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MRI Brain Tumour Classification using Whale Optimization Algorithm with Back Propagation Neural Network (WOBPNN)

A. Mary Ezhilvani, Dr. A. Geetha

[1]*Research Scholar, Department of Computer Science, Chikkanna Government Arts College, Tiruppur, India, ezhilvani78@gmail.com*
[2]*Head of the Department, Department of Computer Science, Chikkanna Government Arts College, Tiruppur, India, geethagac07@gmail.com*

Brain tumors afflict both children and adults, and their prevalence has dramatically increased over the past few years, placing them as the tenth most prevalent type of tumor. If found early enough, it is also one of the most treatable tumor types. Two techniques that are frequently used for slicing and analyzing abnormalities in terms of shape, size, or location of brain tissues that in turn aid in the identification of malignancies are magnetic resonance imaging (MRI) and computer tomography (CT). A common method for enhancing neural networks' generalization capacities is medical research area which may be thought of as implicit regularization. It is essential in situations when the availability of There aren't many sources of high-quality ground truth data, and finding more examples is expensive and timeconsuming. For many applications in the field of medical analysis, the identification and segmentation of brain tumors from magnetic resonance imaging (MRI) are challenging and crucial tasks. Since each type of brain imaging provides distinct information about each tumor component. This work suggests a classification and concatenation approach for early brain tumor diagnosis to address this issue. Results showed that the suggested method for classifying brain tumors beat current cutting-edge deep learning and machine learning-based techniques by concatenating features from pre-trained models. This study gives a rigorous neural network classification to predict brain cell cancers approach using optimization strategies. Comparing the presented system to any other systems now in use in this field of research, the proposed system's Whale optimization with back propagation neural network (WOBPNN) method produces superior results.

Keywords: Back Propagation Neural Network BPNN, Whale Optimization WO, Brain Tumor BT, Magnetic Resonance Imaging MRI, Tumor Classification, Machine Learning ML.

1. Introduction

Medical clinics provide a variety of services to assist patients in detecting health issues. The field of automated medical assistance systems has several innovative ideas have emerged as a result of recent advances in computer research. We can see that clinics are getting new equipment. Tissues and organs are examined using new microscopes. Exams benefit from multimedia systems. Screening and scan results are evaluated HD displays that offer a highquality presentation for in-depth investigations. The different cell types that make up the human body are diverse. The brain is a sensitive and highly specialized organ. A brain tumor is an extremely hazardous condition that affects people. An intracranial lump known as a brain tumor is created when tissue in or near the brain grows abnormally. Brain tumours decrease with age, whereas non-malignant brain tumours increase with age. Furthermore, People aged 0 to 4 years and 15 to 19 years had a greater overall incidence rate of brain tumors than children aged 5 to 14 years (Amin, Javeria, et al. 2020).

Males in the same age group had a higher incidence of GBM, diffuse astrocytoma, and other gliomas than females. Gender differences in non-malignant brain tumours gradually emerged in 20-year-old adults. The meningioma and pituitary tumors were the ones where the gender difference was most obvious. Non-malignant meningioma incidence rates in individuals over 65 were about twice as high as in men. Women's risk of developing pituitary tumors, on the other hand, decreased with age.

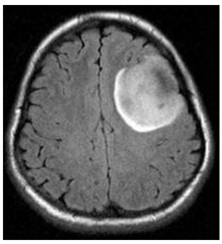
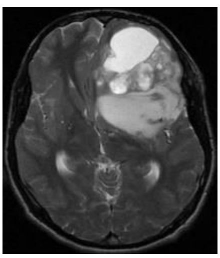
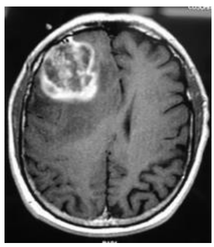
		
meningioma	glioma	pituitary
		
astrocytoma	oligodendroglioma	glioblastoma

Figure 1 types of Tumor cells in Human Brain

Brain tumours are currently a leading cause of death worldwide. Cancer results from the damage to the vital brain tissues. It has a disastrous prognosis, threatens human life (Amin, Javaria, et al. 2019). Despite their therapeutic importance, the mechanisms of CNS involvement are poorly understood. The blood-brain barrier's (BBB) main function is to stop substances from entering the brain from the bloodstream, is critical. Receivers pick up the backscattered bio signals, which are then subjected to the picture reconstruction process in post-processing. Next, the data is post-processed to generate reconstructed images using the image generation procedure (Razzicchia, Eleonora, et al. 2021). To detect brain tumours, various Microwave head imaging techniques have used image reconstruction algorithms. The below figure 1 shows the types of tumor cells from which the hyman brain tissues get affected.

Image Processing Techniques in Healthcare

Medical experts can now diagnose ailments more swiftly thanks to imaging technologies. It also allowed doctors to perform keyhole surgery in order to access internal organs without having to cut too much of the body open. CT scanners, ultrasound, and magnetic resonance imaging have supplanted X-ray imaging because they give medical professionals access to the body's elusive third dimension. To swiftly examine patient complaints, it is best to analyze medical imaging system outputs utilizing image processing algorithms developed for remote sensing data analysis. Digital imaging techniques provide a number of benefits, such as the fact that data is not altered when it is replicated again and maintains its uniqueness, picture enhancement makes work easier for doctors to interpret, and image comparison is quick (Chandy, Abraham. 2019). MRI images can be used to detect brain tumours. Tools for image processing and enhancement are used to raise the caliber of images in medical image processing. The threshold and contrast adjustment techniques are applied to draw attention to specific features in MRI images.

