + HL and LH + HH + HL which represents as vertical, horizontal, horizontal + vertical and horizontal + diagonal feature information + vertical. Tab. 5 shows the SWT sub bands for the selection of features in the brain image using Whole Brain Atlas, CE-MRI and fig share dataset.

Table 5: SWT sub bands of feature selection of brain image

Dataset	LH	HL	LH + HL	LH + HL + HH
Whole brain atlas	91.34%	90.56%	89.98%	97.83%
CE-MRI	89.12%	89.12%	88.45%	96.21%
Figshare	92.89%	91.75%	87.34%	93.78%

From [Tab. 5](#), it is observed that horizontal + vertical + diagonal feature of brain image has produced the best result of 97.83% for Whole Brain Atlas dataset, 96.21% for CE-MRI dataset of and 93.78% for the dataset of figshare. [Tab. 6](#) shows the comparison of various algorithms using figshare dataset.

Table 6: Comparison of various algorithm using figshare dataset

Author name	Algorithm	Accuracy
Ismael et al. [12]	BoW-SVM	91.28%
Yang [13]	DWT-gabor-neural network	91.90%
Deepak et al. [46].	CNN	84.19%
Afsar et al. [1]	CapsNet	90.89%
Proposed	Bat-ELM via transfer learning	98.45%

[Tab. 6](#) provides the comparison of various algorithm in the figshare dataset. The proposed algorithm had produced the best result with 98.45% for accuracy metric measures. This [Tab. 6](#) contains only the accuracy metric measure because it is a common metric measure and uses for various algorithms. [Tab. 7](#) shows the comparison of proposed work BA + ELM-TL model with existing model of Bat algorithm and Extreme Learning Machine model based on the performance metric measures of Disc Similarity Coefficient (DSC) value, FPR, FNR, JSI value.

Table 7: Comparison of various metric measures

Algorithm	DSC %	FPR	FNR	JSI %
Bat algorithm	88.6	0.24	0.011	89.35
Extreme learning machine	83	0.46	0.09	92.12
BA + ELM-TL (Proposed)	96.44	0.0525	0.03	94.56

[Tab. 7](#) describes a comparison between the proposed BA + ELM-TL model result with the existing models in the metric measures of DSC value which has highly achieved 96.44% compared to ELM of 83% and Bat algorithm with 88.6%. FPR rate proposed algorithm had secured 0.0525 rate and FNR rate 0.03 compared to the existing model. It was shown 94.56% for JACCARD Similarity Index (JSI). From [Tab. 7](#), it was noticed that the overall performance of the proposed algorithm had obtained better experimental result. Youden index value is given in [Fig. 5](#).

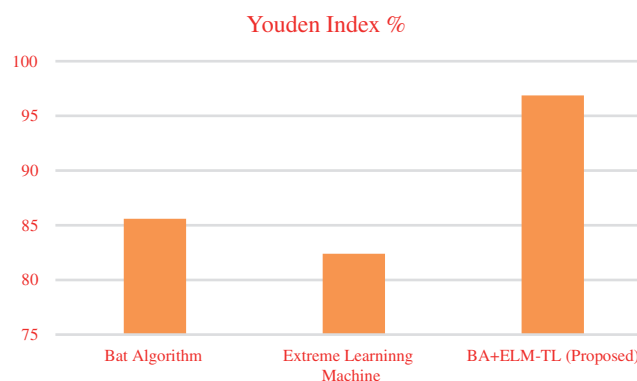


Figure 5: Youden index value for BA + ELM-TL

From the Fig. 5, it is observed that high Youden index value of the proposed work means that high index value produces positive results that are high when compared to the false positive.

In the classification of brain tumor images, accuracy is one of the most extensive of quality index rates [47–53]. Accuracy is defined as the ratio between number of correctly classified brain tumor images and total number of brain images in the dataset. Fig. 6 shows the accuracy of proposed work.

