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ORIGINAL ARTICLE **OPEN ACCESS**

Enhanced Classification Method of Brain Tumor from MRI Images Using Swarm Intelligence based Convolution Neural Networks

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ABSTRACT

Since human brain tumours are the most common form of tumour affecting both men and women, image processing-based medical diagnosis has seen a significant rise in recent years. It is, however, curable if it is detected and classified at an initial stage. Researchers have been working on a complex mechanism for classifying human brain tumours for a long time. The use of image processing to classify tumours from Magnetic Resonance Imaging (MRI) is common in the detection of brain disorders. So, utilizing Convolution Neural Network (CNN) as a deep learning, a swarm Intellect - Based Improved Brain Tumor Segmentation and Classification (I-BTSC) model is built from MRI images in this research work. First, we use the Swarm-based Grasshopper Optimization (SGO) algorithm to segment tumour regions using the conventional K-means concept. Following tumour region segmentation, feature extraction is used to determine the feature collection, and the fitness role is again served by SGO-based feature selection. Finally, CNN is used as a deep learning methodology to train the suggested I-BTSC system, which is then calculated. The suggested I-BTSC system is simulated using a publicly accessible "Contrast-Enhanced MRI Dataset", and the outcomes show that the suggested model is more efficient than previous research work in terms of performance measures.

Keywords*: Cancer, Brain Tumour, Image segmentation, CNN, K-means, PSO, GOA and MRI Images*

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INTRODUCTION

Intellect Image Processing (IIP) method is an effective tool for analyzing an artificial intelligence-based image based on its texture, pattern, shapes, colours, and interactions among existing pixels that are not interpreted by the human eye [1]. IIP approaches have become a popular research subject in the industrial and medical fields due to their ability to deal with a variety of mathematical operations to produce an improved, segmented, and labelled image. In the medical sector, image segmentation to achieve an exact Region of Interest (ROI) is a popular technique that is used to classify a variety of human diseases using imaging. As a result, in today's medical diagnostic method, image segmentation and classification are critical for a variety of applications, including the identification of heart, skin, lung, brain, and other tumours using available features patterns [2]. Many computer assisted diagnostic devices have been proposed by researchers in the history of healthcare imaging to support medical practitioners in detecting the most lethal disorders of human ailments such as brain tumours when evaluating "Magnetic Resonance Imaging (MRI)" scans. In this case, we wanted to build on previous work by using image segmentation and classification of brain tumours from MRI at an earlier level. In the proposed work, we first develop a segmentation model to provide high-end brain tumour classification by extracting the function of exact tumour ROI. Since the brain is the most vital structure (organ) of the human body, it regulates the core nervous system and has an enormous neural network of nearly hundred billion nerve tissues and cells. [3]. Most common cause of tumour growth is uncontrolled tissues, which can be fatal at some stage.

As per the American Cancer Society (ACS), there will be about 23890 people diagnosed with a new malignant brain tumour by the end of 2020 [4]. These diseases affect approximately 57 percent (in count 14000) of males and 44 percent (in count 10800) of females out of a total of 24800. The number of people who are affected by benign brain tumours is lower than those who are affected by malignant brain tumours. The ACS estimated these values based on the previous year study, and the detailed visual examination of previous years of cancer statistics by age group from 2014 - 16 is revealed in Fig. 1.

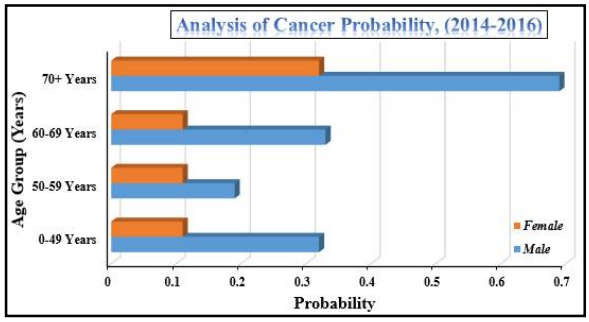

Fig 1: Study of Tumor [4]

Based on ACS survey data from 2014 - 16, the chance of having cancer in men is much higher than in women. As per a 2018 survey done by United News of India (UNI), brain tumour patients ranked tenth position in India, and it is the most serious subject for medical practitioners and experts [5]. There were estimate data of cancer cases from 9,79,786 cases in 2010 to 11,48,757 cases in 2020 [6] in another study at lancent conducted at ICMR (Indian Council of Medical Research). The primary motive for brain tumour segmentation and classification research is to develop an efficient diagnostic method to aid medical professionals in tumour identification at an initial stage, thus saving human lives. In a stable human brain, new cells are formed and old cells die, but if this mechanism is disrupted, old cells existence with surplus evolution of new cells results in a mass of tissue known as a tumour. If early detection of tumours is feasible, medical professionals would be able to save human lives by using the principle of IIP. So, in this study, we suggested a swarm intelligence-based brain tumour classification method focused on MRI images employing deep neural networks, with the following significant contributions:

- The suggested model is tested using a publically accessible Contrast-Enhanced MRI datasets that was collected from two Chinese medical universities between 2005 and 2010, the first being "Nanfang Hospital " and the second being "General Hospital.".
- An Improved Brain Tumor Segmentation and Classification (I-BTSC) method from MRI images is suggested depending on the efficient hybrid segmentation approach, using the principle of CNN (Convolutional Neural Network) as a deep learning with named feature trends.
- An enhanced Brain Tumor Segmentation and Classification (I-BTSC) method from MRI images is implemented using the principle of Convolutional Neural Network (CoNN) as a deep learning with labeled feature patterns, focused on the effective hybrid segmentation approach.

The suggested model for MRI images of the brain in this study includes five steps: “Pre-Processing, Segmentation, Feature Extraction, Feature Selection, and Training/Classification”. Pre-processing steps, on the other hand, are used to boost image quality and data conversion [6]. Final experimental results are analyzed to determine the best grouping of segmentation methods employed in the I-BTSC scheme under examination. The use of swarm intellect at the segmentation and feature selection stages from the extracted named feature set to effectively train the model to help the classification phase exemplifies the innovation of the proposed I-BTSC method. In this research, CNN is used employed at the training and classification stages of the suggested I-BTSC method, with SGO-based feature selection utilizing fitness criterion being used as inputs by CNN to train and classify test MRI images into malignant or benign brain tumours in 3 main groups.

