Ann. For. Res. 67(1): 104-122, 2024
ISSN: 18448135, 20652445
ANNALS OF FOREST RESEARCH
www.e-afr.org

IMPROVED BRAIN MRI CLASSIFICATION USING COMPUTATIONAL INTELLIGENCE APPROACHES

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Abstract: In the history of medical imaging various computer-aided diagnostic systems have been proposed to assist medical professionals for identifying the fatal conditions of brain tumor while analyzing MRI scans. In this context, the author had extended their earlier brain MRI segmentation model to offer high-end brain tumor classification in the proposed work. The already proved improved segmentation procedure based on k-means optimized Firefly Algorithm (FFA) is involved for brain MRI segmentation to identify Region-of-Interest (RoI) highlighting the tumor regions. The feature extraction of segmented RoI image is performed using Speeded Up Robust Features (SURF) followed by implementation of FFA for extracting the best feature set in order to reduce the dimensionality of the feature data that prove to be effective for accurate tumor classification. A hybrid of Support Vector Machine (SVM) and Deep Neural Network (DNN) is used at the training and classification stage in which trained support vectors are used for classification by DNN architecture. The performance of the proposed brain tumor classification work is evaluated using 500 MRI images in terms of precision, recall, f-measure, accuracy and execution time. Simulation analysis demonstrates the attainment of average classification accuracy of 99.08% and average precision of 94.22% with reduced classification time of 1.11%. The work proved to be very advantageous for medical professionals and radiologists involved in analyzing brain tumor using MRI scans.
Keywords: Brain Tumor, MRI scans, Fire Fly Algorithm (FFA), Speeded Up Robust Features (SURF), Support Vector Machine (SVM) and Deep Neural Network (DNN).

Introduction

The brain is the vital organ that governs the central nervous system with a wide neural network comprising of nearly 100 billion nerve cells [1]. Occurrence of any tumor or uncontrolled cell growth in this organ may challenge its apt functioning and at some stage may prove to be fatal. American Cancer Society had predicted that by the end of 2020 there will be around 23890 new malignant brain tumor cases with 13590 males and 10300 females in addition to the benign tumor cases that are less lethal [2]. However, a comprehensive
analysis of past cancer stats 2014-2016 shows that the probability of developing brain tumor is relatively higher after attaining 70 years of age due
numerous factors in addition to aging. Figure 1 illustrates that the probability of developing cancer is found to be much higher in case of males as compared to females [Cancer Statistics, 2020].

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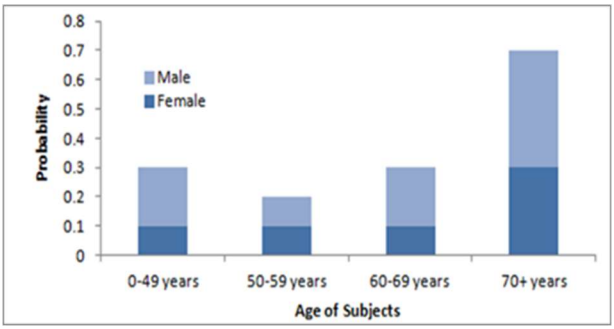


Figure 1 Probability of developing cancer, 2014-2016

Therefore, an early diagnosis holds high significance [3]. Biomedical imaging offers a detailed visualization of anatomical structures in digital format to assist the healthcare system. There are various diagnostic techniques, namely, CT scan, MRI, Tissue sampling, PET-CT scan, molecular testing, lumbar punctures etc that are popularly employed for its front line detection. However, in clinical practice imaging technology such as CT scans and brain MRI scans of the suspected patient is more prevalent among radiologists and experts involved in brain cancer research with MRI being more practiced owing to generating high contrast images at comparatively low radiation level [4]. The major inference drawn from the brain tumor MRI's is used to broadly categories tumor into benign or malignant [5]. Further, World Health Organization (WHO) had ranked the tumor according to its severity and prognosis stage from Grade-I representing benign tumor to Grade-IV representing high malignancy [6]. Despite of medical and technical advancements, the Grade-IV tumor, also known as glioblastoma, are the most lethal among brain tumor with highly challenged therapeutic management [7]. Hence, further treatment totally depends on the diagnosis and accurate interpretation that exclusively rely on the experience and expertise of medical professionals involved in the process. In comparison to histological detections, MRI offers a non-invasive technique to predict tumor prognosis, clinical planning and follow-up in brain tumor management [8]. Infact, the medical imaging has been revolutionised to such an extent that MRI scans could easily diagnose various grades of brain tumor. Evaluation in 3-dimensional format is much complex and also raises computational complexity. Additionally, analysing such images is also quite difficult. Therefore, in recent years 3-dimensional MRI scans are considered in the form of 2-dimensional slices for better interpretation [9]. However, at some point radiologists underperform while interpreting imaging outcomes that may be due to lack of experience, lack of adequate practical training on similar medical technology and tired due to overwork while analysing large volume of imaging results that may result in permeation of misdiagnosis [10]. Thus, computational models assisting in brain MRI classification prove to be very advantageous.

In the field of automated analysis of brain tumors, the authors had earlier published a novel segmentation approach in which they concluded that the involvement of FireFly significantly improved the segmentation of brain tumors in MRI scans. Therefore, in the present paper, the earlier research work is extended to offer an improved brain tumor classification with the involvement of neural networks while taking advantage of already proved segmentation work. The

study would be very advantageous to medical professionals involved in routine analysis of MRI scans while overcoming diagnostic bias arising due to inexperience and fatigue.

The novelty of the work is illustrated with the involvement of swarm intelligence and trained vectors at classification stage. Here, FFA is used as a swarm intelligence technique at two stages: At image segmentation stage to optimize k-means clusters representing tumor and normal classes. At feature extraction stage to select the most relevant and best feature set to improve training.