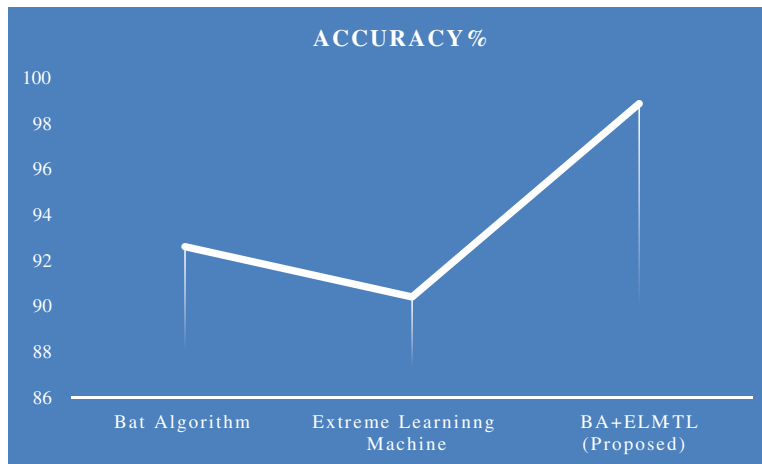


Figure 6: Accuracy

In Fig. 6, the accuracy is calculated for the classification of MRI brain tumor images using Bat Algorithm, Extreme Learning Algorithm and the proposed BA + ELM-TL. The proposed work gives accurate results. However, MRI brain image dataset contains unbalanced dataset. Further evaluation is needed in the proposed work with more performance metric measures that can be used with confusion matrix to evaluate the efficient classification of brain tumor images. The confusion matrix found out the correct and incorrect classification of brain tumor images in the tabular form. Tab. 8 shows a sample confusion matrix for the proposed work in meningioma, glioma and pituitary tumor images.

Table 8: Confusion matrix of the proposed work

		Predicted values		
		Meningioma	Glioma	Pituitary
Actual values	Meningioma	784	44	23
	Glioma	60	1423	2
	Pituitary	12	54	956

Tab. 9 shows the classification of three types of brain tumor images namely, meningioma, glioma and pituitary using proposed work.

Tab. 9 presents the performance of metric measures based on the aspects of precision, recall and specificity for the classification of three different brain tumor types. Here, for the proposed work Bat Algorithm with Extreme Learning Machine via Transfer Learning (BA + ELM-TL) is used. The specificity values for all types of MRI brain tumor images are high. It indicates the exact classification of samples of MRI brain image.

Table 9: Metric measures for classification of brain tumor image

Tumor type	Precision	Recall	Specificity
Meningioma	93.6 ± 0.6	96.3 ± 0.7	97.3 ± 0.4
Glioma	97.2 ± 0.7	95.9 ± 0.3	98.6 ± 0.2
Pituitary	98.2 ± 0.8	97.5 ± 0.2	99.4 ± 0.3

5 Conclusion

This paper presents a novel approach in the classification of brain tumor with an accurate and efficient model. In order to get an appropriate model, pre-processing steps are needed by applying median filter, data augmentation and normalization. The proposed techniques that were applied were from the concept of stationary wavelet transform for extracting the brain features of MRI images. The features selection was used with proven classifier models of Bat Algorithm with Extreme Learning Machine via Transfer Learning which improved the performance. This proposed system recorded the best classification of accuracy compared to all the related works. This paper collected the dataset from figshare, whole brain atlas and TCGA-GBM data set. The accuracy of Bat Algorithm was 92.6%, Extreme Learning Algorithm was 90.4% and BA + ELM-TL got 98.87%. In future, other metaheuristic algorithm can be implemented for further improvement in terms of accuracy, faster in execution.

Acknowledgement: Research Supporting Project Number (RSP-2021/323), King Saud University, Riyadh, Saudi Arabia.

