International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-7 Issue-4, September 2018

A Novel Framework for Detection and Classification of Brain Hemorrhage

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Abstract: ***The proposed work focuses on detecting the correct location and type of the hemorrhage in MR Brain image. The Gradient Recalled Echo MR Images are considered as the input image. Then a region and structure specific Multi level Set evolution algorithm is implemented to segment the hemorrhagic region. An enhanced Local Tetra pattern based feature extraction algorithm is used to extract sharpened tetra features and the features are optimized by applying an enhanced Grey Wolf Optimization algorithm. Finally, a Relevance Vector Machine based Classifier is designed to classify the types of the hemorrhages. The proposed framework is compared with the existing techniques on the scale of accuracy, sensitivity, specificity, precision, Jaccard, Dice and kappa coefficient and proved to be outperforming.***

Index Terms: Brain Hemorrhage, Multi-Level Set algorithm, Local Tetra Pattern, Grey Wolf Optimizer, Relevance Vector Machine.

I. INTRODUCTION

One type of stroke which causes bleeding in the surrounding tissues by an artery in the brain bursting is referred to as Brain hemorrhage [1]. The major causes for brain hemorrhage are high blood pressure, head trauma, smoking, alcohol utility, etc. According to the brain portion in which the bleeding occurs, brain hemorrhage is of five types [2]. They are Subdural hemorrhage (SDH) – blood accumulated in the potential space in the midst of the dura and arachnoid matter of the connective tissue membranes which line the vertebral canal and skull.

Extradural Hemorrhage (EDH) – bleeding in the regions between the skull and dura mater and is caused due to the fracture in skull caused by trauma.

Subarachnoid Hemorrhage (SAH) –occursdue to bleeding in the region around the brain and also due to lack of oxygen when there is an interruption in the supply of blood.

Intraparenchymal Hemorrhage (IPH)- caused by the sudden rupture of an artery or blood vessel within the brain causing increase in pressure, damaging the surrounding brain cells. It is characterized by its distance from the skull, which is the most serious complications in case of preterm birth which were not observed consistently [3].

Intra-ventricular hemorrhage (IVH)- bleeding into the brain's ventricular system, where the cerebrospinal fluid is produced and circulates through towards the subarachnoid space. It can result from physical trauma or from hemorrhage[4].

The diagnosis of brain hemorrhages using manual methods have some disadvantages such as inaccuracy andare time consuming while detection. To overcome this, Computer Aided Detection (CAD) and Machine Learning approaches are used. The integration of data got from the modern devices and prevailing machine learning algorithms forms the major principles for developing computer-aided detection (CAD) systems [5].

The issues of medical imaging are very complicated and important to diagnose correctly for the treatments of diseases in healthcare systems [6]. Among the various imaging modalities, CT and MRI are the most effective in diagnosing the brain diseases. It is essential to understand the sequential changes that occur on the CT and MRI imaging for obtaining the knowledge about the pathophysiology and the development of the hemorrhages. To classify soft tissues of the brain (to get good contrast between different tissues) and to get high resolution images, MR Imaging is used. Thus MRI is considered as an effective modality compared to that of CT [7].

Generally MRI has different imaging sequences such as T1, T2, T2*, FLAIR, DWI and GRE. Due to these different imaging sequences and the multiplanar imaging capability, the diagnostic accuracy of MRI increases as compared to CT. Among these Gradient Recalled Echo (GRE) sequences are extremely sensitive to the vulnerability effects of the

paramagnetic and super paramagnetic breakdown products of hemoglobin. This helps to identify the hemorrhagic lesions. Thus GRE MRI has the capability to detect much smaller hemorrhagic metastases [8]. It is essential to detect the hemorrhages at the early stages otherwise it becomes very complicated due the color intensity changes in the brain images. Thus a framework is proposed to detect an early hemorrhage, which includes;

- To detect and segment the hemorrhagic region from the MRI brain image using a novel region and structure specific Multi-Level Set Evolution Algorithm.
- To extract the features from brain MR image using an Enhanced Local Tetra Pattern based Feature Extraction Algorithm.
- To extract the optimized features by applying an Enhanced Grey Wolf Optimization Algorithm.
- To classify the types of hemorrhagic images using Relevance Vector Machine based Classifier.