Further the research paper is structured as follows: The second part delves into the methods for segmenting and classifying brain tumours. The methodology of suggested I-BTSC's model is outlined in part 3, and the experimental findings are shown in part 4. In Section five, the conclusion is discussed, along with future investigations. Since the medical diagnosis research community is already using several techniques to improve the output frameworks, a brief review of brain tumour segmentation and classification algorithms is discussed in this section. We present a wide range of related research from a lot of researchers who used specific methodologies for segmenting and classifying brain tumours from MRI images. "H Mohsen et al." published a study in 2018 that used a DNN model to classify brain tumours from MRI images into three tumour classifications: "Glioblastoma, Metastatic Bronchogenic Carcinoma, and Sarcoma." At the feature extraction point, the researchers compared the principle of Discrete Wavelet Transform (DWT) with the well-known Principal Component Analysis (PCA). The researchers therefore conclude through the results of experiments that precision, recall, and f-measure were all 0.970, with ultimate classification accuracy of 96.970 percent. Just 64 brain MRI images were used in the research. Authors suggested that the design be changed in the further research work to reduce the execution time for processing large MRI images [9]. Then, in 2019, AR Deepa and WRS Emmanuel implemented a brain tumour classifier model founded on the principle of image processing, which included steps such as pre-processing to reduce fluctuations in MRI images, Gabor wavelet-

oriented feature extraction, and Kernel Principal Component Analysis (KPCA) for selecting the most important features, preceded by feature fusion utilizing Gaussian Radius (GRBF). The computational review of the model's performance over the publicly accessible Brain Tumor Segmentation (BraTS) dataset revealed a high Jaccard coefficient of 96.89 percent, precision of 98.47, and sensitivity of 97.24 percent [10]. By using principle of Convolutional Neural Networks (CNN), M Sajjad et al. developed an efficient model for highly tuned datasets in the same year. Softmax had been employed to train and classify brain tumours during the training and classification stages. The suggested work was simulated using both the enhanced dataset and the initial brain tumour dataset in the assessment report. Ultimately, the results shows a classification rate of success of 94.580 percent against an enhanced dataset [11]. In the year 2020, MM Badza and MC Barjaktarovic carried out research to create a brain tumour classification model from MRI images using CNN as a classifier. The authors of the article create a new CNN model to train and identify brain tumours into three different categories. The new CNN was much less complicated than the current pre-trained CNNs model, and the researchers utilized a dataset of contrast-improved MRI images. Compositions of two 10-fold cross-validation approaches were used to authenticate the model, and the accurateness was approximately 96.56 percent [12]. M Togaçar et al. developed a deep CNN-based framework for MRI-based brain tumour classification. This framework made use of an effective function that was chosen using the RFE technique and an SVM classifier. The use of SVM and RFE at the feature selection level considerably lowered the feature set sizes, culminating in classification precision, sensitivity, and specificity of 96.770 percent, 97.830 percent, and 95.740 percent, respectively. This research also ignored the possibility of using optimization techniques and the Guided Acyclic Graph (DAG) as a deep learning resource to enhance brain tumour classification [13]. In the same year, Cinar and Yldrm suggested a deep learning focused Convolutional Neural Network for brain tumour classification utilizing MRI images in that same year. The last five levels of Resnet50 were substituted with eight new levels in the prototype architecture. The updated deep learning CNN illustrated 97.20 percent classification accurateness when tested against tumour and normal groups. All present models such as Alex-net, Google-net, Densenet201, Resnet50, and Inception [15] had compared with suggested method and the outcomes shows that the proposed model is outperformed all other present models.

The researcher presents a comparison table for classification and optimization methods employed in earlier models that inspired us to develop an I-BTSC method based on the above review of present research work in the field of brain tumour segmentation and classification. Easy classifier-based models, CNN-grounded models, and enhanced CNN-based brain tumour classification models with swarm-dependent optimization are the three types of tumour classification models. The comparable view of the examined work is described in Table I. The alternative steps taken in the evaluated work are shown in the last four sections. We present our own structure to examine the impact of preprocessing methods in the last row. According to the results of the study, medical imaging segmentation and classification of brain tumour regions is extremely difficult. Although the idea of CNN as a classifier is quite successful, few studies concentrated on acceptable segmentation frameworks when it comes to segmentation. As a result, we employed the principle of enhanced segmentation with K-means and SGO as an optimization technique, followed by CNN as a classifier.

Figure 2. Optimizer and classifier used in Survey

Work	Dataset	Techniques
H Mohsen et al., 2018	Harvard Medical School Dataset	**Segmentation:** FCM **Feature:** DWT **Optimizer:** PCA **Classifiers:** DNN
AR Deepa and WRS Emmanuel, 2019	BraTS Dataset	**Segmentation:** FCM **Feature:** Gabor wavelet **Optimizer:** Firefly **Classifiers:** Adaptive firefly backpropagation neural network classifier
M Sajjad et al., 2019	Radiopaedia brain tumor Dataset	**Segmentation:** × **Feature:** × **Optimizer:** × **Classifiers:** CNN
MM Badza and MC Barjaktarovic, 2020	Contrast-Enhanced MRI Dataset	**Segmentation:** × **Feature:** × **Optimizer:** × **Classifiers:** CNN
M Togaçar et al., 2020	Kaggle Brain MRI Images	**Segmentation:** FCM **Feature:** DWT **Optimizer:** Recursive Feature Reduction **Classifiers:** CNN with Support Vector Machine (SVM)
Çinar and Yıldırım, 2020	Kaggle Brain MRI Images	**Segmentation:** × **Feature:** × **Optimizer:** × **Classifiers:** CNN

MATERIAL AND METHODS

We suggested a swarm intelligence-focused I-BTSC method from MRI images utilizing CNN as a deep learning in this research paper. We used a deep learning approach that combined SGO and CNN to train the I-BTSC system by choosing a collection of appropriate feature sets. To simulate and verify the effectiveness, the suggested model comprised of the following main elements: MRI benchmark dataset collection, pre-processing MRI images, recombination for ROI segmentation, feature extraction, feature selection, and training/classification. Figure 3 depicts the I-BTSC system's flow map.

MRI Benchmark Dataset: It comprises approximately 3060 slices of brain MRI images obtained from the BRATS database of two Chinese hospitals, Nanfang Hospital and General Hospital, Tianjin, between 2006 and 2010. This dataset contains three different types of brain tumours. "Meningioma, Glioma, and Pituitary" tumour are represented by images 710, 1425, and 931, collectively. In general, meningioma and glioma are malignant or cancerous tumours, while pituitary tumours are benign or non-cancerous. From 223 patients, all available MRI images data were obtained in three planes: sagittal (1025 images), axial (994 images), and coronal (1045 images). Figure 3 shows a range of different types of tumours in various planes. The ROI of brain tumours is shown by a bright red line.