Following this, SVM-DNN hybrid is used at the training and classification stage, where SVM trained Support Vector (SV) are used by DNN to learn from the optimized features and classify test MRI images into the tumor (benign or malignant) and normal.

Organization of the paper

The research paper is further organized into five sections, with Section 1 dedicated to providing an overview of brain MRI in respect to the tumor. Section 2 discusses the classification approaches proposed by various researchers aimed at improving brain tumor classification using MRI scans. Section 3 summarizes the proposed work while describing the techniques involved at every step. Section 4 describes the experimental outcomes proving the effectiveness of the proposed work. Section 5 concludes the paper with referred work listed under references.

Literature Review

In the present section, a comprehensive literature study had shown that most of the researchers proposed techniques to address illumination challenges that could challenge accurate identification of shape, size, structure and patterns of brain tumor. Studies further involved combinations of segmentation, optimization and classification approaches to improve overall strength of brain tumor prediction models. Jothi had proposed a hybrid technique to offer an automated brain tumor MRI classification that was named as Tolerance Rough Set Firefly based Quick Reduct (TRSFFQR). In the process, Tolerance Rough Set (TRS) and Firefly Algorithm (FFA) were used for feature selection of the brain tumor to demonstrate the highest classification accuracy of 91.51% using J48 classifier when compared with other evolutionary algorithms namely PSO and ABC. Overall the technique outperformed existing optimization techniques [13].

Brain tumor MRI classification work proposed by Sachdeva et al., 2016 first involved segmentation of the MRI images to identify the Region- of-Interest (RoI). This was followed by the Genetic Algorithm (GA) applied for feature selection to improve the classification accuracy of brain tumor to 94.9%. The designed combination GA with Support Vector Machine (SVM) was used to predict preliminary of tumor class followed by GA with Artificial Neural Network (ANN) to measure overall classification accuracy of the proposed work [14].

Mohsen et al. had implemented Deep Neural Network (DNN) to classify brain MRI images into normal and three tumor class, namely, glioblastoma, metastatic bronchogenic carcinoma and sarcoma. At the feature extraction stage, Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) were used to demonstrate precision, recall and f-measure of 0.97 each with an overall classification accuracy of 96.97%. The experimentation had involved only 64 brain MRI images. In future authors proposed that the architecture would be modified to decrease the processing time involving large-sized MRI images [15].

Kumar et al. had proposed a brain tumor classification while analysis MRI images available at BRATs-2015 dataset. The bio- inspired work involved Fire Fly Algorithm (FFA) to significantly decrease the size of the feature set that was used by Support Vector Machine (SVM) for classification of brain tumors. The experimentation involving BRATS-2015 dataset achieved the highest brain tumor classification accuracy of 76.77%. In future work, the authors planed to analyse more optimization algorithms in addition to FFA at feature selection to improve the overall classification accuracy of the proposed work [16].

Deepa and Emmanuel had proposed a brain tumor classification approach that was based on image processing concept involving pre-processing to minimize intensity variations, Gabor wavelet for extracting features in terms of texture information, among these extracted features the most relevant features were selected using Kernel Principal Component Analysis (KPCA) followed by feature fusion using Gaussian Radial Basis Function (GRBF). The experimental analysis over the BRATs dataset demonstrated a high Jaccard coefficient of 96.89% with a precision of 98.47and sensitivity of 97.24% [17].

Sajjad et al., 2019 had improved the dataset to design a finely tuned dataset used for processing using proposed Convolutional Neural Networks (CNN). Softmax was used at the classification stage. Evaluation study involved simulation analysis of the proposed work using both improved dataset and the original brain tumor dataset. Overall, the study demonstrated 94.58% successful classification against improved dataset [18].

Toğaçar et al. had designed a deep convolutional neural network based architecture for brain tumor classification using MRI scans. The design employed efficient features selected using RFE method with involvement of SVM classifier. It was demonstrated that the combination of SVM and RFE at the feature selection stage considerably reduced the feature set dimensions resulting in classification accuracy, sensitivity and specificity of 96.77%, 97.83%, and 95.74%. This study further left out the scope for consideration of optimization approaches and Directed Acyclic Graph (DAG) as deep learning method to improve the brain tumor classification design [19].

In the same year, Çinar and Yıldırım had also proposed a deep learning-based CNN for brain tumor classification using MRI images. In the proposed design, the last five layers of Resnet50 were replaced by eight new layers. The modified deep learning CNN evaluated against a tumor, and normal classes demonstrated 97.2% classification accuracy. The work proved to outperform existing models of Alexnet, Googlenet, Densenet201, Resnet50 and Inception [20].

Bezdan et al. had implemented Convolutional Neural Network (CNN) for achieving high image-based classification of brain tumor. In the proposed work, hyperparameters of CNN were managed with the involvement of a modified FireFly Algorithm (FFA) in order to perform glioma classification. Simulation analysis involved experimentation against 600 images representing different grades of brain tumor to demonstrate a high classification accuracy of 92.6%. However, the adjustment of hyperparametric values was a time-consuming step [21].

Materials and Methodology

This section describes the source of brain image data that are used for processing and evaluation of the proposed work. The steps and the techniques involved in the image processing are also

described here. The first step includes the data acquisition corresponding to the brain MRI representing both tumor and healthy subjects. These brain images undergo pre-processing and segmentation using Fire Fly Algorithm (FFA). Next, features of the segmented region are deduced using SURF followed by FFA based optimization of extracted features to reduce dimensionality of the feature set. Both training and the test image follow the same steps of image processing. Finally, the features of the test brain MRI image are compared with the features present in the reference database to classify the test image into tumor and normal brain images. To improve the overall classification performance SVM trained support vectors are used by DNN for classification of brain MRI images into benign, malignant and normal classes. The flow diagram of the proposed work is illustrated in Figure 2. The performance of the proposed work is evaluated in terms of quality parameters, namely, precision, recall, f-measure, accuracy and execution time.