Revised Manuscript Received on 30 September 2018.
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The region and structure specific Multi-Level Set Evolution Algorithm is enhanced in such a way that it segments the portions of the hemorrhagic brain irrespective of the positions.

The major contribution in the proposed model is the Local Tetra pattern based feature extraction which is implemented to extract the sharpened tetra features by analyzing using the 5x5 windows. The disadvantage of the Grey Wolf Optimization (GWO) algorithm like low convergence rate and bad local searching problem is addressed in the proposed framework.

The related works about the various processes of brain hemorrhage detection are discussed in section II. The procedure and description of the proposed technique is explained in section III. The comparative results of proposed technique with traditional approaches is depicted in section IV. Conclusion of the proposed frameworks included in section V.

II. RELATED WORK

This section reviewed several traditional approaches that are used for detecting and classifying the brain hemorrhage from the medical images. The authors[9] represented an innovative and automated approach for detecting the existence of brain hemorrhage in multiple MRI brain scan. It also detected the types and position of the hemorrhage in the brain. The performance of the implemented approach offered higher accuracy for the three class classification problem whichalso solved the complexity in segmentation problems. A robust technique for the automatic segmentation of hemorrhage, ischemic stroke and tumor lesions from the MRI and CT brain images was devised by utilizing the Decision Tree classification model[10]. The type of the disease was identified and with higher accuracy. The major thrust was to facilitate fast, reliable and accurate results with respect to diagnosis of brain diseases. The authors[11] proposed a novel automatic method for detecting the cerebral microbleeds (CMBs) from the MR images of brain. It utilized a cascaded 3D convolutional neural network (CNN) framework for detecting the CMBs, which reduced the computational cost, had higher sensitivity and lesser false positive rates.

A system for identifying and classifying the presence of brain hemorrhages automatically in the brain images was recommended [12]. The method comprised of six stages such as determination of Hounsfield units, segmentation of images, extraction of brain hemorrhage regions from the image, feature extraction, classification of the hemorrhages and estimation of the timing of hemorrhage. It offered better results with increased detection and classification accuracies and helped to determine the bleeding time. The authors[2] investigated the possibility of detecting the brain hemorrhage by utilizing watershed algorithm. Then the features from the brain image were extracted and classified using artificial neural network with which the errors were minimized but the computation complexity increased. A gamma transformation approach[13]was utilized. The major advantages were its accurate detection and classification of the hemorrhage and lesser time.

The authors [14] presented the computationally intelligent techniques for classifying the brain MR images. Initially, the features were extracted using Gabor filters and the normal and abnormal images were classified using Support Vector Machine (SVM). Finally the images were classified using artificial neural networks. The major drawback was that both the classifiers need to optimize their parameters.A computer aided detection method was introduced[15] for detecting the cavernomas which was also referred to as abnormal development of the blood vessels in the brain. It involved three major steps such as extraction of the brain features based on the deformable contour, template matching to identify the suspected abnormal regions and the post-processing to avoid the false positives due to the information about the shape, size and brightness. It offered better results with high sensitivity. A robust and accurate segmentation method based on a mixture of an atlas-based and active contours segmentation was developed[16]. The experimental analysis revealed an extraordinary correlation with increased accuracy and was well suited for the reliable ventricle segmentation in stroke patients.

A geodesic level set algorithm for segmenting the cerebral from the T1 weighted MRIs was implemented [17]. The multi-region segmentation technique was utilized and the results showed that the proposed algorithm was helpful for both the analysis of morphological as well as volumetric of the ventricle system of IVH brains. The authors[18] focused on the feature extraction of the MRI and CT brain images. The abnormalities such as brain hemorrhage and brain tumor were considered into account which were diagnosed using same methodology. Various phases were explored such as brain image extraction, transformation and progression of the MRI or CT images. The accuracy of detecting the abnormalities in the images were enhanced. The authors[19]employed a wavelet based energy model for automatically classifying the abnormalities from the brain MRIs. Here, the SVM classification approach was utilized to classify the label as normal or abnormal. Also, the Biogeography Based Optimization (BBO) technique was used for an optimization. The proposed approach performed superior than the other approaches, but was not suited for the higher level classification performance.