DM techniques allow for the analysis of large amounts of data from various perspectives, yielding valuable information. Automatic brain tumour detection is important the study of medicine. The brain, usually referred to as the body's processor, is one of the many types of cells that make up the human body playing a vital role (Guiot, Julien, et al. 2022). The most crucial component of our neurological system is the brain. Furthermore, it is the foundation of the human central nervous system. Biological sciences' increasing field of digital image processing (DIP) comprises testing and analyzing vital human body parts as well as tumor detection and classification.

Pre-processing

The process of transforming data before passing it to the model is known as preprocessing. The images in the dataset are of different dimensions, and as a pre-processing step, they were resized to 224*224. Furthermore, we used image augmentation to generate different version images and obtain a generalised model (Russo, Carlo, Sidong Liu, and Antonio Di Ieva. 2022). However, the deep learning algorithm's inputs differ, necessitating a proper preprocessing step to remove noise image.

Segmentation

Image segmentation is a particular image processing technique. Image segmentation encompasses a large class of closely related computer vision problems. The overall goal is to transform feature vectors into segmented images after encoding raw images into a feature space. The conventional method of blood vessel segmentation involves classifying data from the local area, such as picture intensity or manually created characteristics (Wadhwa, Anjali, Anuj Bhardwaj, and Vivek Singh Verma 2019).

Feature Extraction

Deep learning has the advantage of teaching the system how to extract features on its own while being trained. Feature extraction is the method of taking the most crucial information out of unprocessed data. Reduced data size, storage needs, improved prediction accuracy, avoidance of overfitting, and shorter training and execution times from clearly understood variables are just a few benefits of feature selection (Toufiq, Dalia Mohammad, Ali Makki Sagheer, and Hadi Veisi.2021).

Classification

It was difficult to classify leaf patterns using an automated system. To extract and classify leaf features, various classifiers based on high performance statistical approaches were used. The plant identification system's final phase is the classification process. Almost all of the methods in this stage are intended to retrieve the processing input from the extraction process in a vector value format (Ayadi, Wadhah, et al. 2021). To recognise the plants, all values will be trained in classification methods.

The major goal of this study is to review and analyze many research publications in order to find various algorithms, filters, and segmentation strategies for brain tumor identification. The remainder of session 2 will discuss the current system used to forecast brain tumors, session 3 will discuss the design of the WOBPNN system that has been proposed, and session 4 will discuss the results of the WOBPNN classification approaches, concluding the study.

2. Literature Review

The methods for segmenting and categorizing brain tumors from MRI images are covered in this section. Manual segmentation of brain anomalies is the standard clinical method, which is based on prior domain knowledge. Manual segmentation takes a lot of effort and can result in classification mistakes. Researchers have developed a number of automated methods over time to address these issues. Existing research indicates that the feature vector, GLCM, statistical System design features, in conjunction with SVM and BPNN, outperform other methods (Jabber, Bhukya, et al 2020). As a feature vector and classifier, it employs multi fractal segmentation in conjunction with intensity features. Because of the anatomical dissimilarity, it may produce undesirable results. We thoroughly study the approaches employed by competitors in the Multimodal Brain Tumor Segmentation Challenge and review the various brain-tumor segmentation algorithms in the literature (Ghaffari, Mina, Arcot Sowmya, and Ruth Oliver. 2019). The best that we can tell, the most complete brain-tumor dataset utilized for verifying established and new algorithms for identifying and segmenting brain tumors. Additionally, it is diverse in that it contains grade lesions included MRI scans were taken MR Image (Sun, Li, et al. 2021).

A sixth paper also disclosed methodological improvements and a reanalysis of data from one of the core studies (Johnson, Matthew W., et al. 2019). The identified studies included a total of 995,091 patients who had been being irradiated with CT. According to these studies, a head CT exam's estimated total radiation exposure to the brain was 419 mGy. Psychiatric symptoms were classified into seven groups were encountered infrequently (Iorgulescu, J. Bryan, et al.2022) also each category will be discussed in detail. Due to a combination of symptoms, some reports may be classified in more than one category. Depression can occur at various stages of a brain tumor's development. Depression was found in 2.5% to 15.4% of primary brain tumour patients. Depression was identified in 44% of patients with primary and metastatic brain tumors and was linked to functional impairment, cognitive dysfunction, poor quality of life, and shortened survival, according to (Zienius, Karolis, et al. 2019). Depression was also found more frequently in frontal lobe tumours. Left frontal lobe tumours, in particular, were more frequently associated with depression. Manual segmentations served as the basis for training of the segmentation model and assessment of the final segmentation performance. Previously, multimodal data were stacked in the same way that multichannel RGB images were. We used FLAIR images in this study to segment the entire tumour region and tumour regions except edoema, which has been shown to be effective. In this study, MRI images are recognized and categorized using an automated process. The Super Pixel Technique and each Super Pixel's classification are the foundations of this method (Sivanantham, Kalimuthu, et al. 2023).