Data Source

The MRI images used in the experimentation are retrieved from the Brain Tumor Segmentation (BraTS) dataset that offers comprehensive information on brain tumors in the form of DICOM formatted MRI scans. In the proposed work, 50 DICOM files are used that represent multi-frame 3D brain scans. The dataset is accessible from Brain Tumor Segmentation Challenge available online at http://braintumorsegmentation.org/.

Pre-processing

The MRI image offers high quality 3D biomedical scans of anatomical regions of the brain in the form of slices. However, some level of improvement is required in terms of Signal-to-Noise Ratio (SNR) to enhance the visualization of the generated digital image that is inevitable at the sampling stage. First of all, the 2D slices of the 3D MRI images are extracted to simplify the complex MRI scans. This is followed by the pre-processing of the 2D images. It is the foremost step applied after uploading the test MRI image in which intensity-based image enhancement is performed with the concept of limiting. Here, limiting means that the contrast and intensity of each pixel of the image are enhanced within certain limit.

Suppose, original MRI slice image with $'n'$ number of dimensions with its pre-determined maximum and minimum intensity values. The intensity values of the original uploaded MRI image $Imgorg$ are transformed to enhanced image $Imgenh$ using the following mathematical expression. Where, $Inthigh\ and\ Intlow$ are the highest and lowest pixel intensities of the $Imgorg$ and $Intenhhigh\ and\ Intenhlow$ are the modified intensities of the resultant enhanced MRI image$Imgenh$. The pre- processing is further illustrated in Figure 3.

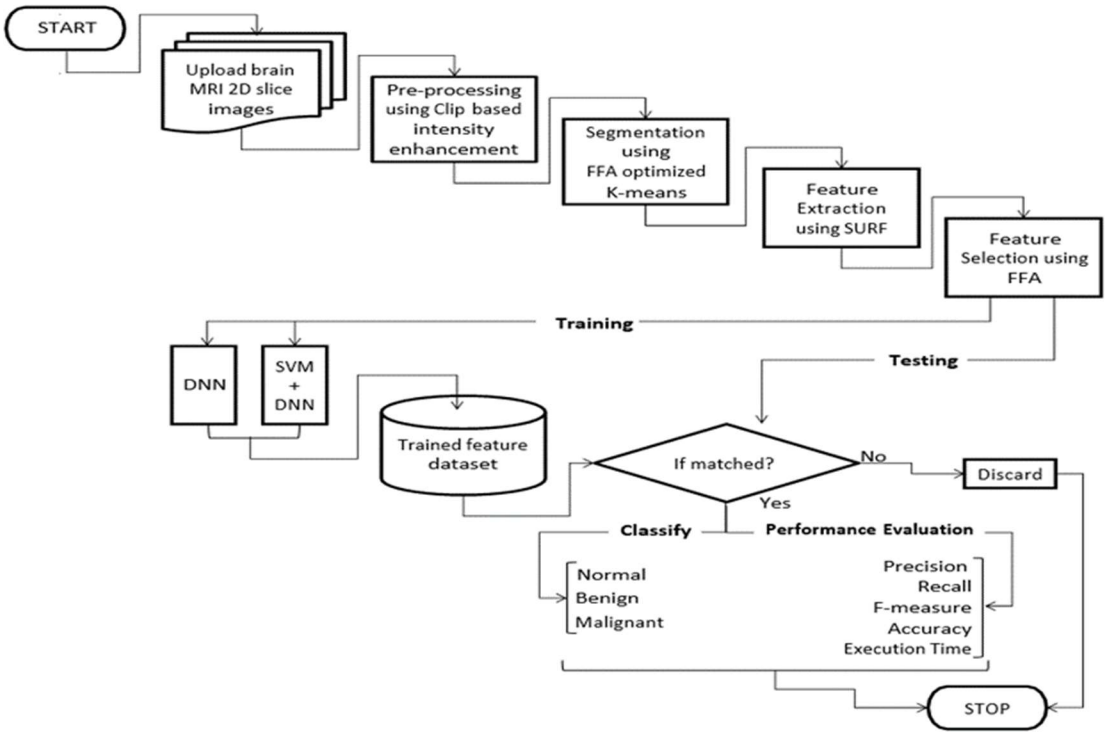


Figure 2 Flow diagram of proposed work

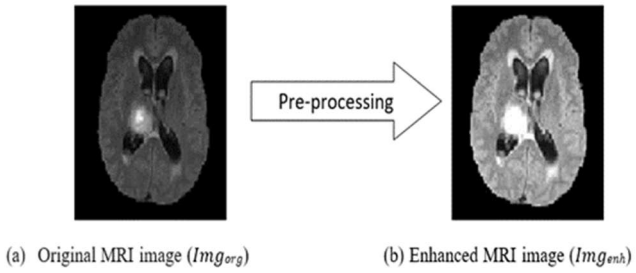


Figure 3 Pre-processing of MRI image

Image Segmentation

This involves partitioning of the entire image into regions based on the number of deciding criteria. Here main idea is to locate regions that exhibit identical properties based on similarity measures. Before actual segmentation, the enhanced image is first labelled to mark out the presence of different regions present within the image. In accordance with the author's earlier proposed MRI segmentation approach, two type of image labelling is involved namely, greyscale labelling and color labelling. Greyscale labeling distinguishes the image regions in different shades of grey and black, making it difficult to distinguish similar shades. Therefore, further color labelling is performed that significantly improves the visual distinction among various regions marked using different colors of light spectrum, as illustrated in Figure 4. This considerably improves the identification and segmentation of the tumor region. Authors had already concluded that k-means with FireFly Algorithm had demonstrated the best brain tumor segmentation using MRI images. The brain tumor segmentation using k- means with FFA is also illustrated in Figure 4. The steps involved in the process are given in Algorithm 1.