A CAD system for detecting the pathology of brain in MRIs was implemented [20]. In this work, the BBO and PSO techniques were hybridized for attaining an accurate classification results. Higher accuracy in detection and classification was achieved. The authors[21] proposed an iterative implementation of level set methodology for the segmentation of MRI brain images which created a hierarchical structure for the precise segmentation. The efficiency of segmentation method was evaluated using various performance metrics such as accuracy, relative error and similarity index. The segmentation method obtained higher accuracy. A new automatic CAD system for the classification of MRI brain images was recommended[22]. The features were extracted by utilizing the 2-D discrete wavelet transform.

The principal component analysis (PCA) and the linear discriminant analysis (LDA) were utilized for reducing the dimensions of the features. The classification was carried out using random forest approach. The proposed approach had better classification accuracy with limited number of features.

III. PROPOSED METHOD

The proposed approach helps to detect and classify the types of hemorrhages form the MRI brain images. The input dataset was collected from SDM Medical College, Dharwad. It consists of 200 images with 90 IPH images, 40 SDH images, 30 IVH images and 10 SAH images (few with more than one type). The flow of the proposed approach is depicted in Figure. 1. Initially the input MR image is preprocessed by using the processes of noise removal, edge and image enhancement. Then the segmentation of hemorrhagic region from the preprocessed image is obtained by using a novel Multi Level Set algorithm. The features from the segmented image is extracted and the best features are selected using an optimization algorithm. From the best selected features, the type of hemorrhage from the brain image is classified using a classification approach.

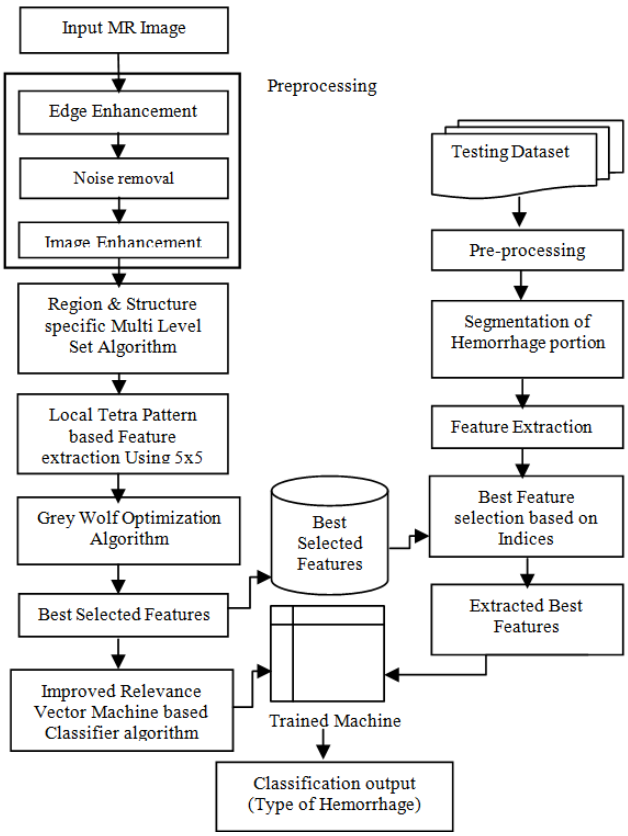

Figure. Flow of the Proposed Framework.

A.A region and structure specific Multi level Set evolution Algorithm for Segmentation Initially the hemorrhage affected regions from the MRI brain image is segmented using multi-level set method. The representation of a contour, as a zero level set for the higher dimensional function(LSF) and, representing the contour motion as the evolution of level set function, are the basic principle behind the level set method. In the applications of computer vision and image processing, the concept of level set method has been presented in the context of active contour for the segmentation process in an image.

The Distance Regularized Level Set Evolution (DRLSE) is utilized in which an edge based active contour model is applied for image segmentation. Generally a contour of interest can be embedded as zero level set of an LSF. It is essential to preserve the LSF in a better condition even though the zero level set of the LSF is the final result of level set method to make it stable and computation accurate. In the level set evolution, the LSF is required to be smooth neither too flat nor too steep. This condition is satisfied by the unique property $|\nabla \phi|=1$ of signed distance functions which is denoted as signed distance property. Here the mask can be required to convert into the desired shape. For that the energy, curvature, distance, gradient flow are to be estimated with this distance regularization. Energy estimation is carried out by using the following equation as,

Let $\phi: \delta \rightarrow R$ be a LSF which can be defined on anarea δ, then the energy estimation $E(\phi)$ can be represented as,

$$En(\phi) = \lambda r_t(\phi) + En_{ext}(\phi) \quad (1)$$

Where, λ is constant, $En_{ext}(\phi)$ is the external energy which rely upon an image for segmentation, $r_t(\phi)$ is the level set regularization term and it is illustrated as

$$r_t(\phi) \triangleq \int_\delta t(|\nabla\phi|)dx \quad (2)$$

Where, t is the potential or energy density function..