Each super pixel into a tumor and a normal class, the ERT classifier is compared to the SVM classifier. This method uses two datasets: 19 MRI FLAIR images and the BRATS 2012 dataset. The results show that this method, which employs an ERT classifier, performs well. Displacement fields on images can be produced by straightforward manipulations like flipping, rotating, shifting, and zooming, but they will not produce training samples with drastically different shapes (Sivanantham, Kalimuthu. 2022). Shear surgery can slightly distort the global shape of a tumour in the horizontal direction, but it is insufficient to obtain enough variable training data because tumours have no definite shape. To address this issue, we used elastic distortion to generate more training data with arbitrary but reasonable shapes. Images obtained from Images from computed tomography (CT) provide more detailed information when compared to images made from standard X-rays. Since it was initially created, the CT scan has been adopted and widely accepted. One study claims that 4 million of India's 62 million CT scans each year are performed on youngsters (Sivanantham, Kalimuthu, I. Kalaiarasi, and Bojaraj Leena. 2022). CT scans depict numerous soft tissues, blood arteries, and bones that make up the human body. The repeated CT scans may raise the risk of developing cancer. The relationship between CT radiation exposures and cancer risks has been measured.

We offer a supervised deep learning method for identifying changes in synthetic aperture radar (SAR) pictures. Using input photos and images produced by applying morphological operators to them, (Zanotto, Anna, et al. 2023). This method's detection performance demonstrates how deep learning-based algorithms can be used to solve challenges involving change detection. A fully automated strategy for classifying brain tumors is suggested and is based on DNN. The suggested networks are designed to be applied to both high- and low-grade glioblastoma illness images a CNN architecture is presented by (Day, Julia, et al. 2022).

Image Enhancement

Lack of contrast is one of the issues with the acquired image that has been found. Image contrast is significantly impacted by the influence of the fault. When contrast is low, the contrast enhancement method comes into play. To improve contrast, in this instance, each pixel's grey level is scaled. Contrast enhancements improve MRI image visualisation (Heinsch, Milena, et al. 2022). The process of dividing Using image segmentation, a digital image is divided into several parts. Each pixel in an image is given a label during the process of image segmentation, allowing pixels with the same name share specific visual information properties (Ghaffari, Mina, et al. 2019). Edge detection is a technique used in image processing to locate the edges of objects in photographs. It detects changes in light to function. Edge detection is used in image processing, computer vision, and machine vision for image segmentation and data extraction. The approaches of Sobel, Canny, Prewitt, Log, and Zero cross are common edge detection algorithms (Uthra Devi, K., and R. Gomathi. 2021). In MRI scans, object boundaries are located using edge detection techniques, and the outcomes are astounding.

3. System Design

This session discussed about the system design of proposed system With the Whale Optimization Algorithm and a back-propagation neural network, classify MRI brain tumors.

Pre-processing

A step before feature extraction and image recognition is called image pre-processing. No matter what image acquisition methods are used, the input images are never sufficient. For instance, the image has noise, the area of interest is blurry, or other objects are interfering with the image, among other things. Different image applications require different pre-processing techniques.

Segmentation

Edge-based segmentation separates an image based on abrupt changes in intensity at the edges, as opposed to region-based segmentation, which splits an image into pieces that are comparable based on a set of predetermined criteria. The key examples of approaches in this area are thresholding, region increasing, region splitting, and region merging.

Feature extraction

In the field of image processing, features are crucial. The sampled image is put through a number of image pre-processing techniques, such as binarization and thresholding, before getting features, scaling, normalizing, etc. Afterward, by utilizing feature extraction methods, features that will be useful in classifying and identifying photographs are obtained. Techniques for feature extraction can be used in many applications for image processing. After preprocessing, character recognition systems do character extraction. To accurately classify an input pattern as one of the possible output classes is the primary objective of pattern recognition.

Whale Optimization

The after the features are obtained from the image it is optimized using whale optimization techniques and classifies using Back propagation neural network. The ground breaking mathematical system known as the "whale optimisation algorithm" mimics the cooperative predation strategies used by humpback whales. The algorithm's update process is made up of the three techniques of encircling prey, attacking with bubble-nets, and looking for prey. Both the coefficient vector A with the random probability component p concurrently have an impact on these tactics. The below figure 2 explain about the whale optimization flow clearly.