Funding Statement: This project is funded by King Saud University, Riyadh, Saudi Arabia.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

- [1] P. Afshar, K. N. Plataniotis and A. Mohammadi, "Capsule networks for brain tumor classification based on MRI images and coarse tumor boundaries," in *Proc. Int. Conf. on Acoustics, Speech, & Signal Processing (ICASSP)*, Brighton, UK, pp. 1368–1372, 2019.
- [2] B. Jabber, K. Rajesh, D. Haritha, C. Z. Basha and S. N. Parveen, "An intelligent system for classification of brain tumours with glcm and back propagation neural network," in *Proc. Int. Conf. on Electronics, Communication and Aerospace Technology (ICECA)*, Coimbatore, India, pp. 21–25, 2020.
- [3] L. M. Deangelis, "Brain tumors," *New England Journal of Medicine*, vol. 344, no. 2, pp. 114–123, 2001.
- [4] D. N. Louis, A. Perry, G. Reifenberger, A. Deimling, D. F. Branger *et al.*, "The 2016 world health organization classification of tumors of the central nervous system: A summary," *Acta Neuropathologica*, vol. 131, no. 6, pp. 803–820, 2016.
- [5] S. Mahajan, A. Raina, M. Abouhawwash, X. Z. Gao and A. K. Pandit, "Covid-19 detection from chest X-ray images using advanced deep learning techniques," *Computers, Materials and Continua*, vol. 70, no. 1, pp. 1541–1556, 2022.
- [6] Z. N. K. Swati, Q. Zhao, M. Kabir, F. Ali, Z. Ali *et al.*, "Brain tumor classification for MR images using transfer learning and fine-tuning," *Computerized Medical Imaging and Graphics*, vol. 75, pp. 34–46, 2019.
- [7] A. Gumaei, M. M. Hassan, M. R. Hassan, A. Alelaiwi and G. Fortino, "A hybrid feature extraction method with regularized extreme learning machine for brain tumor classification," *IEEE Access*, vol. 7, no. 3, pp. 36266–36273, 2019.

- [8] H. Mohsen, E. S. Dahshan, E. S. Horbaty and A. B. M. Salem, "Classification using deep learning neural networks for brain tumors," *Future Computing and Informatics Journal*, vol. 3, no. 1, pp. 68–71, 2018.
- [9] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. Setio, F. Ciompi *et al.*, "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.
- [10] Z. Akkus, A. Galimzianova, A. Hoogi, D. L. Rubin and B. J. Erickson, "Deep learning for brain MRI segmentation: State of the art and future directions," *Journal of Digital Imaging*, vol. 30, no. 4, pp. 449–459, 2017.
- [11] J. Cheng, W. Huang, S. Cao, R. Yang, W. Yang *et al.*, "Enhanced performance of brain tumor classification via tumor region augmentation and partition," *PLoS one*, vol. 10, no. 10, pp. e0140381, 2015.
- [12] M. R. Ismael and I. Abdelqader, "Brain tumor classification via statistical features and back-propagation neural network," in *Proc. Electro Information Technology (EIT)*, Rochester, USA, pp. 0252–0257, 2018.
- [13] X. S. Yang, "A new metaheuristic bat inspired algorithm," in *Proc. Nature Inspired Cooperative Strategies for Optimization (NICSO)*, Granada, Spain, pp. 65–74, 2010.
- [14] T. C. Bora, L. D. S. Coelho and L. Lebensztajn, "Bat inspired optimization approach for the brushless DC wheel motor problem," *IEEE Transactions on Magnetics*, vol. 48, no. 2, pp. 947–950, 2012.