Then the potential t for distance regularization is

$$t = t_1(p) \triangleq \frac{1}{2}(t-1)^2 \quad (3)$$

Which has t=1 as distinctive least point. Using this potential $t = t_1(p)$, the level set regularization term $r_t(\phi)$ is demonstrated explicitly as,

$$r_t(\phi) = \frac{1}{2}\int_\delta (|\nabla\phi| - 1)^2 dx \quad (4)$$

Which illustrates the variation of ϕ from a signed distance function. The algorithm for Novel Multi Level Set Algorithm is described as follows,

Region and Structure Specific Multi Level Set Evolution Algorithm

Input: Input Image I

Output: Segmented result I_{seg}

Procedure:

Step 1: Compute intensity distribution using threshold for low and high intensity.

Step 2: Lower mask detection,

Calculate the threshold value for lower mask L_{th} by estimating the 40% of the maximum intensity of the image using equation (5)

Detection of lower mask region based on the estimated L_{th} using equation 6)

Step 3: Upper mask detection,

Calculate the threshold value for upper mask U_{th} by estimating the 80% of the maximum intensity of the image using equation (7)

Detection of upper mask region based on the estimated U_{th} using equation (8)

Step 4: Initialize the mask for segmentation using equation (9)

Step 5: For iteration = 1 to N

Step 6:Compute the index of the mask using equation (10)

Step 7: Calculate the mask using equation (11)

Step 8:Calculate the energy updation and difference in energy updation using equation (12), (13), (14) and (15)

Step 9:Calculate Direction Updation using equation (16) & (17)

Step 10:Calculate Contour Weight Updation using equation (18)

Initially, the intensity distribution for the low and high intensity is computed using threshold. Then the lower mask and upper mask is detected by determining the threshold value with the estimation of maximum intensity of the image.The threshold value for the lower mask can be calculated by estimating the 40% of the maximum intensity of the image and is given by,

$$L_{th} = \max(I) * 40\% \quad (5)$$

Where, L_{th} - Lower threshold

Based on this L_{th} estimation, the lower mask region is detected by,

$$LM_{ij} = \begin{cases} I_{ij} I_{ij} \le L_{th} \text{ and } I_{ij} \ne 0 \\ 0 \quad \text{else} \end{cases} \quad (6)$$

LM_{ij} – Lower mask region

Similarly the threshold value for the upper mask can be calculated by estimating the 80% of the maximum intensity of the image and is given by,

$$U_{th} = \max(I) * 80\% \quad (7)$$

Where, U_{th} - Upper threshold

Based on this U_{th} estimation, the upper mask region is detected by,

$$UM_{ij} = \begin{cases} I_{ij} I_{ij} \ge U_{th} \\ 0 \quad \text{else} \end{cases} \quad (8)$$

UM_{ij} – Upper mask region

After detecting the upper and lower mask region of the image, the mask is initialized for segmentation by,

$$M_{ij} = \begin{cases} 1 \;\; LM_{ij} > 0 \;|\;|\; UM_{ij} > 0 \\ 0 \quad else \end{cases} \quad (9)$$

The index of the mask image, curvature, energy updation and the direction updation are calculated for n number of iterations using the multi-level set algorithm. Finally the contour weight updation is also calculated. Let the index of the image is calculated as,

$$\text{Idx} = \text{Index}(M) \quad (10)$$

Curvature of the image is calculated as,

$$\frac{\partial f}{\partial t} = \nabla f M(\text{Idx}) + k \quad (11)$$

Where, k – Constant, f – Variation in pixel (I) at 8 dissimilar direction at the angles of 0°, 30°, 45°, 60°, 90°, 120°, 135°, 180° and also its respective opposite angles.

