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A Crossbred Approach for Effective Brain Stroke Lesion Segmentation

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Abstract: An Ischemic stroke is expressed as lost neurological brain work because of the sudden loss of blood dissemination in the specific territory of the brain. The sub-acute ischemic stroke is the most basic illnesses reason for death on the planet. In this paper we utilize a hybrid way to deal with detecting the ischemic stroke from the alternate pathologies in magnetic resonance (MR) images utilizing Kernelized Fuzzy C-means (KFCM) clustering with adaptive threshold algorithm and the Support Vector Machine (SVM) classifier. In the existing method, the Otsu's method incorporated with SVM classifier method is utilized for the segmentation of the ischemic stroke image, but it has the limited accuracy 88%, specificity 66% and the sensitivity value is 94%. For the exact identification and segmentation the KFCM algorithm is utilized. The distance and the intensity of the lesion tissue is identified by this method. The accuracy and segmentation aftereffects of the classifier are measured in the testing and training phase by looking at the comparable and a decent variety of sample sets by considering diverse groupings. Our test comes about demonstrating that, the performance of the proposed technique is assessed in view of the precision, recall, sensitivity, accuracy and overlap metrics of the framework. Compared with the existing classification method, the proposed method has 17.64% RMSE (Root Mean Square Error), 6.24% MAPE (Mean Absolute Percentage Error) and 2.55% MBE (Mean Bias Error), consumption time is 6.45 (s) and also the sensitivity and the accuracy ranges are 98.8% and 99%. The proposed approach is actualized using MATLAB and the realtime datasets are used for our examination.

Keywords: Ischemic stroke, Kernelized fuzzy c-means (KFCM) clustering, Gray level Co-occurrence matrix feature extraction technique, Support vector machine (SVM) classifier.

1. Introduction

Stroke or cerebrovascular accident is a disease which affects the vessels that supply blood to the brain. The blockage of the blood vessel and the bursts of the blood vessels causes the brain stroke [1-2]. There are three main kinds of stroke: Ischemic strokes (severely reduced blood flow), Hemorrhagic strokes (leakage of blood) and Transient ischemic attacks (TIAs-also referred to as mini-strokes) [3, 4]. Ischemic brain stroke is one of the leading causes of death and disability in major industrialized countries [5]. To detect the Ischemic brain cells, the computed tomography (CT) and Magnetic Resonance Image (MRI) is the two important screening tests [6, 7]. The existing methods used the conventional threshold techniques, but this method only has the limited accuracy and repeatability [8, 9]. The clear image of the affected region of the brain image is not provided by the above techniques, but, for the early identification of the brain infection, the MRI is more efficient than the CT [10].

The brain stroke detection techniques consolidate many methods such as preprocessing, segmentation, feature extraction and classification [11-13]. The researchers proposed many techniques for the segmentation and classification of images. A fuzzy clustering approach [14] to the segmentation followed by 3D connected components to build the tumor shape, Atlas-based medical image segmentation techniques [15] which convert the segmentation of an MR image into a nonrigid registration problem between the MR image of the patient and the MR image used to create the brain atlas. Unfortunately, this requires using a large seed that mask atlas structures, potentially leading to erroneous results. The drawback of FCM (Fuzzy C-Mean) [16] is that the spatial neighborhood term is computed at each iteration step, which is very time-consuming. Fast generalized FCM (FGFCM) algorithm [17] which introduces a local similarity measure, but the computational cost is very high in this method.

After extracting the features of the segmented image, the researchers introduce many types of classification techniques to classify the stroke and non-stroke regions. The Artificial Neural Networks (ANN) [18] which is used to anticipate the fate of ischemic tissues on three different stroke groups. But it may suffer from an overfitting problem. The Random Decision Forests [19] is a popular classifier, but it can contain errors, noise and image artifacts, which may lead to uncertainties.

In this paper, we use the joint execution of the KFCM algorithm and the SVM classifier for the ischemic stroke segmentation and detection. On the underlying stage, the image resizing and the grayscale conversion are done through the preprocessing step. In the second stage, the better segmentation is finished by using the KFCM clustering with the adaptive thresholding algorithm. The distance and the intensity of the stroke area are recognized by this algorithm. After the segmentation procedure, the features of the segmented image are separated through the Gray Level Co-Occurrence Matrix (GLCM) feature extraction technique. At long last, the acute and the sub-acute stroke regions are classified by using the SVM classifier.