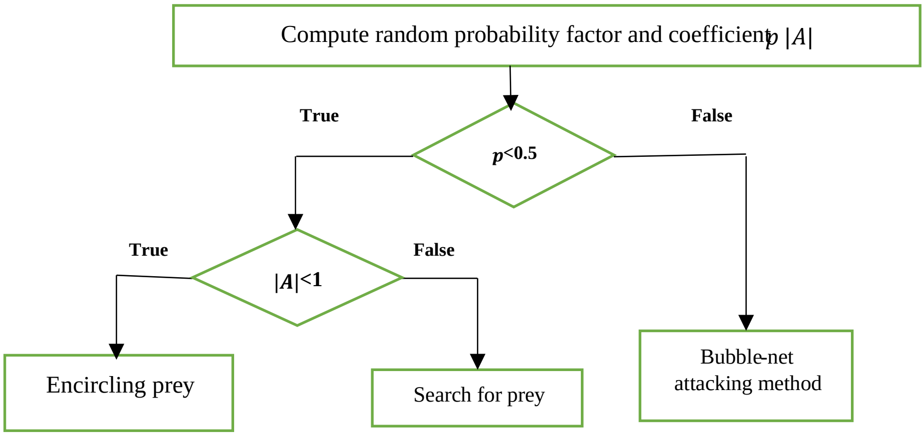


Figure 2 Whale Optimization Flow

Encircling prey

The best candidate solution at the time is treated by the WOA algorithm as the prey or approximate optimum because the optimum cannot be predetermined during population initialization. After locating the prey (the ideal whale individual), gradually change their posture to approach the prey closer. The appropriate location update formula has the following definition:

$$\vec{D} = |\vec{C} \cdot \overrightarrow{X(t) - \vec{X}}(t)| \qquad (1)$$

$$\vec{X}(t+1) = \vec{X}(t) - \vec{A} \cdot \vec{D} \qquad (2)$$

X (t) If a better position is found in a later iteration, the value will be changed if t represents the current iteration and X represents the current individual whale, (X*) indicates the multiplication of one element by one element, the length of the renew-step, and (A) D, the best whale (the prey) so far. The formulas below can be used to calculate the coefficient vectors for A and C. Where a=22t/ t_{max} is a convergence factor and t_{max}.

$$\vec{D}' = |\vec{X}^*(t) - \vec{X}^*(t)| \qquad (3)$$

$$X(t+1) = \overrightarrow{D'} . e^{bl} . \cos(2\pi l) + X^*(t) \qquad (4)$$

Whale Optimization Algorithm (WOA) Input:

Number of whales in the pack, n;

Control Coefficient, au;

Maximum number of iterations, MAX_ITER; Output:

Global best whale position, Y_{best}

Best fitness value, fit (Y_{best})

begin

Create the initial n whale population Y_i (i=1,2,...,n)

Set iteration counter $t_{our} = 0$

Compute the fitness of each whale

Decide which whale is the best depending on fitness, i.e., Ybest while (t_{our}<MAX_ITER) for each whale do

Using Eqs. 3 and 4, calculate the control coefficients A and C.

if (Rand <0.5) if (|A|<1)

Update the position of the current whale by Eq.2

else if (|A|>=1)

Select a random whale, Y_{rand}

Update the position of the current whale by Eq. 9

end if

else if (Rand ≥ 0.5)

Update the position of the current whale by Eq. 5

end if end for

Compute the fitness of all whales

Update the value of Y_{best} based on fitness Increment the current iteration t_{our} by 1.

end while

return the best solution, Y_{best} end

Figure 3 Pseudo-code of whale optimization algorithm

In the equation [1,1], in most cases, has the value 1. This constant determines how the spiral will look. When |A|1 in the optimization process occurs, whales choose the optimal choice bubble-net 50% likely to approach the target by assaulting or encircling it. The above figure 3 explain about the Pseudo-code of WO algorithm.

Search for prey

Whale Optimization with Back Propagation Neural Network (WOBPNN)

After the optimization process is over BPNN is used for classification process that are listed in the below.

BPNN Back Propagation neural network

Parameter Initialization

Here, the weights and biases of an artificial neuron are randomly initialized. The network feeds the input forward and creates associations with weights and biases in order to produce the output. With such random values, the outcome is almost probably wrong. We will now examine feedforward propagation as our next topic.

Feedforward propagation

After initialization, the input is propagated into hidden units at each layer when it is sent to the input layer. The nodes in this system do not adapt their operations in response to the findings since they are unaware of how accurate they are. The output layer is then responsible for producing the output. The back propagation algorithm's primary objective is to minimize the error values in weights and biases that are randomly assigned in order to produce the desired result. By demonstrating to the system the gap between its output and a known expected output and then using that knowledge to change the system's internal state, the supervised learning method is used to train the system. To get the least overall loss, we must change the weights. This is how neural network back propagation functions.