- [15] K. Khan, A. Nikov and A. Sahai, "A fuzzy bat clustering method for ergonomic screening of office workplaces," in *Proc. Conf. on Software, Services & Semantic Technologies (S3T)*, Bourgas, Bulgaria, pp. 59–66, 2011.
- [16] X. S. Yang and A. H. Gandomi, "Bat algorithm: A novel approach for global engineering optimization," in *Engineering Computations*, vol. 29, no. 5, pp. 464–483, 2012.
- [17] A. H. Gandomi, X. S. Yang, A. H. Alavi and S. Talatahari, "Bat algorithm for constrained optimization tasks," *Neural Computing and Applications*, vol. 22, no. 6, pp. 1239–1255, 2013.
- [18] I. Fister, D. Fister and X. S. Yang, "A hybrid bat algorithm," *Arxiv Preprint Arxiv:1303.6310*, 2013.
- [19] X. S. Yang, "Bat algorithm for multiobjective optimization," *International Journal of Bio-Inspired Computation*, vol. 3, no. 5, pp. 267–274, 2011.
- [20] R. S. Parpinelli and H. S. Lopes, "New inspirations in swarm intelligence: A survey," *International Journal of Bio-Inspired Computation*, vol. 3, no. 1, pp. 1–16, 2011.
- [21] I. Abd El Kader, G. Xu, Z. Shuai, S. Saminu, I. Javaid *et al.*, "Brain tumor detection and classification on mr images by a deep wavelet autoencoder model," *Diagnostics*, vol. 11, no. 9, pp. 1589, 2021.
- [22] S. Ramesh, S. Sasikala and N. Paramanandham, "Segmentation and classification of brain tumors using modified median noise filter and deep learning approaches," *Multimedia Tools and Applications*, vol. 80, no. 8, pp. 11789–11813, 2021.
- [23] J. Amin, M. Sharif, M. Yasmin and S. L. Fernandes, "A distinctive approach in brain tumor detection and classification using MRI," *Pattern Recognition Letters*, vol. 139, pp. 118–127, 2020.
- [24] D. R. Nayak, R. Dash, B. Majhi, R. B. Pachori and Y. Zhang, "A deep stacked random vector functional link network autoencoder for diagnosis of brain abnormalities and breast cancer," *Biomedical Signal Processing and Control*, vol. 58, pp. 101860, 2020.
- [25] M. M. Badža and M. Č. Barjaktarović, "Classification of brain tumors from MRI images using a convolutional neural network," *Applied Sciences*, vol. 10, no. 6, pp. 1999, 2020.
- [26] M. A. Khan, I. Ashraf, M. Alhaisoni, R. Damaševičius, R. Scherer *et al.*, "Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists," *Diagnostics*, vol. 10, no. 8, pp. 565, 2020.
- [27] P. K. Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen *et al.*, "Brain MRI image classification for cancer detection using deep wavelet autoencoder-based deep neural network," *IEEE Access*, vol. 7, pp. 46278–46287, 2019.
- [28] J. Seetha and S. S. Raja, "Brain tumor classification using convolutional neural networks," *Biomedical & Pharmacology Journal*, vol. 11, no. 3, pp. 1457, 2018.
- [29] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah *et al.*, "Multi-grade brain tumor classification using deep CNN with extensive data augmentation," *Journal of Computational Science*, vol. 30, pp. 174–182, 2019.