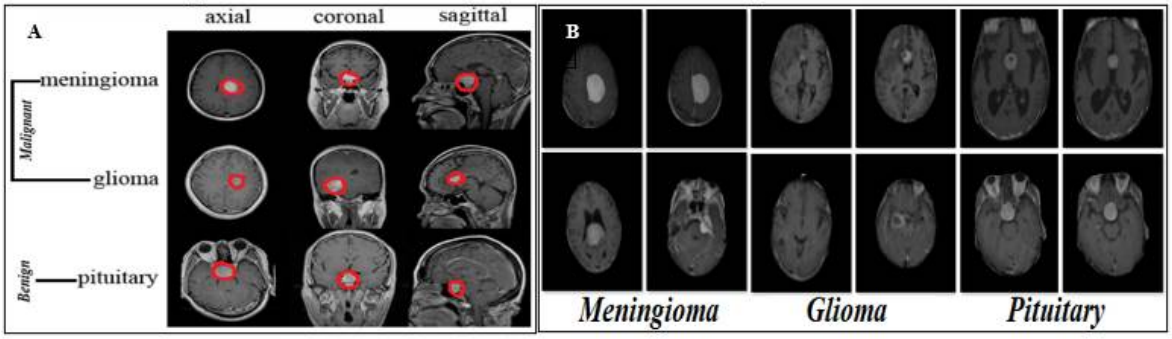

Fig. 3. Illustration of Magnetic resonance images (A) with plane (B) considering tumor categories

An I-BTSC framework is constructed who based on aforementioned. dataset and the entire process is depicted in Fig.4. The suggested model's entire operating phase portrays the operational structure of a module that aids in the segmentation and classification of brain tumours from Magnetic Resonance images.

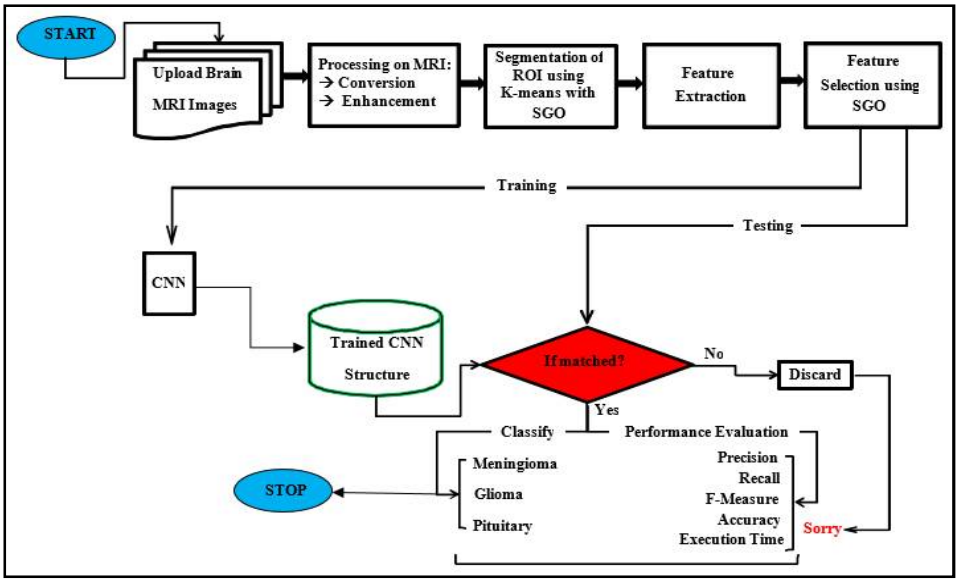

Fig.4. Flow chart of the Proposed I-BTSC System

The operating framework of the suggested model, which is illustrated in the flowchart, consists of four stages: "Pre-processing, Segmentation utilizing K-means with SGO method, Feature Extraction, and SGO-based feature selection again". An additional phase is included here, known as the CNN-based I-BTSC scheme, which involves both preparation and classification.

The following section goes through all of the stages involved in designing an I-BTSC device in great detail:

MRI Image Pre-processing:

The first step in designing an I-BTSC device is to enhance the MRI image quality. It is the first step after upload the MRI images, and it involves performing intensity-focused image enhancement with the principle of limiting. Limiting means that, the contrast and intensity of every pixel of the image are enhanced within some range by utilising the mathematics formula of equation 1.

$$I_{MRI} = (MGRI - MGRI_{I_L}) \frac{MGRI_{I_H} - MGRI_{I_L}}{MGRI_{I_H} - MGRI_{I_L}} + MGRI_{I_L} \quad (1)$$

Assume that MGRI is the initial MRI image with 256 X 256 dimensions and total 'n' no. of pixels, each with its own pre-determined max. and min. intensity values based on restricted clipping and averaged pixel value. The average number of pixels in an MRI image is defined by equation 2.

$$PX_{avg} = \frac{PX_{(reg-x\_axis)} \times PX_{(reg-x\_axis)}}{GMRI_{Image}} \quad (2)$$

Where, $P_{(reg-x\_axis)}$ indicates the number of pixels along x-axis in a clipped region (PCLIP). The minimum and maximum intensity value of the MRI image is illustrated by MGRIIL and MGRIIH respectively. The implemented pre-processing process on MRI image is illustrated in Fig. 5.

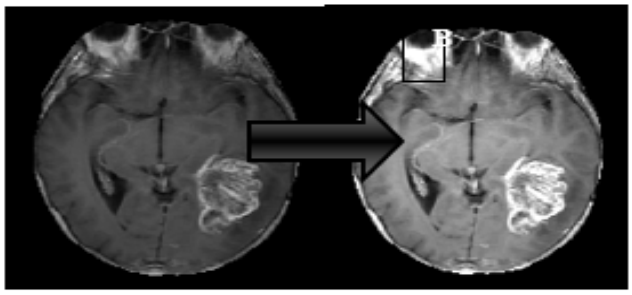

Fig.5.Pre-processing of MRI image

The principle of color transformation using equations is used in the initial stage of pre-processing of MRI images (3).

$$GMRI_{Image} = 0.3R + 0.59G + 0.115B \quad (3)$$

Where, GMRI Image is the grey level MRI image that is achieved afterward the color transformation utilizing above equation and in next stage MRI image improvement is accomplished that is shown in the Fig. 5. With of aid of the restricted clipping principle, an intensity-based image quality improvement is performed after the colour transformation process. Pre-processing allows for more accurate tumour ROI segmentation from MRI images.

Tumor ROI Segmentation:

Tumor area segmentation is done utilizing conventional and hybrid mechanisms after pre-processing of MRI images. The brain tumour ROI is segmented using the standard K-means segmentation method, but since K-means is an un - supervised clustering technique, it faces the irrelevancy segmentation issues depending on the pixel range. The segmentation stage is depicted in Figure 6.