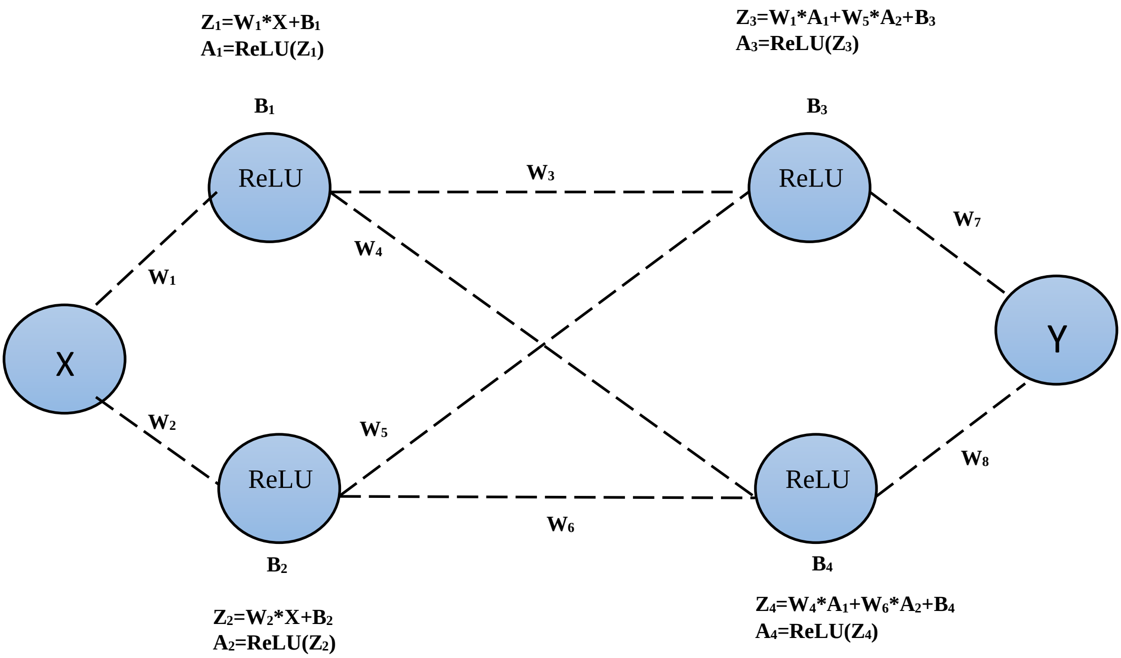


Figure 4 Back propagation neural network classification

By linearly combining the input x with w1 and b1 and w2 and b2, respectively, we can obtain z1 and z2. The values a1 and a2 are obtained by independently applying the RelU activation function to z1 and z2, respectively. A1 and A2 from the preceding layer are linearly mixed with w3, w5, b3, and w4, w6, b4 to produce z3 and z4. A3 and A4 of the preceding stratum.

4. Result and Discussion

According to our system, the main focus of the suggested system is on the prediction of human brain tumors utilizing the WO+BPNN algorithm approach in conjunction with our system to predict the brain tumor using machine learning. The input image for our suggested system is shown in Figure 5 a). After obtaining the MRI input that was distorted. To remove noise from the input image, the system is then processed to pre-processing mode. The diseased and unaffected parts of the brain are likewise divided using this technique. After the noise in the MRI Brain image has been eliminated, Figure 5 b) shows an accurate image.

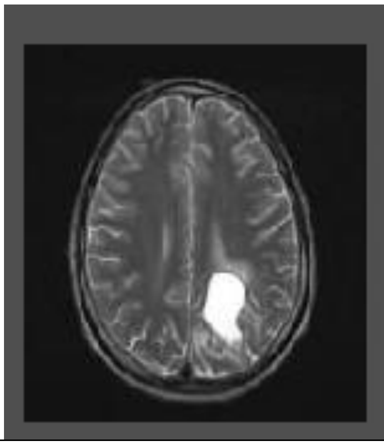
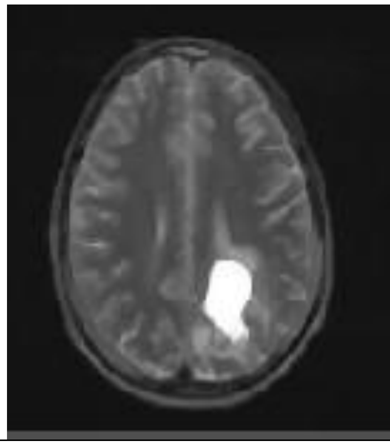
	

Figure 5 a) Input image	b) Pre-processed image

Segmentation of result

In the input MRI Brain, our method separates the damaged and unaffected parts. The following stage is to segment the brain. During this session, just the affected portion of the brain was kept; the rest was discarded. Figure 6 displays our system's segmentation results.

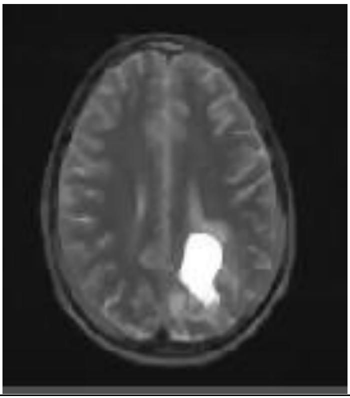
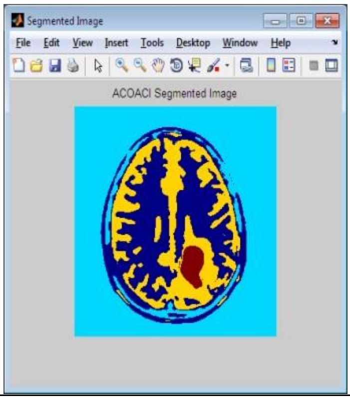
	

Figure 6 Pre-processed image	Segmented image

Whale Optimization

Based on optimization techniques, the suggested algorithm is applied to the detection of leaf diseases. The whale optimization is being used in this case. Figure 7 below displays the photos used for optimization.