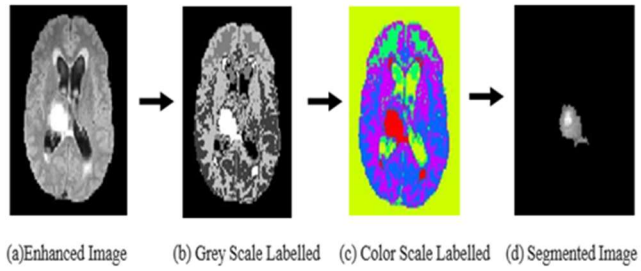


Figure 4 Image processing for segmentation of MRI Image

Algorithm 1: MRI image segmentation using FFA optimized k-means

1. Input: Img_{enh_C} → Labeled enhanced MRI image
2. Output: Img_{RoI} → Brain Tumour RoI Image
3. Determine the size of the input image
4. $[Row, Col, Plane] = size\ (Img_{enh_C})$ // size in the form of number of rows, columns and plane
5. $Img_{enh_C} = double\ (Img_{enh_C})$ //image matrix transformation
6. $Num_{parts} = 2$ //variable representing the number of clusters is defined
7. $Simg_{Index} = kmeans\ (Img_{enh_C}, Num_{parts})$
8. $Seg_{LabelImg} = reshape\ (Simg_{Index}, Row, Col)$ //reshaped for k-means cluster matrix
9. $Data_{Pos} = find\ (Seg_{LabelImg} > 0)$ //identify the data with Color labelling greater than zero
10. $Data = Seg_{LabelImg}(Data_{Pos})$ // retrieves data corresponding to the $Data_{pos}$
11. Initialize FFA parameter
12. itr → Number of Iterations
13. S → Population Size
14. L_B → Lower Bound
15. U_B → Upper Bound
16. f_{fun} → Fitness function
17. N → Number of selection
18. Compute image size
19. $P = Size\ (Img_{enh_C})$
20. $For_{each}\ i\ in\ P$
21. $fs = \sum_{i=1}^{p} Data(i)$
22. $ft = \frac{\sum_{i=1}^{p} Data\ \{i\}}{Length\ of\ the\ feature}$
23. Call FFA Fitness function
24. $f_{fit} = \begin{cases} 1 & \text{if fs} \leq \text{ft} \\ 0 & otherwise \end{cases}$
25. $Thvalue = FFA(P, itr, LB, UB, N, ffit)$ //determine threshold value
26. $Endfor$
27. $While\ (itr \sim = Maximum)$
28. $Threshold = Thvalue$
29. $MaskImg = Morphological\ (SimgIndex, Threshold)$ // determine mask of the image
30. $Boundaries = bwboundaries\ (MaskImg)$
31. $SegmentedRegion = Boundaries$ // determine segmented tumor region

32. $Foreach\ j\ in\ plane\ P$
33. $ImgRoI = Imgenhc\ \ *SegmentedRegion$ // determine RoI in the image
34. $Endfor$
35. $Endwhile$
36. Return: $ImgRoI \rightarrow$ Segmented Image as RoI of Brain Tumour

The above algorithm improves the clustering strength of k-means to segment color labelled brain MRI image using FFA as a swarm intelligence technique. FFA is used for the selection of threshold value using its fitness function that is determined by four factors, namely, distance, position, velocity and light intensity. The optimized values are used for image segmentation returning MRI image with marked tumor Region-of-Interest RoI.

Feature Extraction (SURF)

Feature extraction refers to the process of deducing the quality information from the segmented RoI such as shape, texture, contrast and color. Speed Up Robust Features (SURF) was initially put forward by Bay et al. and was inspired from the Scale Invariant Feature Transform (SIFT) [23]. However, SURF uses square filter to find out the features and therefore is more robust and surpasses SIFT in computation speed. Studies had demonstrated very efficient results when applied to object recognition and 3-dimensional reconstruction work [24]. Recently, Ayadi et al. had evaluated various techniques for feature extraction of MRI images for automated classification, and based on his study, he established the effectiveness of the SURF algorithm at feature extraction stage for brain MRI images [25] Later, Zulpe and Bhosle also concluded the effectiveness of SURF to deal with high dimensional feature extraction of brain MRI scans [26] Inspired by these research works and the characteristics of the SURF technique, the authors had involved SURF for feature extraction of the brain MRI 2D slice images. The steps involved in the process are listed in **Algorithm 2.**

Algorithm 2: Feature extraction of segmented brain MRI using SURF

1. Input: $Img_{RoI} \rightarrow$ Segmented Image as RoI of Brain Tumour
2. Output: $Img_{fpoints} \rightarrow$ Feature points of RoI
3. Load Img_{RoI} // load segmented RoI data
4. $[Row, Col] = size(Img_{RoI})$ // compute size of image in terms of row and column
5. $For_{each}\ r\ in\ Row$
6. $For_{each}\ c\ in\ Col$
7. $Img_{scale} = scaling(foreground(r, c), scale_{size})$
8. $Key_{point}local \rightarrow localization(Img_{scale}(r,\ c))$ // determine key localization points
9. $Keypoint_{orient} \rightarrow orientation\ (Key_{point}local\ (r,\ c),\ angle)$ // determine angle of orientation ifrequired
10. $RoI_{fpoints} = filtering(Keypoint_{orient}\ (r, c), square_{filter})$ // select the best feature points
11. End_{for}
12. End_{for}
13. Return: $RoI_{fpoints}$ // key feature points of the segmented region

The segmented brain MRI marked as RoI $ImgRoI$ is mainly focused on the above algorithm. In the proposed work, features of both training and testing images are extracted using SURF to identify the extreme values that further guide for the identification of the feature description vector. The technique works by producing various reproducible orientations in case reorientation is required by key local points $Keypointlocal$. Finally, the square filter is applied to extract the best features among the extracted features and are returned as $RoIfpoints$ representing features of the marked RoI of brain MRI.