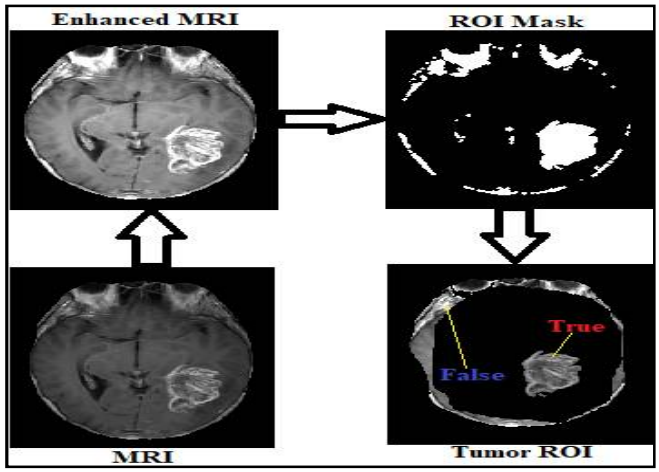

Fig.6. ROI Segmentation

Because of their matching ability, the segmentation of the K-means clustering method is accurately outlined with a yellow colour line coded with "False" in the above diagram, and it is necessary to reduce it by using the definition of the SGO optimization. To conclude on the SGO method as an optimization, we combined K-Means with SGO and used it to substitute an uncommon methodology with a good combination and create a compatible solution in the suggested I-BTSC method based on MRI images. We used a hybridization of ROI segmentation and colour labels using K-means, as shown in Fig 6, where CL stands for colour label utilizing K-means.

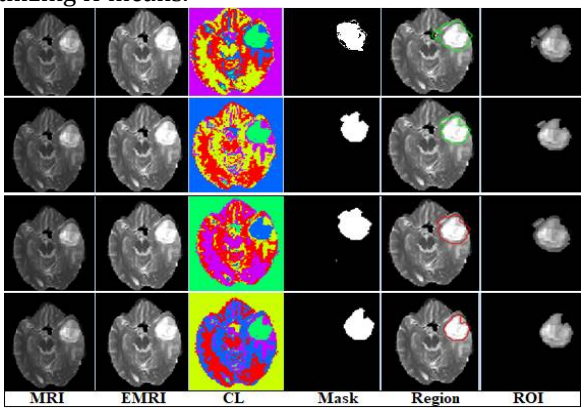

Fig.7. ROI Extraction using K-means with SGO

According to the findings, the suggested K-means using SGO algorithm solved the pixel merging problem better. The improved algorithm of K-means with SGO is as given below:

Algorithm 1: Improved K-means using SGO

Input: "IMPROVED MRI IMAGE →IMRI_IMG"
Output: "BACKGROUND AND FOREGROUND OF MRI IMAGE IN TERMS OF TUMOR REGION OF INTEREST →BACKGROUND-IMAGE AND ROI-IMAGES"
Prepare segmentation
START the cluster group for segmentation (G = 2)
Compute size of IMRI-IMG = [R, C. and D]
Set number of cluster for segmentation, C = BI and FI // Where BI for "BACKGROUND-IMAGE" and FI for ROI_IMG (FOREGROUND IMAGE)"
Set Cluster Reiterations, IR = M
Repeat Loop until IR ≠ MX (until not equal to maximum iteration) [Outer Loop]
Repeat in Loop variable x from 1to R [Inner Loop-1]
Repeat in Loop variable y from = 1to C [Inner Loop-2]
IF M_IMG (x, y) == B1, THEN
BI (x, y) =IMRI_IMG (x, y)
ELSE IF IMRI-IMG (x, y) == FI
ROI_IMG (x.y) =IMRI_IMG (x, y)
END – IF
Alter Centroid C utilizing specified in mathematical equation 4

$$\boldsymbol{C_{xy}} = (\sum_1^n [\boldsymbol{BI}, \boldsymbol{FI}]\,(\boldsymbol{\gamma_G^m} * \boldsymbol{x_G}) / \sum_1^n \boldsymbol{C1}, \boldsymbol{C2}]\,\boldsymbol{\gamma_G^m} \quad (4)$$

Reiterate till all pixel information is not visible in the image, then determine data distance (d) and describe membership function using equation 5.

$$[\boldsymbol{BI}, \boldsymbol{FI}] = \sum_1^n (\boldsymbol{d_{Gx}^2} / \boldsymbol{d_{Gy}^2})^{1/x-1}]^{-1} \quad (5)$$

STOP INNER LOOP-2
STOP INNER LOOP-1
STOP OUTER LOOP
To improve the region of interest image, Grasshopper optimization method is utilized
Initialize primary parameters of Grasshopper optimization:
"GRASSHOPPER POPULATION (POG) – TOTAL AMOUNT OF PIXELS IN IMRI_IMG"
Define objective function for position:

$$\boldsymbol{V(r)} = \boldsymbol{V_0} \times \boldsymbol{exp}(-\boldsymbol{distance^p}), \quad \boldsymbol{if\ p} \geq \boldsymbol{1}$$

Where, distance= distance among any two grasshoppers

V0 = initial velocity at D=0
p = Position of Grasshoppers (POG)
Initialize, ROI_IMG AND BI-IMAGES = [ ]
Repeat in loop x from 1to R
Repeat in loop y = 1→C
CGP = M_IMG (x, y)
MGP = $\sum_1^x \sum_1^y \frac{IMRI\_IMG(x,y)}{x \times y}$
image_threshold = ghoa (fitness_function, CGP, MGP)
STOP INNER LOOP-2
STOP OUTER LOOP-1
IF IMRI_IMG (PIXEL_COUNT) > IMAGE_THRESHOLD, THEN
ROI-IMG = IMRI_IMG
ELSE
BI = IMRI-IMG
END – IF
Set optimization iterations, OIR = M
Repeat until OIR ≠ M (if not reached max iteration)
MSK_IMG = Binary (ROI_IMG, IMAGE_THRESHOLD)
BOUNDARY = Locate boundary value (MSK_IMG)
ROI_REG= BOUNDRY
Repeat in loop variable k from 1to D
ROI_IMG = IMRI-IMG × ROI_REG
STOP LOOP
Outcome_Return: BI_IMG and ROI_IMG as a segmented background and foreground of IMRI_IMG
EXIT

The step-by-step method described earlier is employed to segment brain tumour ROI from improved and pre-processed MRI images, and afterwards the function from region of interest (ROI) is evaluated.