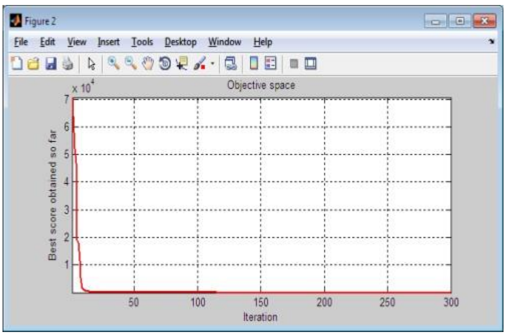
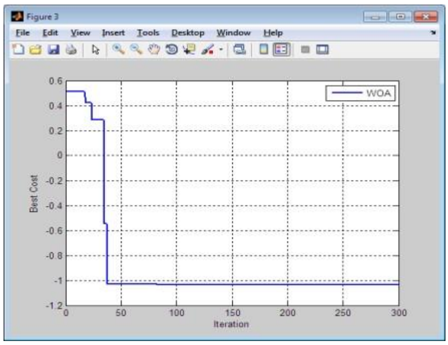
 	

Figure 7 Whale Optimization	

Back propagation neural network Classification

The diseases that influence each tumor type are taught to the BPNN classifiers. The classifier, which has been trained to categorize a range of brain tumors, is called up using the classification results. The process of classification divides a given collection of data into classes. The model is trained, evaluated for performance, enhanced with a cost function, and then prepared for deployment after the problem has been formulated.

Confusion Matrix

A strategy that is substantially more effective for assessing a classifier's performance is looking at the confusion matrix. The fundamental concept is to count the instances of the class that are marked as class B.

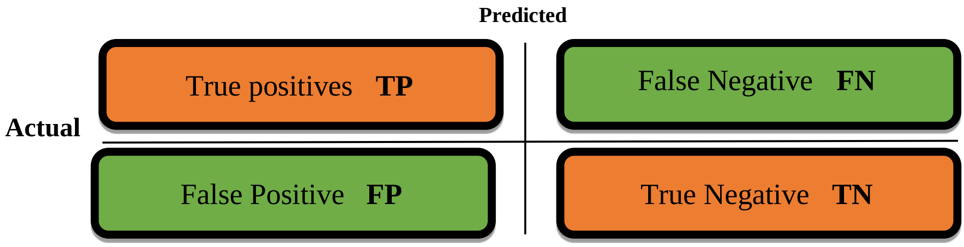


Figure 8 confusion matrix

True Positives: When we predicted "Yes," the actual result was also "Yes".

True Negatives: When we predicted "No," the actual result was also "No".

False Positives: When we expected "yes," the outcome was really "no".

False Negatives: This is the situation that we predicted. No, but in reality, it was.

Time consumption: Choosing the best machine learning model to solve a problem can be time-consuming if done carelessly.

Table 1 table for Time consumption

	Existing system				Proposed System
Algorithm	Decision tree	SVM	KNN	BPNN	WOBPNN
Time consumption	6.71	5.6357	4.88	8.618	3.21

The results from the existing and suggested systems are explained in the above table 1. In addition, the suggested system of WO with BPNN gives a Time consumption of 3.21 Ms, which is 1.67 Ms faster than the existing system. It demonstrates that the present system of Decision Tree, SVM, KNN, and BPNN gives results of (6.71, 5.6357, 4.88, and 8.618). The below figure 9 shows the result of the table 1 in the form of graph.

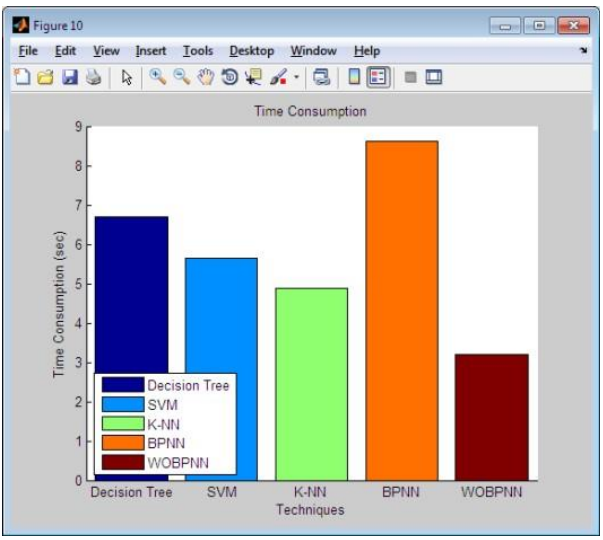


Figure 9 Time consumption Graph

Precision: False positives are abbreviated as FP, whereas true positives are abbreviated as TP. A straightforward method to obtain perfect precision (precision = 1/1 = 100%) is to make one correct prediction. This would not be particularly useful because the classifier will discard everything but the one affirmative occurrence.

Precision = (TP) / (TP+FP)

Table 2 table for Precision

	Existing system				Proposed System
Algorithm	Decision tree	SVM	KNN	BPNN	WOBPNN
precision	85.87	87.91	85.13	95.08	97.89

The results from the existing and suggested systems are explained in the above table 2. In addition, the suggested system of WO with BPNN gives a precision of 97.89%, which is 2.81% greater than the existing system. It demonstrates that the present system of Decision Tree, SVM, KNN, and BPNN gives results of (85.87, 87.91, 85.13, and 95.08). The below figure 10 shows the result of the table 2 in the form of graph.