Feature Selection (FFA)

The processing in the last step resulted in a larger number of features that increases the dimensions of the feature set. However, all the features obtained are also not viable to be used for training and carried further in the classification stage. Therefore, again swarm intelligence technique, FFA, is involved in selecting the most reliable and relevant features from the feature set obtained using SURF. This nature-inspired algorithm analyses the search space and determines the most relevant features based on feature function. The optimization of the extracted features is performed using following steps.

Algorithm 3: Feature selection using FFA

1. Input: $RoI_{fpoints} \rightarrow key\ feature\ points$ of segmented region
2. Output: $ORoI_f \rightarrow$ Optimized feature set
3. Initialize FFA parameters
4. $[Row, Col] = size(RoI_{fpoints})$ // determine size of key points in terms of row and column
5. $For_{each}\ i\ in\ Row$
6. $For_{each}\ j\ in\ Col$
7. $f_s = key_{fpoints}(i, j)$ // current feature value
8. $f_{th} = threshold(i, j)$ // assign a threshold value
9. Define fitness function
10. $f_{fit} = \begin{cases} \text{True} ; if\ fs > fth \\ \text{False} ; otherwise \end{cases}$
11. Call fitness function
12. $f_{fit} = call\ f_{fit}(f_s, f_{th})$
13. $Num_{variable} = 1$ //assign number of variables
14. $OT_{data} = FFA(f_{fit}, Num, FFA_{function})$
15. End_{for}
16. End_{for}
17. Return: $OT_{data} \rightarrow fit\ data\ as\ optimized\ feature\ set$

The above-listed steps represent a decision-making step that is inspired by the nature inspired FFA. This algorithm helps in selecting the most relevant feature among the best features returned by SURF algorithm. This not only reduces the dimensionality of the data but also contributes towards the most distinct set of features that may result in fast and accurate training and classification of MRI images.

Training and Classification

At this stage, a novel hybrid of computational intelligence is implemented that comprises of a binary classifier Support Vector Machine (SVM) for the training of the FFA optimized feature sets followed by strengths of the multiclass classifier as Deep Learning Network (DNN) for the classification of brain MRI images based on learning from trained SVs. SVM is majorly studied as a machine learning approach that separates two classes with larger margin in order to place them maximally apart, which is usually implemented in the case of linear classification as illustrated in Figure 5. However, for nonlinear classification, it implements a kernel trick in which low dimensional input space is transformed to high dimensional input space. Recently, this kernelized SVM trick has been widely used to address a variety of classification challenges [27].

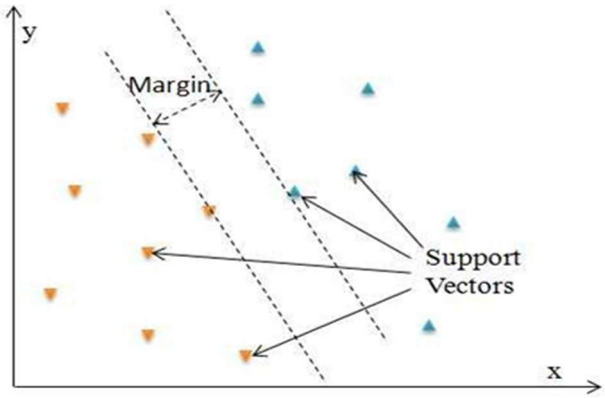


Figure 5 Linearly separable classes with a large margin

Despite this, it has been established that SVM significantly raises the computational complexity in applications that involve clustering, ranking or classification involving more than two classes [28]. Therefore, SVM are usually proves to be best for binary classification. To overcome this limitation, it is used in combination to a multiclass classifier in the present work to offer brain MRI classification. SVM is implemented to enlarge the space between the two classes and hence maximize the margin principle. Among various kernel functions, Radial Basis Function (RBF) has been used as a kernel transformation to map the data to n dimensional data. Mathematical expression for Gaussian RBF is represented as follows:

$$K(c_1, c_2) = \exp(-\gamma \, \|c_1 - c_2\|)$$

Where $K(c_1, c_2)$ represents the kernel function for two classes, $\gamma > 0$ *and represented* as $\gamma = \gamma = \frac{1}{2\sigma^2}$

Now, the trained Support Vectors (SVs) representing each of normal, benign and malignant classes is used for learning by DNN architecture. Deep learning has recently emerged with potential applications to deal with multiclass classification. Even it has been explored by Mohsen et al. to offer brain MRI classification into three cancer classes. However, their work involved a small dataset comprising of only 64 MRI images [15]. Later, Mostapha and Styner had presented a comprehensive study on the role of deep learning techniques in reference to brain MRI to face challenges posed by medical image analysis applications [29]. In a similar context, the authors had implemented MRI classification with deep learning neural networks in combination to SVM.

DNN consists of an input layer in which trained SVs are used, each representing a different category. This information is passed to the hidden layer where weights are applied and refined iteratively with the knowledge gained from the SVs. Finally, after deep-learning, the test MRI image features are analyzed by the neural network to categorize the test image among the three classes. Algorithm 4 lists the combined architecture of SVM-DNN.