Feature Extraction from ROI:

We will have to extract the feature pattern depending on their pixel utilizing the terms feature descriptor after tumour region of interest segmentation. Because of the consistency and invariance design of features, we choose the SURF descriptor as a feature pattern extraction in this case. SURF returns a more suitable feature set for segmented ROL. The SURF descriptor is a quick and reliable method for extracting the regional, invariant, and centered feature set from the ROL of epiluminoscopic images. The SURF descriptor step by step process is written as:

Algorithm 2: Named Feature Extraction

Input: Region of Interest →Brain tumor ROI_IMG
Output: FS_set →set of extracted features from region of interest
START
Initialize the process of feature extraction
[R, C, P] = Size (Region of Location)
Repeat in loop variable X from 1 to R
Repeat in loop variable Y from 1to C
FS_set = ROI_IMG [Centroid Level Region, Eccentricity, Orientation, Attribute Maximum_Intensity, Average_Intensity Minimum_Intensity, Image_contrast, Relationship, Energy, Homogeneity, Mean, Standard-Deviation, Entropy, Root Mean Square, Variance, Softness, Kurtosis, Skewness, IDM]
STOP Inner Loop
STOP Outer Loop
Outcome_ Return: FS_set as a feature trends of Region of Interest
EXIT

SGO-based Feature Selection:

This phase is critical for improving the classification validity of the developed I-BTSC model, and it involves selecting the required feature set based on the fitness criterion. Since many of the features data in the FS_set are obsolete or common among three tumour types, it should be removed from the Feature-set. Step by Step method of SGO for feature selection is described as follows:

Algorithm3: SGO-based Feature Selection

Input: FS_set →Feature set from ROI
Output: OFS_set →Optimized set of extracted features from region of interest.

Prepare feature selection
Initialize SGO Attributes
PG – population set of Grasshopper depending on the FS_set
Gpos –Grasshopper position
OFS_set– Optimized set of extracted features from region of interest.
Derive fitness function employing mathematical equation- 6

$$\boldsymbol{FT(f)} = \begin{cases} \mathbf{1}; & \boldsymbol{if\ F_{se} * (Gpos) \geq F_{afs} = Threshold_{value}} \\ \mathbf{0}; & \boldsymbol{else} \end{cases} (6)$$

Where, F_{se} : feature selected form the FS_set
F_{afs}: This is an average of FS_set
[R C, P] = Size (FS_set)
Repeat in Loop variable J from 1 to R × C
Fse = FS_set (J)
Fafs = $\frac{\sum_{j=1}^{R} FS\_set(J)}{R \times C}$

$$Fitness(function) = Fitness\ Function\ (F_{se}, F_{afs})$$

OFS_set (J) = SGOA (Fitness (function), Initialization of SGO)
STOP LOOP
If OFS_set = 1 then
OFS_set = select feature form FS_set
ElSE
OFS_set = Null (Invalid features)
End – If
Outcome_return: OFS_set as an optimized feature set
EXIT

By utilizing the SGO-dependent feature selection method, we pick only certain features that are relevant to the different types of brain tumours, such as "Meningioma, Glioma, and Pituitary". When a selection of optimised features is chosen, Convolutional neural network is used as a classifier to train the prototype, and then CNN is utilized to identify the different types of tumours.

CNN-based I-BTSC System Training:

The final stage of the technique involves using CNN as a deep learning-depending classifier to train the system model focused on the three distinct tumour categories. As a result, the optimised feature set is used as a input source to convolutional neural network with various label names such as "Meningioma, Glioma, and Pituitary", and this portions shows the suggested training/classification approach in depth using convolutional neural network, which serves to enhance the brain tumour classification accurateness of the suggested I-BTSC model. As a result, the presented CNN is known as the I-BTSC net, and its design is depicted in Fig. 7.

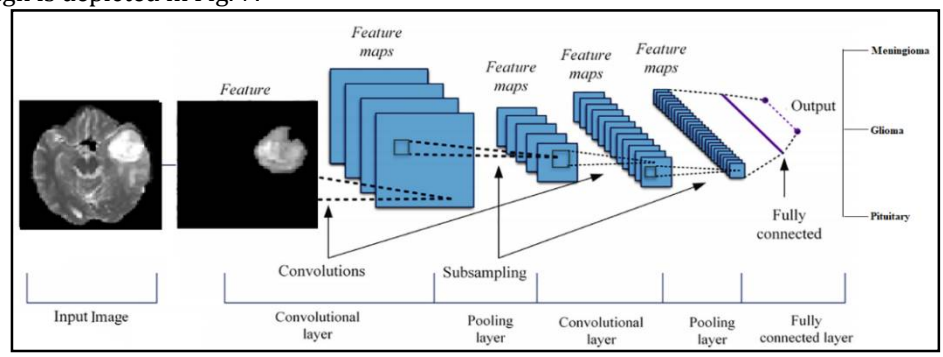

Fig.8.Model structure of I-BTSC method

I-BTSC net's structure is designed on the basis deep learning techniques, making it a more complicated version of obedient Artificial Neural Networks (ANNs). As shown in Fig. 7, the framework of the I-BTSC net consisting of an source input layer, a hidden convolutional layer, pooling, and fully interconnected output layers and the step by step method of I-BTSC net is explained as follows:

Algorithm 4: I-BTSC net

Input: OFS_set ← dataset of selected optimized features
T ←Type of tumors

NU ←Neurons to carry the data
Output: Model-System ←CNN trained system
Output←Classified outcomes of model-system
Start training
Setting UP CNN: – Number of Epochs (EP) // Reiterations utilized by ConvNet
– Total input of Neurons (NU) // Utilized as a transferor
– Performance: Cross entropy of classes, Gradient, and Validation
– Training Datasets: Depend on Random values
[ROW, COLUMN, PLANE] = Size (OFS_set)
Repeat in LOOP variable I from ROW × COLUMN
CHECK IF OFS_set ϵ Meningioma
Tumor Category = Feature from meningioma
ELSEIF CHECK OFS_set ϵ Glioma
Tumor Category = Feature from glioma
ELSE CHECK (OFS_set ϵ Pituitary)
Tumor Category = = Feature from pituitary
END-IF
STOP LOOP
Setting up the ConvNet, I-BTSC network= Pattern-fcoused ConvNet, (NU)
I-BTSC network= Training (I-BTSC ConvNet, OFS_set, Tumor Category)
Testing Outcomes = Simulation (I-BTSC ConvNet, Test MRIOFS_set)
IF Testing Outcomes == 1 (Meningioma)
Findings = Meningioma brain tumor with improved accuracy
ElSEIF Testing Outcomes == 2 (Glioma)
Findings = Glioma brain tumor with improved accuracy
ElSEIF Testing Outcomes == 3 (Pituitary)
Findings = Pituitary brain tumor with improved accuracy
ElSE
Findings = Irrelevant results cannot be classified into tumor type
END-IF
Outcome_return: I-BTSC ConvNet as a trained architecture with findings as classified outcomes of suggested model-system
EXIT

The suggested framework is developed and implemented using MATLAB Programming Language with the toolbox of Image Processing, Neural Network, and Optimization. The aforesaid I-BTSC net method is utilized for brain tumour classification process. The experimental findings and analysis are presented in the upcoming portion of this research paper to verify the effectiveness of the proposed method algorithm.