The rest of the paper is organized as follows; various methods have been used in the literature as given in Section 2, the proposed technique is described in section 3. Simulation results are given in Section 4 and the concluding remarks are described in Section 5.

2. Related work

To delineate infarct lesion in diffusion-weighted imaging (DWI) MR images of the brain, A. Subudhi et al. [20] have proposed a watershed-based lesion segmentation algorithm. The main goal of their work was, to detect lesion boundaries appropriately through combining the strength of guided filter and watershed transform through relative fuzzy connectedness (RFC). Over segmentation and poor detection rate are the major drawbacks of the watershed based algorithm.

For the Sub-Acute Stroke Lesion Segmentation (SISS) and Stroke Perfusion Estiamtion (SPES), O. Maier et al. [21] have developed a common evaluation benchmark framework. However, algorithms applied to sub-acute lesion segmentation in SISS still lack accuracy.

To detect the ischemic stroke automatically, a new computer aided detection technique is proposed by N. Hema Rajini and R. Bhavani [22]. The application of their method is, early detection, accuracy and efficiency improvement. But this technique detects stroke in only CT images.

For the image segmentation, an improved fuzzy C-means (FCM) algorithm was proposed by M. Gong et al. [23], they have also introduced a kernel distance measure to its objective function, to enhance its robustness to noise and outliers. Here, the spatial neighborhood term is computed at each iteration step, which is very time-consuming. This is the main drawback of this system

To detect and classify stroke in skull CT images via Analysis of Brain Tissue Densities (ABTD) was proposed by P. Rebouças Filho et al. [24]. Their method used to extract the features based on the radiological density pattern of the brain. But this method requires much time to detect the stroke lesions at the time of bleeding.

E. Rebouças et al. [25] have presented an Analysis of Human Tissue Densities (AHTD) to extract features from the medical images. The proposed method uses radiological densities of human tissues in Hounsfield Units to tackle the extraction of features from the medical images.

K.G. Satheesh et al. [26] have proposed a multiple kernel fuzzy c-means (MKFCM) algorithm for early detection of Tuberculosis (TB). In their approach, hybrid classifier is an integration of Support Vector Machine (SVM) and Artificial Neural Network (ANN) which are applied to computed tomography (CT) scan lung images to provide results with high accuracy. However, the CT method only has the limited accuracy and repeatability when compared with the MRI scans. So in their method, the early detection process does not provide a clear image of the exact affected region. Also the MKFCM method utilized the composite or multiple Kernels for the image segmentation approach.

The above assigned existing works supplanting many difficulties. Be that as it may, a large portion of the methods used the CT image for early recognition of sub-acute and acute ischemic stroke. In any case, the CT image doesn't give the unmistakable image of the influenced region, so the proficiency is less and furthermore numerous procedures give the misclassification comes about. Be that as it may, our approach used the MR image for the early discovery of sub-acute and acute ischemic stroke. For the early recognizable proof of the brain infection, the MRI is more productive than the CT. The proposed approach utilized Kernelized Fuzzy C-means (KFCM) clustering with an adaptive threshold algorithm for the segmentation of low contrast images and medical images. Our method is good for detecting large and small images concurrently and also the adaptive threshold algorithm using the morphological filter to fill the small gaps between images. When the training data are less than 750, applying only one kernel based KFCM provides a much performance than the multiple kernel based MKFCM, when the number training data is higher than the 750, at that place only the multiple kernel based MKFCM is show their advantages. Furthermore, our proposed approach utilized an SVM classifier for the exact identification of ischemic brain stroke areas and the SVM classifier is a single kernel based classifier. Since the SVM classifier is one of the well-known classifier, it is enough to classify the sub-acute and acute ischemic stroke region.

3. Proposed method and implementation

The proposed method implements a crossbred approach for ischemic stroke segmentation and detection using KFCM algorithm and SVM classifier. To detect the ischemic stroke in appropriate time, efficient techniques are developed for physician's help. In our method, the MR images are acting as the input data and our method consolidates four stages, preprocessing, image segmentation, feature extraction and classification. In the initial stage, the image resizing and the grayscale conversion are done by preprocessing. In the second stage, the preprocessed images are segmented by the KFCM algorithm, then the features of the segmented images are extracted by using the GLCM feature extraction techniques for the left and right side of the brain, this process is done in the third stage. Finally, the extracted features are acting as the input of the SVM classifier to classify the acute and sub-acute stroke lesions. Then the performance of the classifier is measured in terms of accuracy, sensitivity and specificity.