Energy updation as,

$$E_I = \begin{cases} M & \text{if } (M \le 0) \\ 0 & \text{else} \end{cases}, \text{ Internal Energy} \quad (12)$$

$$E_E = \begin{cases} M & \text{if } (M > 0) \\ 0 & \text{else} \end{cases}, \text{ External Energy.} \quad (13)$$

$$\text{Energy}, I_E = \frac{(I(\text{Idx}) + \sum E_I)}{\max((I(\text{Idx}) + \sum E_E))} + \alpha * \frac{\partial f}{\partial t} \quad (14)$$

Energy updation difference is also deliberated as,

$$dt = \frac{t}{\max(I_E)} \quad (15)$$

Direction Updation as,

$$P^+ = \sqrt{\max(ap^2, bn^2) + \max(cp^2, dn^2)} \quad (16)$$

$$P^- = \sqrt{\max(an^2, bp^2) + \max(cn^2, dp^2)} \quad (17)$$

Where,

ap, an, bp, bn, cp, cn, dp, dn – Positive and negative position of backward, forward, Right and left respectively.

P^+- Positive position, P^- - Negative position.

Contour Weight Updation is calculated as

$$\delta_{i+1} = \delta_i - dt * \frac{\delta_i}{20 * \sqrt{\delta_i^2 + 1}} * (M + dt * I_E) \quad (18)$$

Where, δ_i – Direction of level set contour model for i = 1 to number of iteration, dt - variation in energy updation

A. Feature Extraction

Then the feature extraction process is carried out using local patterns. In this work, Local Tetra Patterns are used for extracting the features from the MRI brain image which are defined by the adaptation of local patterns such as LBP, LDP and LTP. The spatial structure of local texture is described by the Local Tetra Patterns with the utilization of the direction of center gray pixel.

Generally, 3x3 matrix is considered for determining the spatial structure. But in this work, 5x5 matrix is taken account into account for spatial structure of the local patterns along with various directions of the center pixel. The estimation of Local Tetra Pattern for each pixel of the block can be obtained using,

$$Gc = \sqrt{(B_{i-1,j} - B_c)^2 + (B_{i,j+1} - B_c)^2} \quad (19)$$

Where,

$B_c - center\ pixel\ and\ B_{ij}\ neighboring\ pixel$

Compute the estimation for each pixel in the 5x5 matrix for extracting the features from the MRI brain image. The algorithm for feature extraction is given as follows;

An Enhance Local Tetra Pattern based Feature Extraction *Algorithm*

Input: Segmented result, I_{seg}

Output: LTP features, Fea

Procedure:

Step 1: Divide the image into 5*5 block,

$[m\ n] = size(I_{seg})$

for ii = 3:m-3

for jj = 3: n − 3

$B = I_{seg}(ii - 2{:}ii + 2, jj - 2{:}jj + 2)$

Step 2: Perform local tetra pattern estimation for each pixel of the block using equation (19),for all elements in 5*5.Calculate and assign values as shown (for ex. G1).

$$G1 = \sqrt{(B_{i-2,j-1} - B_{i-2,j-2})^2 + (B_{i-1,j-2} - B_{i-2,j-2})^2}$$

If Gc > G1

P(1) = 0,

Else

P(1) = 1

End

B. Optimization Algorithm for Feature Selection

From the extracted features, the best features are selected using optimization algorithm. Here the Grey Wolf Optimizer algorithm is used for extracting the best features from the extracted features of the MRI brain image. Generally there are four types of features which are categorized depending upon the fitness value and are arranged as alphas, betas, deltas and omegas.With this categorization the best features are selected. The Grey Wolf Optimization Approach has three main phases such as

Following, racing, and impending the prey.

Tracking, surrounding, and troubling the prey till it stayswithout moving

Attack in the direction of the prey.

During the hunt, the Wolves encircle the prey and this encircling behavior is designatedby utilizing the mathematical model as,

$$\vec{E} = |\vec{A}.\vec{Y}_p(n) - \vec{Y}(n)| \quad (20)$$

$$\vec{Y}(n+1) = \vec{Y}_p(n) - \vec{B}.\vec{E} \quad (21)$$

Where, n is the present iteration

$\vec{B}$ and $\vec{A}$ are coefficient vector,

$\vec{Y}_p$ is the position vector of the prey,

$\vec{Y}$ is the position vector of the grey wolf

The vectors $\vec{B}$ and $\vec{A}$ are expressed as,

$$\vec{B} = 2\vec{b}.\vec{t}_1 - \vec{b} \quad (22)$$

$$\vec{A} = 2.\vec{t}_2 \quad (23)$$

Where, the elements of $\vec{b}$ are decreased linearly from 2 – 0 over the iterations, t_1, t_2 are the random vectors.