RESULTS AND DISCUSSION

Step 1: Preprocessing: Fig 9 illustrates the source test image that is pre-processed as shown in fig 10

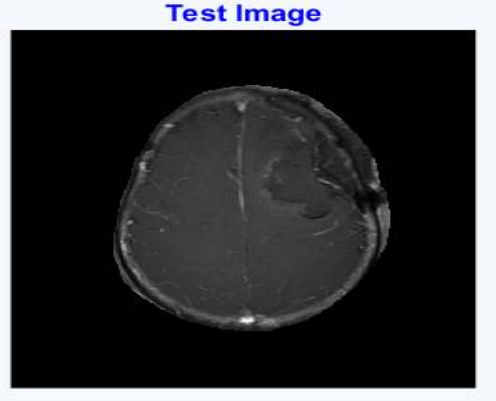

Fig 9: Input image

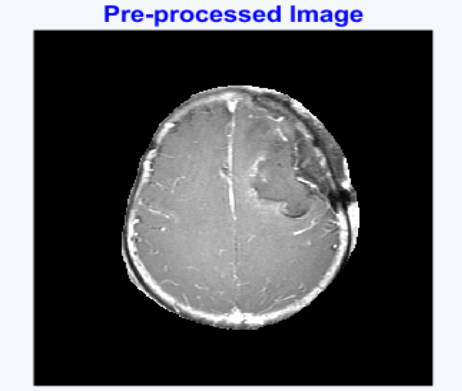

Fig 10: Pre-processed Image

Step 2: Segmentation: Figure 11 shows the outcome of image segmentation using K-means and GOA on a source input test image.

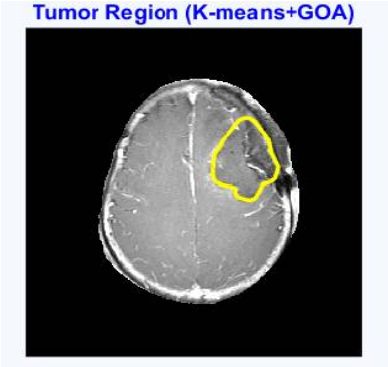

Fig 11: Segmented output

Step 3: Feature Extraction: As shown in table, the feature set is created by extracting 25 features from the given dataset.

Table 2: Extracted features of test image

S.No	Set of features (F set)	Obtained value of features
1	Centroid	0.3295
2	Extent	0.0006
3	Eccentricity	8.154
4	F Area	0.0006
5	Area	8.088
6	MjAL	0.1172
7	MiAL	0.0914
8	Orientation	0.0876
9	Perimeter	0.3558
10	Max Intensity	0.159
11	Mean Intensity	0.0502
12	Min Intensity	0.026
13	Contrast	1.9838
14	Correlation	0.0008
15	Energy	0
16	Homogeneity	0.0001
17	Mean	0.0016
18	Standard Deviation	0.009
19	Entropy	0.0004
20	RMS	0.0012
21	Variance	0.0687
22	Smoothness	0.001
23	Kurtosis	0.0379
24	Skewness	0.0058
25	TIDM	0

Step 4: Feature Optimization: The resulting features have selected depending on the fitness of a fit grasshopper. The following table shows the current, adult, and fit grasshopper data:

Table 3: Optimized features set of a test image

Count	Current Grasshopper	Adult Grasshopper	Fit Grasshopper
1	329.51	782.81	782.81
2	0.6498	782.81	782.81
3	8154	782.81	8154
4	0.6259	782.81	782.81
5	8088	782.81	8088
6	117.18	782.81	782.81
7	91.38	782.81	782.81
8	87.63	782.81	782.81
9	355.75	782.81	782.81
10	159	782.81	782.81
11	50.16	782.81	782.81
12	26	782.81	782.81
13	1.98E+03	782.81	1.98E+03
14	0.8376	782.81	782.81
15	1.29E-04	782.81	782.81
16	0.07	782.81	782.81
17	1.5934	782.81	782.81
18	9.0122	782.81	782.81
19	0.3756	782.81	782.81
20	1.2254	782.81	782.81
21	68.68	782.81	782.81
22	1	782.81	782.81
23	37.92	782.81	782.81
24	5.833	782.81	782.81
25	0	782.81	782.81

Step 5: Classification: The outcomes achieved form the framework designed using the principle of CNN with SGO method for three specific tumour types are examined in this portion. The number of MRI images utilized for modeling from the Contrast-Enhanced MRI Dataset is tabulated in Table IV. Seventy percent of the data is used in the training phase, and thirty percent in the testing phase for classification.

Table 4: MRI Image Ratio for I-BTSC System

Types	CE-MRI Dataset		
	Total (100%)	Training (70%)	Testing (30%)
Meningioma	710	495	210
Glioma	1425	997	429
Pituitary	931	652	280

We implemented tumour classification utilizing CNN depending on the above dataset description, and the outcomes are shown in Table IV. The specific tumour area is segmented from pre-processed or improved MRI images using K-means with SGO technique. After tumour ROI segmentation, all phases are implemented one after another, and output metrics such as Precision, Recall, F-measure, Accuracy, Error, and Execution Time are measured. These output parameters are computed statistically by utilizing the equations Seven to Eleven described as below:

$$\boldsymbol{Precision} = \frac{\mathbf{T_{postive}}}{\mathbf{T_{postive}+F_{positive}}} \quad (7)$$

$$\boldsymbol{Recall} = \frac{\mathbf{T_{positive}}}{\mathbf{T_{positive}+F_{negative}}} \quad (8)$$

$$\boldsymbol{F_{measure}} = \mathbf{2} \times \left(\frac{\boldsymbol{Precision} \times \boldsymbol{Recall}}{\boldsymbol{Precision}+\boldsymbol{Recall}}\right) \quad (9)$$

$$\boldsymbol{Accuracy} = \frac{\mathbf{T_{positive}+T_{negitive}}}{\mathbf{T_{positive}+T_{negative}+F_{positive}+F_{negative}}} \quad (10)$$

$$\mathbf{Error\%} = \mathbf{100} - \mathbf{Accuracy} \quad (11)$$

Where, T_{+ve} → True positive (+Ve) discoveries

T_{-ve} → True negative (- Ve) discoveries

F_{+ve} → False positive (+ve) discoveries and

F_{-ve} → False negative (-Ve) discoveries

To find execution time built in function expertise is used in MATLAB.