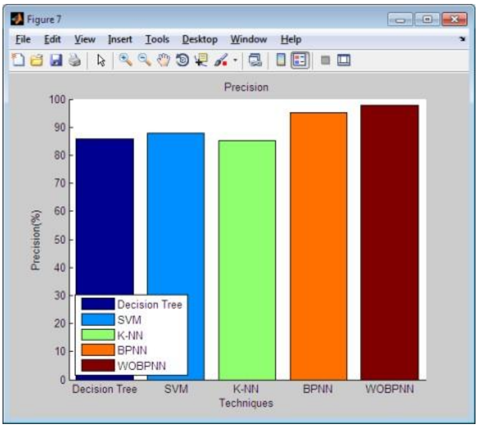


Figure 10 Precision Graph

Accuracy: Accuracy (ACC) is calculated by dividing the total number of correct predictions by the size of the entire dataset. From 1.0 (highest) to 0.0 (least), the accuracy scales.

Accuracy = (TP+TN) / (TP + TN + FN+FP)

Accuracy = (TP+TN) / (P+N)

Table 3 table for Accuracy

	Existing system				Proposed System
Algorithm	Decision tree	SVM	KNN	BPNN	WOBPNN
Accuracy	82.41	87.07	83.69	93.68	97.08

The outcomes of the recommended and existing systems are described in the table 3 above. Additionally, the proposed WO with BPNN system provides an accuracy of 97.08%, which is 3.4% higher than the current system. It proves that the current Decision Tree, SVM, KNN, and BPNN system produces results of (82.41, 87.07, 83.69, and 93.68). The table'3 results are presented as a graph in the figure 11 below.

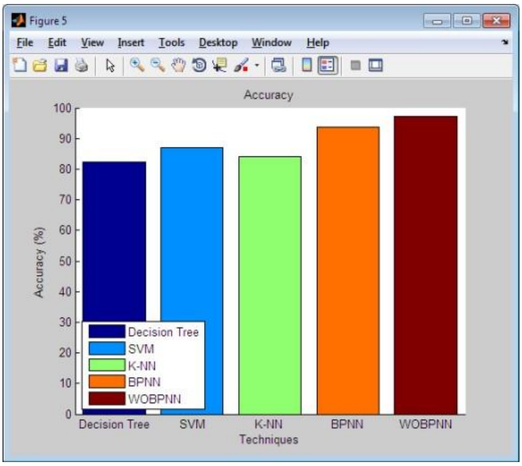


Figure 11 Accuracy Graph

Sensitivity: Sensitivity is obtain by dividing the proportion of TP predictions to all positive predictions. It is also known as the true positive rate (TPR) or the recall (REC). The highest sensitivity is 1.0, and the lowest is 0.0.

Sensitivity = (TP) / (TP+FN)

Table 4 table for Sensitivity

	Existing system				Proposed System
Algorithm	Decision tree	SVM	KNN	BPNN	WOBPNN
sensitivity	79.40	87.50	83.62	93.17	96.88

The table 4 above lists the results of the suggested and current systems. Additionally, the Sensitivity of the proposed WO with BPNN system is 96.88%, which is 3.71% greater than the Sensitivity of the existing system. It demonstrates that the results produced by the existing Decision Tree, SVM, KNN, and BPNN system are (79.40, 87.50, 83.62, and 93.17). The findings of the table 4 are shown as a graph in the figure 12 below.

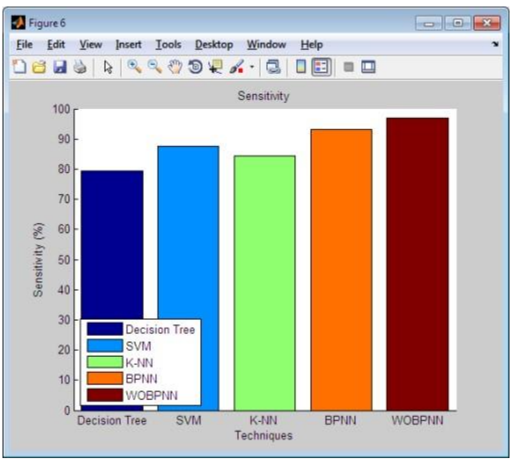


Figure 12 Sensitivity Graph

Specificity: It is calculated by dividing the sum of negatives divided by the quantity of accurate negative forecasts. The term "true negative rate" (TNR) is another name for it. Specificity ranges from 1.0 to 0.0, with 1.0 being the highest.

Specificity = (TN) / (TN+FP)

Table 5 table for Specificity

	Existing system				Proposed System
Algorithm	Decision tree	SVM	KNN	BPNN	WOBPNN
Specificity	85.71	86.60	83.62	94.29	97.33

The outcomes of the proposed and existing systems are shown in the table 5 above.