3.1 Preprocessing

The quality of the image is improved by the preprocessing techniques. All image segmentation and the classification technique consist the training phase and the testing phase and it is generated by the preprocessing step. It removed the skull region surrounding the tissues. The quality of the image is enhanced by the Image resizing and grayscale conversion.

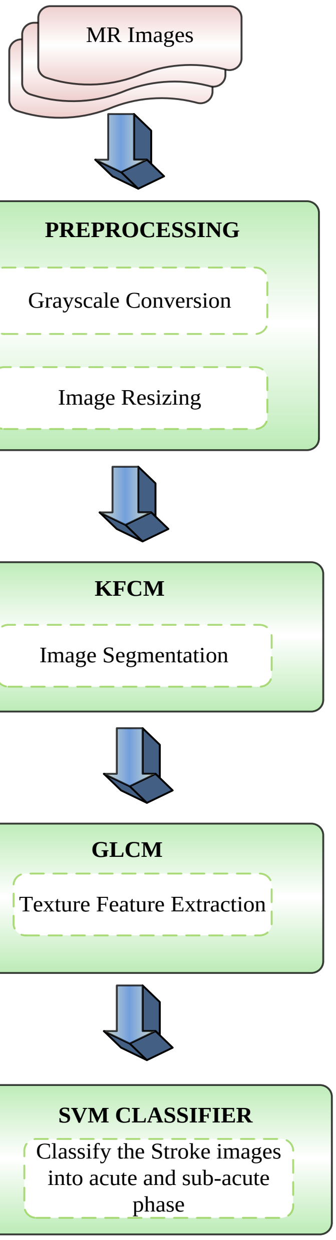

Figure.1 Flowchart of the proposed method

3.1.1. Grayscale conversion of image

In preprocessing, the accurate information about the tissues is identified by the contrast image. All the images have the contrast but its level is below the threshold level of the human perception. To increase the contrast between the human brain and the stroke region, the enhancement is required. So the MR images are converted into grayscale images to make the image contrast. The intensity of light at each pixel is identified as per the particular weighted combination of frequencies.

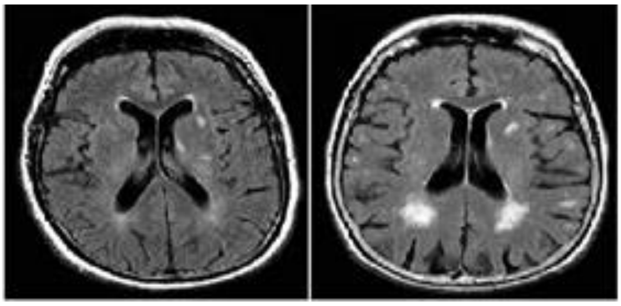

Figure.2. Grayscale conversion: (a) original image and (b) grayscale image

3.1.2. Image resizing

For display, storage and transmission of image, the image resizing is the important step in preprocessing. As the size of an image is enlarged, so the pixels which contain the image turn increasingly visible, making the image by image soft. The obtained image is resized according to the requirement of the system. Here, the dimension of the image is changed by the resizing step. The image resizing is required for minimizing a grayscale image into 200*200 pixel size.

3.2 KFCM algorithm for image segmentation

The KFCM is the standard segmentation algorithm used to segment the preprocessed MR images. Only gray level between the pixels is considered by this algorithm, the spatial information is not considered by this. A novel Kernelized Fuzzy C-means algorithm is modified by an objective function in FCM with the original Euclidian distance is replaced by a kernel-induced distance metric.

Let us consider, the input image $P= \{p_1, p_2, \ldots p_n\}$ ((i.e) $\{P_k\}^{N}_{k-1}$) has N pixels, here, the i-th pixel's gray value is represented as P_k. The given dataset is partitioned into $C= \{c_1, c_2 \ldots c_n\}$ and the objective function of the FCM is given as follows,

$$J_s = \sum_{i=1}^{c}\sum_{k=1}^{N} V_{ik}^{s} \left\| P_k - u_i \right\|^2 \quad (1)$$

In the above equation, the center of the each cluster is represented as $\{u_i\}^{c}_{i=1}$, the array V_{ik} satisfies the following constraints

$$V_{ik} \in [0,1] \mid \sum_{k=1}^{c} V_{ik} = 1 \quad \text{And} \quad 0 < \sum_{k=1}^{N} V_{ik} < N \quad (2)$$