Table 5: CNN Architecture layers with their properties [13]

Layer No.	Layer Name	Layer Properties
1	Image Input	256 × 256 × 1 images
2	Convolutional	16 5 × 5 × 1 convolutions with stride [2 2] and padding 'same'
3	Rectified Linear Unit	Rectified Linear Unit
4	Dropout	50% dropout
5	Max Pooling	2 × 2 max pooling with stride [2 2] and padding [0 0 0 0]
6	Convolutional	32 3 × 3 × 16 convolutions with stride [2 2] and padding 'same'
7	Rectified Linear Unit	Rectified Linear Unit
8	Dropout	50% dropout
9	Max Pooling	2 × 2 max pooling with stride [2 2] and padding [0 0 0 0]
10	Convolutional	64 3 × 3 × 32 convolutions with stride [1 1] and padding 'same'
11	Rectified Linear Unit	Rectified Linear Unit
12	Dropout	50% dropout
13	Max Pooling	2 × 2 max pooling with stride [2 2] and padding [0 0 0 0]
14	Convolutional	128 3 × 3 × 64 convolutions with stride [1 1] and padding 'same'
15	Rectified Linear Unit	Rectified Linear Unit
16	Dropout	50% dropout
17	Max Pooling	2 × 2 max pooling with stride [2 2] and padding [0 0 0 0]
18	Fully Connected	1024 hidden neurons in fully connected (FC) layer
19	Rectified Linear Unit	Rectified Linear Unit
20	Fully Connected	3 hidden neurons in fully connected layer
21	Softmax	softmax
22	Classification Output	3 output classes, "1" for meningioma, "2" for glioma, and "3" for a pituitary tumor

The simulations results of the suggested system utilizing CNN are described in Table IV, and from the evaluation, we found that the method classification accuracy is the highest, but we compare these outcomes to previous research work by MM Badza and MC Barjaktarovic, 2020, to confirm these. The CNN modulation graphs including cross-entropy, training stats, uncertainty matrix, and others with CNN framework reflect the numbers/percentages of accurately trained MRI images with optimised feature sets. The suggested system's overall accuracy is illustrated in all diagrams.

Table 6: Execution Results of I-BTSC System

SAMPLES	ACCURACY (%)	RECALL	PRECISION	F-MEASURE	ERROR (%)	EXECUTION TIME (S)
1	99.98	0.96390	0.9898	0.96	0.0182	0.00062
2	99.95	0.9672	0.958	0.9626	0.0460	0.000345
3	99.96	0.9670	0.9584	0.9626	0.0391	0.00055
4	99.93	0.9676	0.9588	0.9632	0.0636	0.000322
5	99.95	0.9661	0.9556	0.96085	0.0486	0.000795
6	99.98	0.9663	0.9570	0.9616	0.01092	0.000043
7	99.96	0.9671	0.9880	0.9625	0.0324	0.000045
8	99.96	0.9662	0.987	0.9616	0.032	0.00004
9	99.97	0.965	0.987	0.961	0.0222	0.00004
10	99.95	0.967	0.988	0.962	0.044	0.000042
Average	99.959	0.96634	0.9727	0.9617	0.035	0.000284

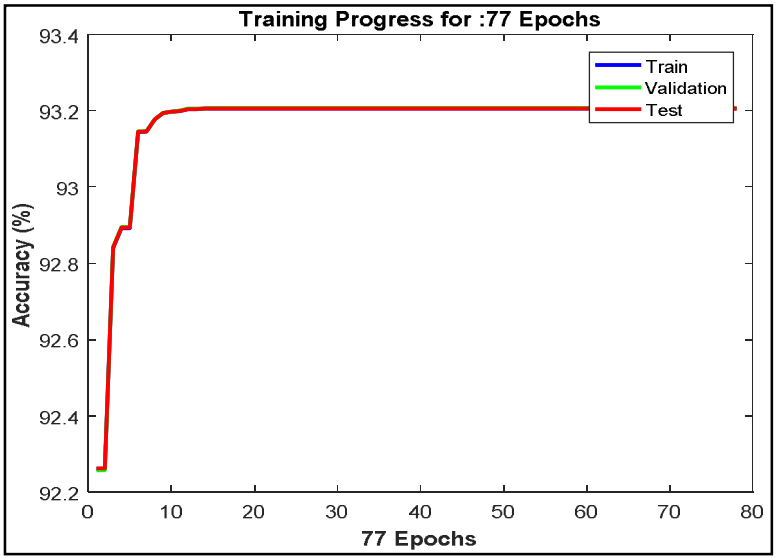

Fig.12. Accuracy of I-BTSC System

The suggested system's all-inclusive accuracy as shown in Fig. 12 using convolutional neural network. The retrieved model accuracy for training is 93 percent, as shown in the diagram by the red color line. The low cross-entropy for training, testing, and verification, as shown in Figure 12, is the key explanation for the high accuracy.

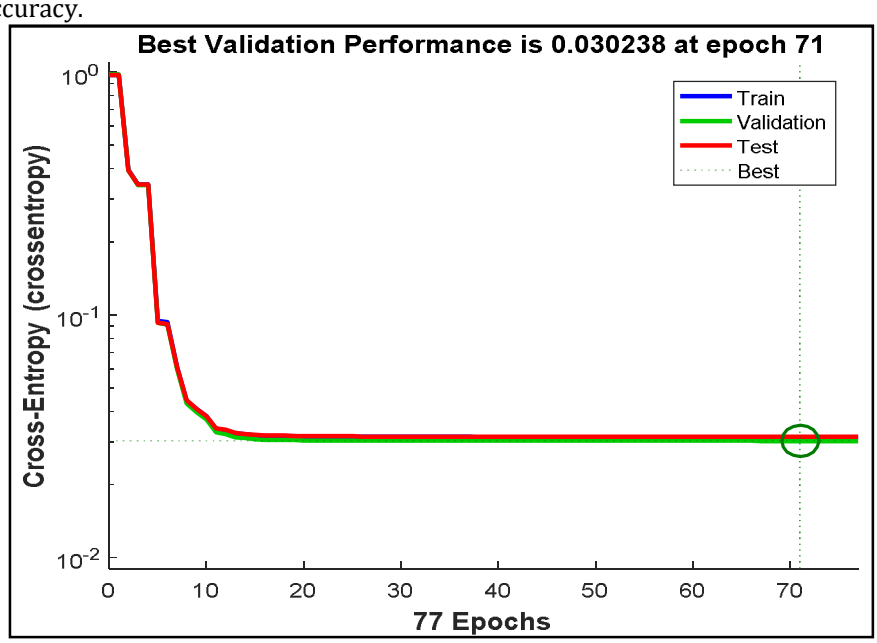

Fig.13. Training Performance of I-BTSC System

Above mentioned figure depicts the training performance of the suggested method using the CNN with respect to the epochs (iterations). To accurately train the model, a series of seventy seven epochs has been utilized, with the better training performance calculated at seventy one epoch. The cross-entropy loss would be minimal for best model accuracy, and as shown in the figure, it is close to 0.030238 at seventy seven epochs, indicating that the optimal accuracy of the suggested model is significant. For better exploration, as per the optimised feature set as shown figure. 15, we measure the confusion matrix for preparation, testing, and verification.