Then the process of hunting is carried out by the guidance of alpha. The mathematical model for the hunting behavior is expressed as,

$$\vec{E}_\alpha = |\vec{A}_1.\vec{Y}_\alpha\vec{Y}|, \vec{E}_\beta = |\vec{A}_2.\vec{Y}_\beta\vec{Y}|, \vec{E}_\delta = |\vec{A}_3.\vec{Y}_\delta\vec{Y}| \quad (24)$$

$$\vec{Y}_1 = \vec{Y}_\alpha - \vec{B}_1.(\vec{E}_\alpha), \vec{Y}_2 = \vec{Y}_\beta - \vec{B}_2.(\vec{E}_\beta), \vec{Y}_3 = \vec{Y}_\delta - \vec{B}_3.(\vec{E}_\delta) \quad (25)$$

$$\vec{Y}(n+1) = \frac{\vec{Y}_1 + \vec{Y}_2 + \vec{Y}_3}{3} \quad (26)$$

For the attacking behavior, the grey wolves completes the hunt by attacking the prey during the movement of the prey is stopped. The value of $\vec{b}$ is decreased for the mathematical model of attacking prey. The GWO procedure permits its search proxies to update their position depending up on the position of the alpha, beta, and delta; and attack in the direction of the prey.The GWO algorithm supports 23 benchmark functions. The multimodal benchmark function F10 has been implemented for better optimized features.The GWO algorithm is as follows

Grey Wolf Optimization Algorithm

Input: Extracted Features Fea

Output: Best features $Best_{fea}$

Procedure:

Step 1: Generate initial search agents G_i *using equation (27)*

Step 2: Initialize the parameter vector's for grey wolf optimization process,

For l=1: $MIter$

Control coefficients are, a, A and C

$a = 2 - l\frac{2}{MIter}$ // *l –linearly variable, l=1 to* $MIter$, $MIter$*-Maximum Iteration.*

$A = 2ar_1 - a$ // r_1 *- random number*

$C = 2r_2$ //r_2 *– random number*

Step 3: Calculate the fitness function for the features using (28)

Perform logistic map for the features,

$X = Fea$

$X_{n+1} = a.X_n(1 - X_n)$

// n – number of iteration

Step 4: Choose the first three best fitness value as the best hunt agent,

$G_\alpha = (Fit_{val} \quad if\ Fit_{val} < \alpha)$

$G_\beta = (Fit_{val} \quad if\ Fit_{val} > \alpha\ and\ Fit_{val} < \beta)$

$G_\delta = (Fit_{val} \quad if\ Fit_{val} > \alpha\ and\ Fit_{val} > \beta\ and\ Fit_{val} < \delta)$

Step 5:Update the positions based on the best hunt agent using (29)

$Best_{fea} = Fea\ (:, P)$

End for

In this algorithm, the initial search agents are generated and the parameter vectors for the grey wolf are initialized. Then the fitness function for the features are calculated by performing the logistic map for the features. From the calculated fitness function, the first three best fittest values are selected as the best hunt agents. Depending upon the position of the best hunt agent, the positions are updated. This process is repeated and updated the position until the best fittest values for the features are obtained.

The initial search agent is obtained by,

$$\forall\, i = 1{:}size(Fea, 1) \quad (27)$$

Where, $Size(Fea, 1)$ is the Extracted feature dimension

$G_i = Fea_i$

The fitness value for the features are calculated using,

$$Fit_{val} = \frac{\sum_{k=1}^{n} x}{n} \quad (28)$$

The first three best fittest values are represented as $G_\alpha, G_\beta, G_\gamma$

Where, G_α – First best hunt agent,

G_β – Second best hunt agent,

G_δ – Third best hunt agent

α – Alpha score,

β – beta score,

δ-delta score

The positions are updated using the following equation,

$$P = \frac{X_1 + X_2 + X_3}{3} \quad (29)$$

Where,

$X_1 = Fit_{val} * AG_\alpha$,

$X_2 = Fit_{val} * AG_\beta$,$X_3 = Fit_{val} * AG_\delta$

Figure. 2 shows the simulation results of GWO. From the graph it is shown that the GWO helps to select the optimal features for the segmentation process.