Furthermore, the suggested WO with BPNN system has a Specificity of 97.33%, which is 3.04% higher than the Sensitivity of the current system. It illustrates that the current Decision Tree, SVM, KNN, and BPNN system produces the following results: (85.71, 86.60, 83.62, and 94.29). The graph in the following figure 13 displays the table 5 results.

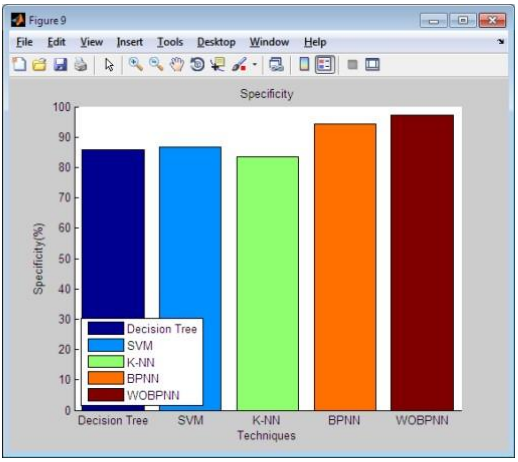


Figure 13 Specificity Graph

F1- Score: The F1-score is one of the most important evaluation metrics in machine learning. By merging two previously incongruent signs, it elegantly represents a model's performance in making predictions.

F1- Score = (TP) / (TP+FP)

Table 6 table for F1-score

	Existing system				Proposed system
Algorithm	Decision tree	SVM	KNN	BPNN	WOBPNN
F1-score	82.51	87.70	84.69	94.12	97.38

The table 6 above displays the results of the suggested and current systems. Additionally, the F1-score of the proposed WO with BPNN system is 97.38%, which is 3.26% higher than the Sensitivity of the existing system.

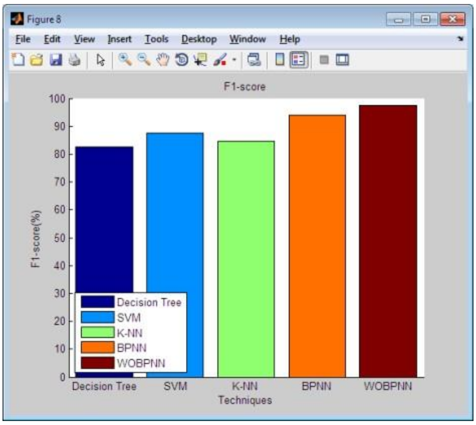


Figure 14 F1-score Graph

The results show that the existing Decision Tree, SVM, KNN, and BPNN system generates the following outcomes: (82.51, 87.70, 84.69, and 94.12). The outcomes of the table 6 are shown in the graph in the following figure 14.

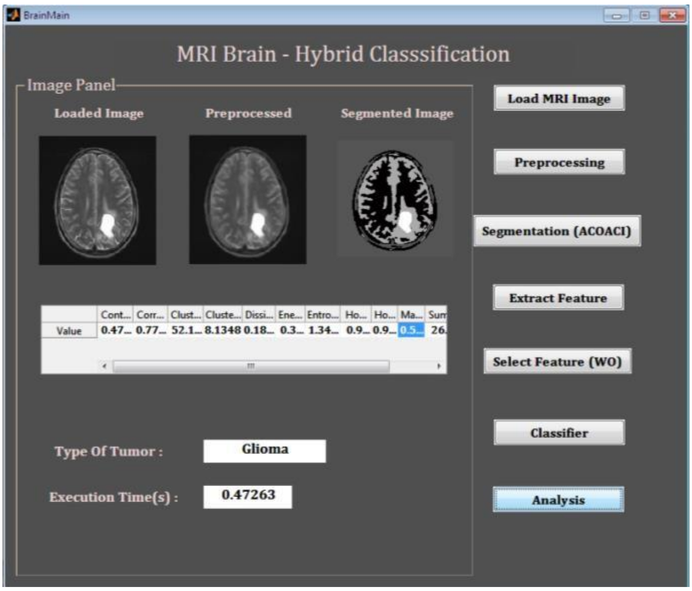


Figure 15 Final GUI image for Brain tumor prediction

The most important stage of categorization sessions is determining which tissues a glioma tumor would affect and how much of it will damage in a certain area, as shown in the above image 15.

5. Conclusion

The characterization of the MRI modalities has helped us create a new brain tumor classification architecture in this research. The brain tumor was then classified using a softmax classifier after these features were concatenated. Because the number of occurrences of brain tumors had significantly increased in recent years, researchers and scientists working in related fields have found it the interesting task of developing accurate tumor diagnosis techniques. Although the findings of the suggested approach are superior to those of other recently released models, our algorithm still has more restrictions than the current whole brain tumor prediction system. This is as a result of a decrease in feature extraction efficiency brought on by an increase in the estimated tumor area. The proposed approach achieved the highest performance in the detection of brain tumors, resulting in testing samples with a testing accuracy of 97.08%. In the future, we will investigate and put these methodologies to use to classify brain cancers, we applied data augmentation techniques on scratch-based models and pre-trained models that were trained with additional layers. Finally, the proposed techniques WOBPNN in this research help in both single-modal and multi-modal scans can readily use these methodologies, often by synthesizing false instances individually for each picture modality.

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