Fig.14. Confusion Matrix of I-BTSC System

For an in-depth knowledge of the suggested system's effectiveness, we defined the confusion matrix for triple types of brain tumours: Meningioma (1), Glioma (2), and Pituitary tumour (3). Overall accuracy for preparation, monitoring, validation, and aggregate is 93.2 percent, 93.4 percent, 93.1 percent, and 93.2 percent, accordingly, in the graph. Depending on the confusion matrix, the receiver operating characteristic (ROC) curve is illustrated in figure 16.

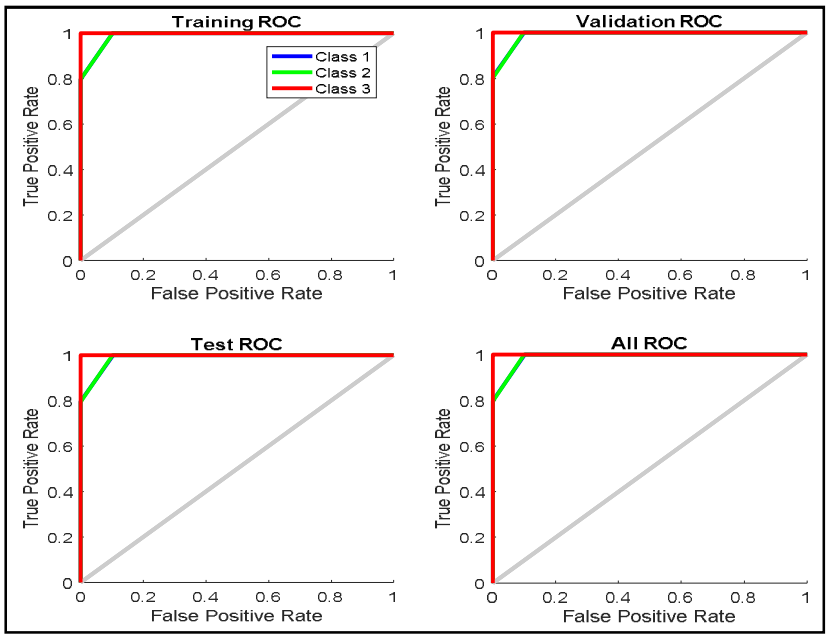

Fig.16. ROC of I-BTSC System

The Region of curve is a relationship among True Positive Rate (TPR) and False Positive Rate (FPR) which is employed to describe the suggested model performance. In these times, convolutional neural network-based tumour detection and classification is widely utilized in healthcare data diagnosis, but there is an problem issue that arises during classification because of invalid feature sets, and to tackle this limitation, we utilize the principle of SGO with CNN to improve classification.

Table 7: Comparison with earlier existing Methods

Works	Accuracy %	Precision rate	Recall value	F set-measure
Existing work	95.400	94.810	95.070	94.940
Proposed Method	99.95	97.27	96.63	96.17

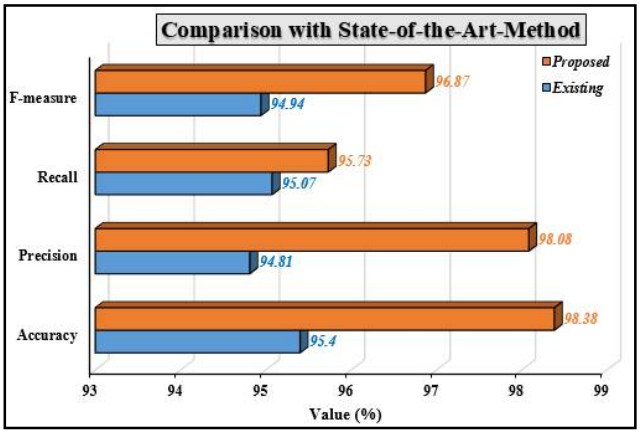

Fig.17.Assessment of I-BTSC System with Existing Work

Based on four quantities parameters called accuracy, precision, recall, and f-measure, listed in Table V and Fig.17 compare the proposed method with current research work by MM Badza and MC Barjaktarovic. The recall, precision, and feature-measures of proposed method from actual work was 1.56 percent, 2.46 percent, and 1.23 percent, respectively, indicating a substantial improvement in classification accuracy of 4.91 percent. The output of the suggested I-BTSC system is better than the current work, however the recall has only a substantial improvement, and the primary reason for this enhancement is the hybridization of of the SGO technique for segmentation and training or classification utilizing CNN.

CONCLUSION

A swarm intelligence-dependent I-BTSC model is developed in this research paper for tumour classification from MRI images utilizing CNN as a deep learning approach. This study presents an improvement in CNN framework model for brain tumour classification dependent on tumour area segmentation using SGO-based K-means methodology. The implementation of improved segmentation techniques is a key factor for healthcare data diagnosis and aims to enhance the brain tumour classification outcomes, according to the comprehensive experimental research to segment the precise area of tumour. In comparison to other methods, hybrid segmentation utilizing SGO-based K-means is recommended. As seen in the result section, optimization of selected feature sets employing a swarm intelligence -based Meta heuristic procedure is also reflected in medical image investigation tasks such as classification and segmentation. As a deep learning, triple types of tumours are examined using the Convolutional Neural Network, with optimised features used as feedback to differentiate between "Meningioma, Glioma, and Pituitary" tumours. Previously, numerous investigations for tumour classification using only CNN were suggested, but in this research work, we employed the SGO algorithm in conjunction with the Convolutional Neural Network to strengthen classification and segmentation accurateness. To validate and analyze the performance of the suggested I-BTSC method, we evaluated the values of following performance approaches such as Accuracy, Recall, Precision and Feature- measure, and found a 4.43 percent enhancement in precision, recall, and f-measure when compared with the earlier work. We will improve the feature extraction methodology in the coming times by combining other methods with swarm-based optimization, making the I-BTSC model more robust and reliable.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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