In Eq. (1), the weighting exponent of every fuzzy membership is represented as S. For clustering the image, the intensity of the pixel values and the gray level values are the two important features. The main goal of the FCM algorithm is to comprise the center of each cluster as a linearly combined sum of all $\eta(P_k)$ (feature space). In that place, we implement a KFCM algorithm and its objective function is given as follows,

$$J_s = \sum_{i=1}^{c}\sum_{k=1}^{N} V_{ik}^{s} \left\| \eta(P_k) - \eta(u_i) \right\|^2 \quad (3)$$

Where, μ_i – i-th Cluster center

V_{ik} - k-th sample membership from the i-th category

s - coefficinet of fuzziness

$\eta(P)$ - Nonlinear transformation from the original input space to a high dimensional feature space

The form of the above Eq. (3) is given as follows,

$$\left\| \eta(P_k) - \eta(u_i) \right\|^2 = K(p_k, p_k) + K(u_i, u_i) - 2K(p_k, u_i) \quad (4)$$

In KFCM, the Gaussian kernel function $K\ (p,\ q)\ =\ \eta(P)^T \eta(q)$ and the Gaussian kernel parameter ϖ are given as follows,

$$K(p,q) = \exp\left(\frac{-\left\| p - q \right\|}{\varpi^2} \right) \quad (5)$$

The partition matrix V and the center of the cluster is estimated by adopting the Lagrange multipliers and the partition matrix is given as follows,

$$V_{ik} = \frac{\left[1/K(p_k,p_k) + K(u_i,u_i) - 2K(p_k,u_i) \right]^{\frac{1}{s-1}}}{\sum_{i=1}^{c} \left[1/K(p_k,p_k) + K(u_i,u_i) - 2K(p_k,u_i) \right]^{\frac{1}{s-1}}}, \quad 1 \le k \le N, 1 \le i \le c \quad (6)$$

The cluster center u is given as follows,

$$u_i = \frac{\sum_{k=1}^{N} V_{ik}^{s} K(p_k, u_i) p_k}{\sum_{k=1}^{N} V_{ik}^{s} K(p_k, u_i)}, 1 \le i \le c \quad (7)$$

In the KFCM algorithm, the above estimated partition matrix V and the cluster center u_i are updated iteratively until the termination criterion is met. Our implemented algorithm is detected the ischemic stroke regions effectively compared to FCM method.

The proposed KFCM algorithm can be depicted in the following steps,

Step 1: Compute the preprocessed image. The preprocessed image is one of the inputs of KFCM

Step 2: Fix *c, s* and set $s>1$ and $\in>0$ for some positive constant.

Step 3: generalize the partition matrix V_{ik} and the cluster center u_i

Step 4: Estimate the value of K (p_k , u_i)

Step 5: Update the partition matrix V_{ik} and the cluster center u_i

Step 6: Repeat step (4-5) until $\| u_n - u_0\| < \in$ (u_n – new cluster center and u_o is old cluster center) is satisfied.

3.3 Feature extraction from gray level co-occurrence matrix (GLCM)

After the image segmentation process, the GLCM technique is adopted to extract the texture features from the image. In the texture image, the gray level secured distribution properties are provided by the GLCM. The pairwise statistics of pixel intensities are utilized to estimate the co-occurrence matrix of the image. The statistical features are extracted based on smoothness and the texture related information on the image. The contrast, correlation, homogeneity, dissimilarity, average, energy and entropy features are extracted from the image. The normalized feature vectors are estimated for each pixel in the generated data. The co-occurrence of pixels is counted by the co-occurrence matrix $X\,(i\ ,j \mid d,\ \phi)$. Here, $X\,(i, j)$ is the intensity of the point $(i,\ j)$ of the image. The following notations are used by us: the mean value of X is represented as μ. The standard deviation of X is represented as the σ and the size of the co-occurrence matrix is represented as S. The following features are extracted by using the GLCM method.

The homogeneity of the image is estimated by using the angular second moment (ASM). In the image, only few gray levels are contained by homogeneous image, so the intensity value of $X\,(i\ ,j)$ being high. The ASM is computed as follows,

$$ASM = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}\left(X\,(i,\ j)\right)^2 \tag{8}$$

The local variation of the image is estimated by the contrast measure. Here, the contrast is very high, if the image has large variation. The contrast is estimated as follows,

$$Contrast = \sum_{w=0}^{S-1} w^2 \left\{ \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}\left(X\,(i,\ j)\right)^2 \right\} \tag{9}$$

Where, $w=|\ i\text{-}\ j|$.