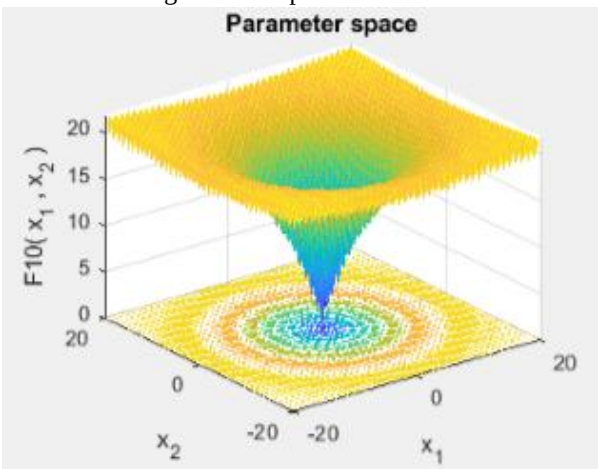

Figure.2 Simulation Results of GWO

C. Classification

phase and it is given as $\{i_m, C_m\}_{m=1}^{M}$ Where, i_m is the input feature vector of size 1xN, C_m is its respective class or target, M represents the number of samples.

The main motive of RVM learning is to map a function $f(i_m)$ in order to predict the class or target $C_m$and the ability to predict a class or target C_* for any new input i_*. The mathematical representation of a mapping function $f(i_m)$ which is a sigmoid function is given as,

$$f(i_*, \omega) = \rho\left(\omega^T \phi(i_*)\right) = \frac{1}{1 + exp\left(-\omega^T \phi(i_*)\right)} \quad (30)$$

Where, ω is the weight matrix, $\phi(i) = [\phi_1(i), \phi_2(i), \dots, \phi_M(i)]^n$, $\phi(i)$ is the generator matrix with$\phi_M(i) = L(i, i_m)$, Where, $L(i, i_m)$ is the kernel function.By, using this RVM approach, the types of hemorrhages in the MRI brain image is classified effectively. The simulation results of the proposed framework is given Figure.3.

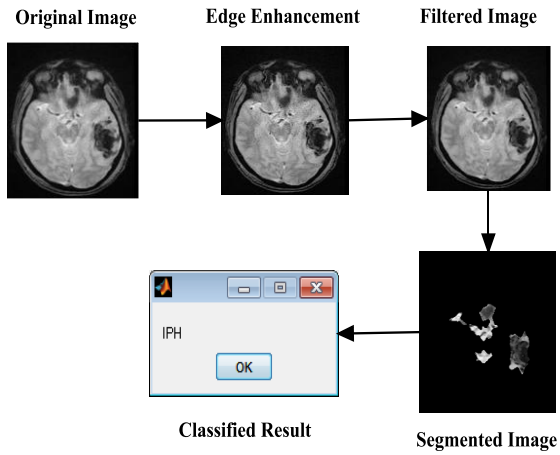

Figure.3 Simulation Results

IV. RESULTS AND DISCUSSIONS

Several performance metrics such as accuracy, sensitivity, specificity, precision, recall, predictive rate, Jaccard coefficient, dice coefficient and kappa coefficient are used for analyzing the performance of the proposed approach.

Precision- is the definition of random errors which is a degree of statistical variability.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (31)$$

Accuracy-is defined as the closeness of a measured value to the standard values.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (32)$$

Sensitivity-is referred to as the measure of the ratio of True Positive that are recognized accurately by the analytical test.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (33)$$

Specificity-is described as the ratio of True Negatives that are detected correctly.

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (34)$$

Jaccard Coefficient-is characterized as the ratio of intersection of two similarity images to the union of same similarity images. It is calculated as

$$\text{Jaccard Coefficient} = \frac{A \cap B}{A \cap B} \quad (35)$$

Table 1 shows the performance analysis of the accuracy sensitivity and specificity for both the proposed and existing approaches. Figure.4 depicts the comparative analysis of the proposed and existing approaches for the metrics such as accuracy, sensitivity and specificity. Here the existing techniques such as SVM, KNN and PNN are compared with the proposed RVM technique. Form the results it is observed that the proposed RVM techniques performs better with increased accuracy, sensitivity and specificity compared to that of the existing techniques.