Algorithm 4: Training and Classification using SVM-DNN

1. Input: OT_{data} // optimized feature data of MRI image
2. Output: $Classes$ // disease categories of ECG signal
3. Initialize parameters
4. $Class_{data}$ // Type of classes
5. N_{num} // number of neurons in DNN
6. SVM_{kernel} // Kernel function for SVM
7. Initialize SVM with a kernel function
8. Set SVM_{kernel} = RBF //define the type of kernel function
9. Train using SVM
10. $SVM_{train}data$ = $SVM.Train(OT_{data}, Class_{data}, SVM_{kernel})$// train using SVM RBF kernel function
11. $Trained_{data}$ = $SVM_{train}data.SV$ // construct a trained data structure using SVM support vector
12. Initialize DNN with the following parameters
13. $Trained_{data}$ → initialize training data for DNN
14. $Performance_{parameter}$ → $Mutation, Validation\ Points, MSE, Gradient$
15. $Training_{tech}$ → $Levenberg - Marquardt$
16. Compute size of the trained data obtained from SVM
17. T_s = $size\ of\ Trained_{data}$
18. $For_{each}\ i\ in\ T_s$
19. $if\ Trained_{data}(i) \leq Cat_{data}(1);\ \ Class_{normal} = True$
20. $if\ Trained_{data}(i) \leq Cat_{data}(2);\ \ Class_{benign} = True$
21. $if\ Trained_{data}(i) \leq Cat_{data}(3);\ \ Class_{malignant} = True$
22. End_{if}
23. $Net = patternet(N)$
24. $Class_{results} = simulate(net, Class_{data})$ // perform classification
25. $if\ Class_{results} = True$
26. Show $Class_{results}\ in\ terms\ of\ Class_{categories}$
27. Calculate $Performance_{parameters}$
28. End_{if}
29. End_{for}
30. $Return$: $Class_{results}\ and\ Performance_{parameters}$ //Classification results and performance parameters

The above algorithm first calls SVM and computes trained data structures $Traineddata$ using SVM's SVs. The $Traineddata$ represents the best training data that could be obtained in respect to optimized feature data $OTdata$. $Traineddata$ here represents the class information for three classes, namely, normal, benign, and malignant. After completion of the learning using trained SVs, information is stored in the training database. In the testing phase, the brain MRI image follows all the steps of pre-processing, feature extraction, feature selection. After feature selection the features of the test image are compared with the trained feature set using the deep learning architecture of DNN that classifies the test image based on its deep learning over SVM trained features. Finally, the algorithm returns the class category and performance parameters corresponding to the test image.

Performance Evaluation

In the presented research, 500 MRI images from the BraTS dataset are used for evaluation purposes. The prediction results are followed by the determination of quality parameters to determine the strength of the implemented techniques to classify brain MRI images into two classes representing tumor and healthy subjects. The performance parameters returned as a result of classification are precision, recall, f-measure, accuracy, and execution time involved in each simulation. Mathematically, these parameters are computed as follows:

$$Precision = \frac{\mathrm{Tp}}{\mathrm{Tp+Fp}} \quad (1)$$

$$Recall = \frac{Tp}{Tp+Fn} \quad (2)$$

$$Fmeasure = 2 * \left(\frac{Precision*Recall}{Precision+Recall}\right) \quad (3)$$

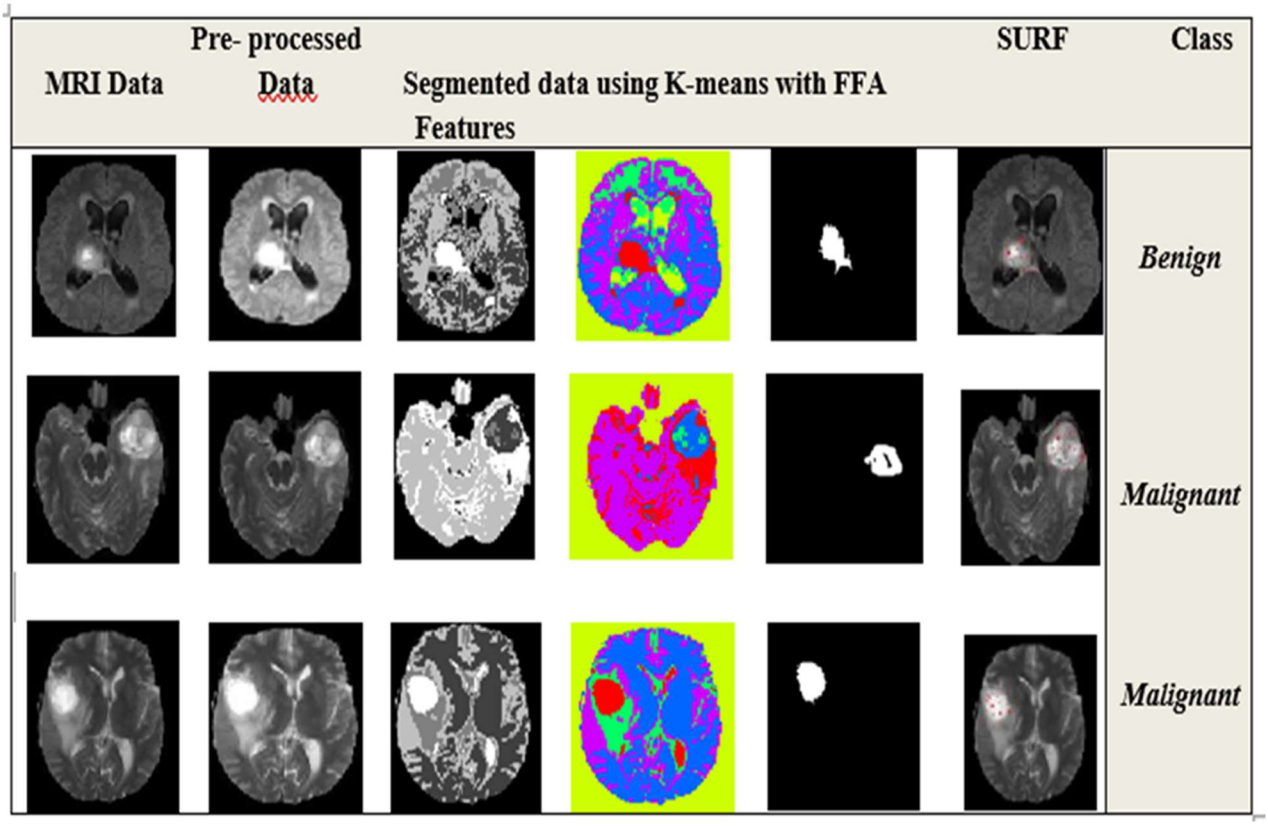
$$Accuracy = \frac{Tp+Tn}{Tp+Tn+Fp+F} \quad (4)$$

Where, True positive detections are represented by T_p, true negative detections by T_n, false positive by F_p and false negative by F_n.