The inverse difference moment (IDM) of the images is computed as follows,

$$IDM\ = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}\frac{1}{1+(i-j)^2}\,X\,(i,\ j) \tag{10}$$

The disorders and the complexity of the images is computed based on the entropy measure, and it is given as follows,

$$E = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1} X\,(i,\ j)\times \log\left(X\,(i,\ j\right) \tag{11}$$

Correlation is a measure of gray level linear dependence between the pixels at the specified positions relative to each other and it is estimated as follows,

$$Correlation = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}\frac{(i\times j)\times X\,(i,\ j) - \{\mu_a \times \mu_b\}}{\sigma_a \times \sigma_b} \tag{12}$$

In the above equation, μ_a and μ_b is the mean value of the $X\,(i\ ,j)$ and the standard deviation of the $X\,(i\ ,j)$ is represented as σ_a and σ_b.

At a certain distance d, the dispersion of the gray level difference is known as variance and it is computed as follows,

$$Variance = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}(i-\mu)^2\,X\,(i,\ j) \tag{13}$$

The distribution of gray scales in the image is known as the inertia and it is computed as follows,

$$Inertia = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}(i-j)^2 \times X\,(i,\ j) \tag{14}$$

When the shade is large, the image is not symmetric, the cluster shade is computed by,

$$C.S = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}(i+j-\mu_a-\mu_b)^2 \times X\,(i,\ j) \tag{15}$$

When the prominence of the image is high, the image is not symmetric and the prominence is computed by,

$$\mathrm{Prom} = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}(i+j-\mu_a-\mu_b)^4 \times X(i,j) \tag{16}$$

The uniformity of the texture is measured by the energy computation. In the constant image the energy level is one.

$$Energy = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}\left(X(i,j)\right)^2 \tag{17}$$

Homogeneity restores an esteem that measures the closeness of the appropriation of components in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM. A homogeneous picture will bring about a co-occurrence matrix with a blend of high and low esteems *X [i, j]*.

$$H = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}\frac{X(i,j)}{1+|i-j|} \tag{18}$$

The evenness between the two groups is known as dissimilarity and it is computed as follows,

$$D = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}|i-j|X(i,j) \tag{19}$$

The sum of the difference between the intensity of the central pixel and its neighborhood is known as the difference in variance and it is computed as follows,

$$D.V = \sum_{i=0}^{S-1}\sum_{j=0}^{S-1}(i-j)^2 X(i,j) \tag{20}$$

After extracting the texture features, that has been acting as the input of the classifier to classify the acute and sub-acute stroke region of the brain.

3.4 Classification based on SVM classifier

In this work, the SVM classifier is implemented for the classification which takes the output of the feature extraction techniques to their input and then determines which class is actually belonging to. The SVM is a powerful supervised classifier and an accurate learning technique. The main goal of the SVM classifier is classification error minimization and discrimination margin maximization. This goal is achieved by determining a distinct hyper plane to differentiate different classes of data.

The feature vectors of the training set P are considered as p_k , $k = 1,2,3,\ldots, N$. The training set belongs to any one class of the classes β_1 and β_2. To find an optimal hyper plane, these two classes are separated by the SVM utilizes the training data. The hyper plane can be computed as follows,

$$h(p) = Y^T p + Y_0 = 0 \tag{21}$$

In this work, four different kernel functions are utilized, they are; linear, polynomial, Radial Basis Function (RBF) and sigmoid and it is given as follows,

The linear kernel equation is given by,

$$K(P,P_k) = P_i^{\,T} P \tag{22}$$

The polynomial kernel is given as follows,

$$K(P,P_k) = \left(1+\frac{p_1^{\,T} p}{c}\right)^d \tag{23}$$

The RBF is computed as follows,

$$K(P,P_k) = \left(\frac{-\|p-p_1\|}{\sigma^2}\right)^2 \tag{24}$$

The sigmoid kernel function is computed as follows,

$$K(P,P_k) = \tanh(Kp_k^{\,T} p + \varphi) \tag{25}$$

The scaling of the inputs in the kernel functions is represented as c, σ and K. The SVM classifier takes the contribution from the as of now created feature vectors and a learning model is acquired as yield toward the finish of this stage. On the off chance that the created display classifies a given example as anomalous, at that point it will be subjected to segmentation venture for identifying the injury structure of the input image, i.e. for the given MRI test, the injury part was isolated out from the other brain tissues and it is exhibited independently.