Table.1 Performance of Sensitivity, Specificity, Accuracy and Precision.

Measures	RVM	SVM	KNN	PNN
Sensitivity	87.1162	63.3333	55.5	85
Specificity	95.2008	92.0714	91.9935	93.6372
Accuracy	93.2432	88.5246	89.3443	90.5405
Precision	85.986	50.4736	54.7748	83.7733

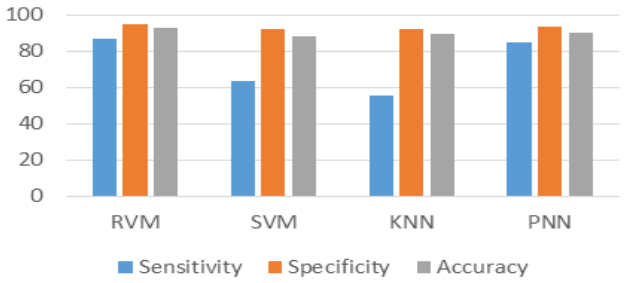

Figure. 4 Sensitivity, Specificity and Accuracy

Table 2 indicates the performance analysis of the Jaccard, dice and kappa coefficient for both the proposed and existing approaches. Figure.5 illustrates the comparative analysis of the proposed and existing approaches for the metrics such as dice, Jaccard and kappa coefficients. Here the existing techniques such as SVM, KNN and PNN are compared with the proposed RVM technique. Form the results it is noted that the proposed RVM techniques performs better compared to that of the existing techniques.

Table.2 Performance of Jaccard. Dice and kappa coefficient

Measures	RVM	SVM	KNN	PNN
Dice	86.3715	54.359	55.0314	80.1882
Jaccard	76.1196	45.5492	45.3571	68.7733
Kappa	0.8153	0.4819	0.4736	0.7456

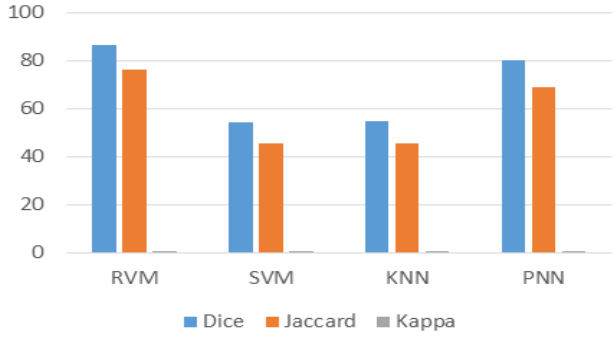

Figure.5 Dice, Jaccard and Kappa coefficient

Table. 3 Comparative Results.

Techniques		SVM	KNN	PNN
% of increase of RVM approach	Accuracy	5.1%	4.2%	2.9%
	Sensitivity	27.3%	36.3%	2.4%
	Specificity	3.3%	3.4%	1.6%
	Precision	41.3%	36.3%	2.6%
	Recall	27.3%	36.3%	2.4%
	Jaccard	40.2%	40.4%	9.7%
	Dice	37.1%	36.3%	7.2%
	Kappa	40.9%	41.9%	8.5%

V.CONCLUSION AND FUTURE WORK

The research work proposed an efficient early detection and classification of the brain hemorrhage. The performance of the proposed framework is evaluated using various parametric measures as depicted in table 3. The effectiveness of the proposed framework is proved by comparing it with the SVM, KNN, and PNN methods. The accuracy of proposed RVM method is 5.1% more than SVM, 4.2% more than KNN, and 2.9 % more than PNN. The sensitivity of proposed RVM method is 27.3% more than SVM, 36.3% more than KNN, and 2.9 % more than PNN. The specificity of proposed RVM method is 3.3% more than SVM, 3.4% more than KNN, and 1.6 % more than PNN. From the results it is concluded that the proposed framework has improved performance in detecting and classifying the brain hemorrhagic images compared to that of the existing techniques. However, the proposed framework can be enhanced and tested with a larger dataset.

ACKNOWLEDGEMENT

Authors wish to thank Dr. Preetam Patil Associate Professor, SDM Medical College, Dharwad and also the Members of Ethical Committee for providing data set of real time images and helping to verify the results.

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