Experimental Results

The present section describes the evaluated results of the proposed brain tumor segmentation and classification model on the Brain Tumor Segmentation (BraTS) standard dataset for DICOM to PNG converted images. Here, three different classes of tumors are considered for the evaluation named as Normal, Benign and Malignant. The proposed model classifies the brain tumor class having four different steps. The first step is the pre-processing of MRI data, and it is performed to enhance the quality of data to locate the exact region of tumors. The second step involves the segmentation of tumor RoI by improved K-means method using the FFA with a novel fitness function. In the third step, SURF features are extracted, and relevant features according to the class are selected using the FFA, which is selected based on the fitness criteria. In the very next step, DNN with SVM is implemented for best model taring as well as the classification of tumor types. Samples of these steps are shown in Table 1.

Table 1. Processing steps of proposed brain tumour segmentation and classification model



The simulation experiments are performed in two different modules, the first module discusses results using only DNN and the second module discusses results using DNN with SVM. At last, we compare the results of proposed brain tumor segmentation and classification model with state-of-the-art methods to validate the performance of model. The performance of the models is calculated in terms of Precision, Recall, F-measure, Accuracy and Classification Time. All experiments are performed under the Image processing toolbox in MATLAB 2016a using a personal computer/laptop with more than 8 GB of RAM and a minimum 500
GB of hard drive space. The proposed model is tested on 500 brain MRI data; however, for illustration purpose, the experimental results on the 10 sample data with a ratio of 70:30 for training and testing is presented. The simulation results in terms of precision, recall, f-measure, accuracy, and classification time of both modules, i.e., DNN and DNN with SVM, is tabulated for ten image samples in Table 2. It is observed from the table that the performance of DNN with SVM is slightly higher than DNN alone. The experimental results are further graphically illustrated in Figure 6 to Figure 10.

Table 2. Classification results for BraTS dataset

Images	Precision		Recall		F-measure		Accuracy (%)		Time (s)	
	DNN	SVM+DNN	DNN	SVM+DNN	DNN	SVM+DNN	DNN	SVM+DNN	DNN	SVM+DNN
Image 1	0.895	0.989	0.897	0.982	0.895	0.985	94.843	99.69	2.50	1.87
Image 2	0.903	0.997	0.915	0.999	0.908	0.998	93.73	98.58	3.51	1.76
Image 3	0.998	0.992	0.889	0.974	0.940	0.982	94.14	98.99	2.01	2.53
Image 4	0.899	0.993	0.907	0.992	0.902	0.992	94.62	99.47	2.39	2.59
Image 5	0.897	0.991	0.893	0.978	0.894	0.984	94.36	99.21	4.78	1.37
Image 6	0.890	0.984	0.913	0.998	0.901	0.991	94.33	99.18	2.91	1.98
Image 7	0.937	0.994	0.927	0.962	0.931	0.977	93.71	98.56	2.09	1.89
Image 8	0.973	0.997	0.959	0.986	0.965	0.991	93.41	98.26	4.27	2.29
Image 9	0.954	0.998	0.897	0.982	0.924	0.989	94.20	99.05	2.29	2.41
Image 10	0.963	0.997	0.908	0.993	0.934	0.994	94.92	99.77	5.51	2.53
Average	0.931	0.993	0.911	0.985	0.919	0.988	94.226	99.08	3.23	2.12

The precision of the two modules is represented using a bar graph in Figure 6 with number of image samples shown along X-axis and precision values along Y-axis. It is observed that for all the 10 image samples the precision obtained using DNN with SVM is higher as compared to DNN alone except for Image 3 where reverse trend is observed. However, DNN with SVM results in higher average precision of 0.993 as compared to DNN of 0.931. This means that DNN with SVM exhibits 6.2% higher precision than only DNN is implemented.

Figure 7 represents recall comparison of the two modules involved for evaluation of the proposed brain MRI classification wok. Similar observations are also demonstrated by the two modules with DNN with SVM outperforming DNN framework with an average recall of 0.985 and 0.911, respectively. In other words, in spite of variable recall values, it is observed that overall DNN with SVM exhibits a 7.4% higher recall over ten image samples used for evaluation purposes.