- [30] K. Weiss, T. M. Khoshgoftaar and D. Wang, "A survey of transfer learning," *Journal of Big Data*, vol. 3, no. 1, pp. 1–40, 2016.
- [31] S. Gupta, N. S. Punj, S. K. Sonbhadra and S. Agarwal, "MAG-Net: Mutli-task attention guided network for brain tumor segmentation and classification," *Arxiv Preprint Arxiv:2107.12321*, 2021.
- [32] R. Suter, J. R. Blanco and N. G. Ayad, "Epigenetic pathways and plasticity in brain tumors," *Neurobiology of Disease*, vol. 145, no. 3, pp. 105060, 2020.
- [33] C. Ge, I. Gu, A. S. Jakola and J. Yang, "Enlarged training dataset by pairwise gans for molecular-based brain tumor classification," *IEEE Access*, vol. 8, pp. 22560–22570, 2020.
- [34] L. Scarpace, L. Mikkelsen, T. Cha, S. Rao, S. Tekchandani *et al.*, "Radiology data from the cancer genome atlas glioblastoma multiforme [TCGA-GBM] collection," *The Cancer Imaging Archive*, vol. 11, no. 4, pp. 1, 2016.
- [35] P. S. Raja, "Brain tumor classification using a hybrid deep autoencoder with Bayesian fuzzy clustering-based segmentation approach," *Biocybernetics and Biomedical Engineering*, vol. 40, no. 1, pp. 440–453, 2020.
- [36] M. Toğaçar, B. Ergen and Z. Cömert, "BrainMRNet: Brain tumor detection using magnetic resonance images with a novel convolutional neural network model," *Medical Hypotheses*, vol. 134, pp. 109531, 2020.
- [37] N. V. Chavan, B. Jadhav and P. Patil, "Detection and classification of brain tumors," *International Journal of Computer Applications*, vol. 112, no. 8, pp. 1–18, 2015.
- [38] S. Pereira, A. Pinto, V. Alves and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1240–1251, 2016.
- [39] D. J. Hemanth, J. Anitha, A. Naaji, O. Geman and D. E. Popescu, "A modified deep convolutional neural network for abnormal brain image classification," *IEEE Access*, vol. 7, pp. 4275–4283, 2018.
- [40] F. Özyurt, E. Sert and D. Avci, "An expert system for brain tumor detection: Fuzzy C-means with super resolution and convolutional neural network with extreme learning machine," *Medical Hypotheses*, vol. 134, pp. 109433, 2020.
- [41] R. Chelghoum, A. Ikhlef, H. Hameurlaine and S. Jacquir, "Transfer learning using convolutional neural network architectures for brain tumor classification from MRI images," in *Proc. Int. Federation for Information Processing (IFIP)*, Hersonissos, Crete, Greece, pp. 189–200, 2020.
- [42] E. S. S. Biratu, F. Schwenker, T. G. G. Debelee, S. R. R. Kebede, W. G. G. Negera *et al.*, "Enhanced region growing for brain tumor MR image segmentation," *Journal of Imaging*, vol. 7, no. 2, pp. 22, 2021.
- [43] T. Saba, A. S. Mohamed, M. El-Affendi, J. Amin and M. Sharif, "Brain tumor detection using fusion of hand crafted and deep learning features," *Cognitive Systems Research*, vol. 59, pp. 221–230, 2020.
- [44] R. N. Lazuardi, N. Abiwinanda, T. H. Suryawan, M. Hanif and A. Handayani, "Automatic diabetic retinopathy classification with efficientnet," in *Proc. IEEE Region 10 Conf. (TENCON)*, Osaka, Japan, pp. 756–760, 2020.
- [45] A. Pashaei, H. Sajedi and N. Jazayeri, "Brain tumor classification via convolutional neural network and extreme learning machines," in *Proc. Int. Conf. on Computer Engineering and Knowledge (ICCKE)*, Mashhad, Iran, pp. 314–319, 2018.
- [46] S. Deepak and P. Ameer, "Brain tumor classification using deep CNN features via transfer learning," *Computers in Biology and Medicine*, vol. 111, pp. 103345, 2019.
- [47] M. Abdel-Basset, R. Mohamed, N. M. AbdelAziza and M. Abouhawwash, "HWOA: A hybrid whale optimization algorithm with a novel local minima avoidance method for multi-level thresholding color image segmentation," *Expert Systems with Applications*, vol. 190, no. 1, pp. 116145, 2022.
- [48] H. Seada, M. Abouhawwash and K. Deb, "Towards a better diversity of evolutionary multi-criterion optimization algorithms using local searches," in *Proc. of the 2016 on Genetic and Evolutionary Computation Conf. Companion*, Denver, USA, pp. 77–78, 2016.
- [49] M. Abouhawwash and K. Deb, "Karush-kuhn-tucker proximity measure for multi-objective optimization based on numerical gradients," in *Proc. of the 2016 on Genetic and Evolutionary Computation Conf. Companion*, Denver, USA, pp. 525–532, 2016.
- [50] M. Abouhawwash, M. A. Jameel and K. Deb, "A smooth proximity measure for optimality in multi-objective optimization using benson's method," *Computers & Operations Research*, vol. 117, no. 3, pp. 104900, 2020.

- [51] M. Abouhawwash and A. Alessio, “Develop a multi-objective evolutionary algorithm for pet image reconstruction: Concept,” *IEEE Transactions on Medical Imaging*, vol. 40, no. 8, pp. 2142–2151, 2021.
- [52] S. T. Suganthi, A. Vinayagam, V. Veerasamy, A. Deepa, M. Abouhawwash *et al.*, “Detection and classification of multiple power quality disturbances in microgrid network using probabilistic based intelligent classifier,” *Sustainable Energy Technologies and Assessments*, vol. 47, no. 4, pp. 101470, 2021.
- [53] N. Mittal, H. Singh, V. Mittal, S. Mahajan, A. K. Pandit *et al.*, “Optimization of cognitive radio system using self-learning salp swarm algorithm,” *Computers, Materials & Continua*, vol. 70, no. 2, pp. 3821–3835, 2022.