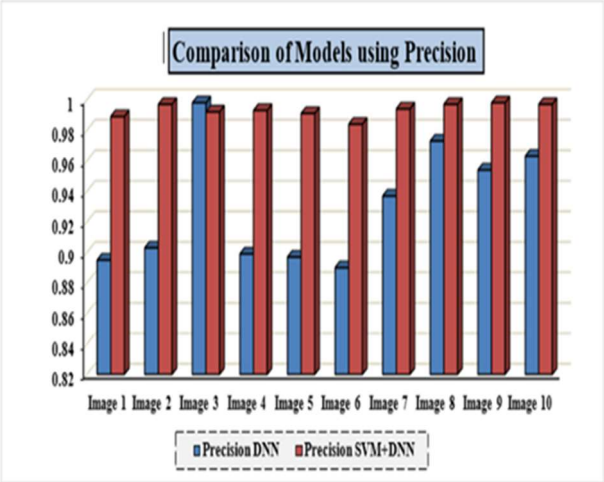


Figure 6 Precision comparison of model using DNN and DNN with SVM

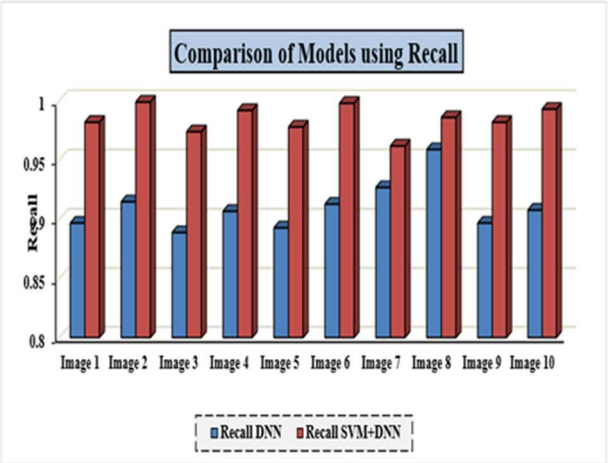


Figure 7 Recall comparison of model using DNN and DNN with SVM

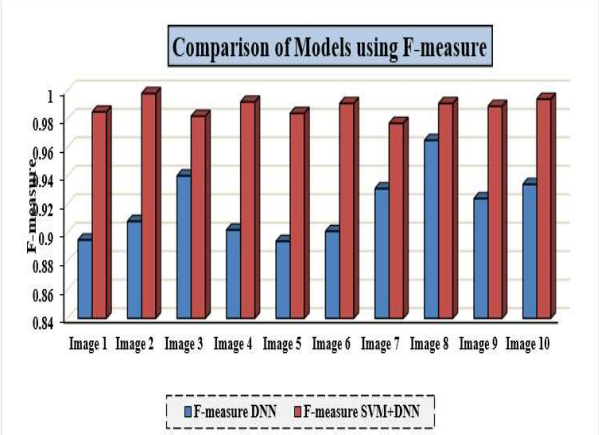


Figure 8 F-measure comparison of model using DNN and DNN with SVM

Comparative analysis of the f-measure of the two modules is illustrated in Figure 8, with a number of image samples represented on the X-axis against f-measure values along the Y-axis. F-measure is the harmonic mean of precision and recall. Therefore a similar trend is exhibited by f-measure analysis. Analysis of over 10 brain MRI image samples shows that an average f-measure of 0.988 is observed using DNN with SVM and 0.919 using DNN. In means that the average f-measure of DNN with SVM is 6.9% higher than the average f-measure computed using DNN. This reflects that DNN with SVM outperforms the DNN module for f-measure analysis.

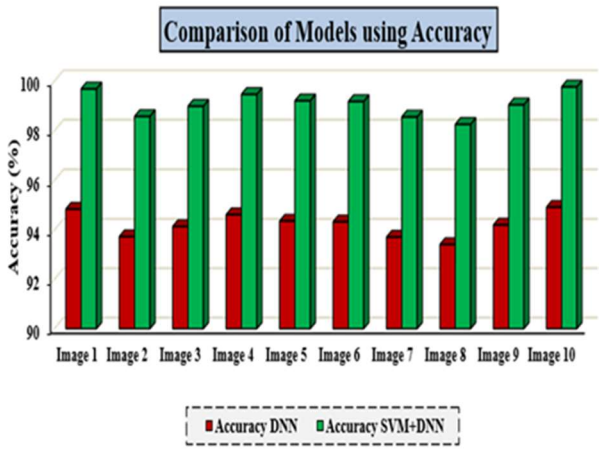


Figure 9 Accuracy comparison of model using DNN and DNN with SVM

The classification accuracy exhibited by the two modules is plotted together in Figure 9. It is observed that the average accuracy demonstrated by DNN with SVM over 10 image samples is 99.08%, and using DNN is 94.22%. This shows that with the involvement of SVM to DNN based architecture, the overall classification accuracy of the proposed work gets improved by 4.85%. This improved classification accuracy is observed due to the involvement of pretrained SVs in the classification of MRI images using DNN.

The classification time involved in the processing of the image samples is plotted for individual image samples in Figure 10, involving both the modules. The bar graph represents the number of image samples along the X- axis against the classification time required by each image for respective modules. It is observed that DNN with SVM that classifies the images based on the trained SVs reduced the average classification time to 2.12 secs as compared to the average classification time of 3.23 secs using DNN. This shows that the involvement of SVM considerably reduces the classification time of the proposed work.

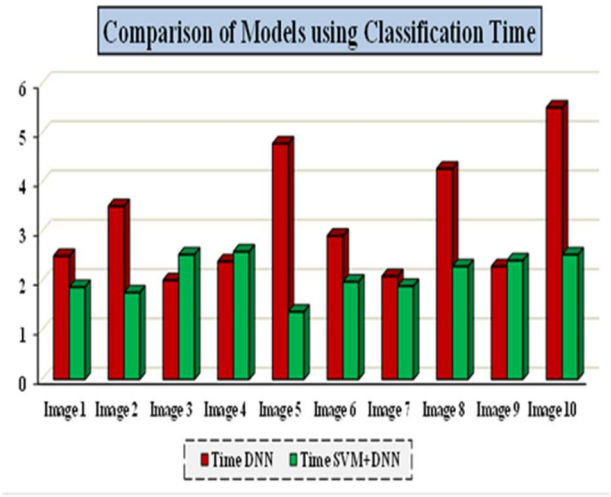


Figure 10 Classification time comparison of the model using DNN and DNN with SVM

Conclusion

In the paper, the authors had addressed a very important challenge in the field of medical imaging, i.e., the brain MRI classification attracts the attention of numerous researchers around the world. The proposed work involves FFA optimized K-means clustering for the selection of tumor regions in the MRI scan. The directionality of the marked feature data is reduced with the SURF algorithm followed by FFA for the feature selection process. The salient feature of the proposed classification architecture is that the trained SVs obtained from SVM is used for the classification performed by DNN. The performance of the proposed work is evaluated over two modules, namely, DNN with SVM and DNN alone, in terms of performance parameters, namely, precision, recall, f- measure, accuracy and classification time. The simulation analysis over 10 image samples shows that DNN with SVM outperforms the DNN module with improved precision of 6.2%, recall of 7.4%, f-measure of 6.9%, and accuracy of 4.85% with a reduction in classification time by 1.11%. This justifies the improved overall performance of the proposed work, which is due to the involvement of the trained SVs that are fed to DNN for classification.

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