4. Results and discussion

In this section, the performance of the proposed explore is tried by using the medical images and this medical image consolidates standard MRI pictures of the brain and the brain tumor images. The MRI of the ischemic stroke influenced patients unites the acute and sub-acute stage and these are taken as source images. For the examination purposes, the proposed framework used the real time database and it is gathered from the "Pramodhini Appolo Diagnostics". Here, the noises exhibited in the image are evacuated through the preprocessing stage. For the precise segmentation, the evacuations of little undesirable areas like eye ventricle locales are essential. The proposed test experiments are analyzed by utilizing the MATLAB.

4.1 Quantitative analysis

The effectiveness of the segmentation and the classification results are compared to the existing segmentation techniques such as current Fuzzy C-mean (FCM) clustering, K-means clustering algorithm, Decision tree classifier, Artificial Neural Network and K-Nearest Neighbor (K-NN) and the effectiveness of these results are quantitatively computed by the human expert. Each pixel of the image consists of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) classes. The stroke region is correctly identified by these four classes. Here, TP is the positive pixels that were correctly labeled by the classifier. TN is the negative pixels that were correctly labeled by the classifier. FP is the negative pixels that were incorrectly classified by the classifier and FN is the positive pixels that were incorrectly labeled as negative. To evaluate the segmentation results there are three quantitative metrics are utilized. They are delineated in the following Eqs. (26)-(28).

$$\mathrm{Pr}\,ecision = \frac{TP}{TP+FP} \tag{26}$$

$$recall\ (or)\ specificity = \frac{TP}{TP+FN} \tag{27}$$

$$Overlap\ Metric = \frac{2\times TP}{2\times TP+FP+FN} \tag{28}$$

Fig. 3 demonstrates the segmentation result of the proposed technique. In the proposed strategy, the KFCM clustering with adaptive thresholding algorithm is used for the segmentation procedure. The overlap, recall and precision of the proposed technique contrast with the current Fuzzy C-mean (FCM) clustering [27], K-means clustering algorithm [28] and it takes three data sets (data 1, data 2, and data 3) for the procedure. In that examination, the proposed KFCM algorithm has preferable execution over the traditional FCM and the K-Means clustering technique. The parameters such as precision, recall and the overlap enhances our KFCM technique. It exhibits that most of the physically segmented region is fused into the programmed segmentation which may satisfy our need. In the proposed technique, the precision, recall and the overlap ranges for data 1 is, 83.85 %, 98.08% and 77.12% individually, in data 2 90.08, 98.97, 80 separately, in data 3, 92.35%, 94.25% and 90.56% individually.

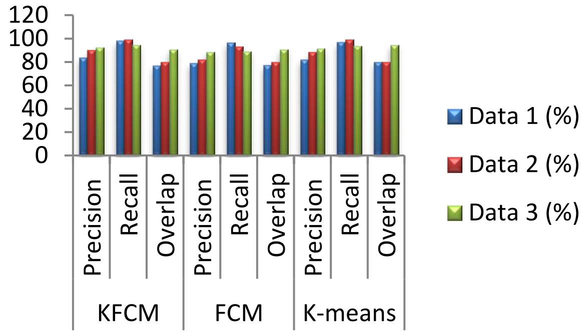

Figure.3 Segmentation results

To evaluate the performance of the classifier, (i.e.), if the person is affected by the ischemic stroke or not is evaluated by the following metrics,

$$Sensitivity = \frac{TP}{TP+FN} \tag{29}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{30}$$

In the above equation, if the sensitivity value is positive, (i.e.) true positive fraction, the person is affected by the ischemic stroke. If the specificity value is negative, (i.e.) true negative fraction that means the person is not affected by the stroke.

Fig. 4 shows the classification result of our proposed method. In our method, the SVM classification technique is utilized for the classification process. The sensitivity and accuracy of our method are compared with the existing Decision tree classifier [29], Artificial Neural Network [18] and K-Nearest Neighbor (K-NN) [30].

Here, the existing classification method evaluates the sum average, IDM and entropy, in any case, these assessment comes about are hazy thus the above existing classification techniques provide zero value results. In that comparison, our SVM classification method has better performance than

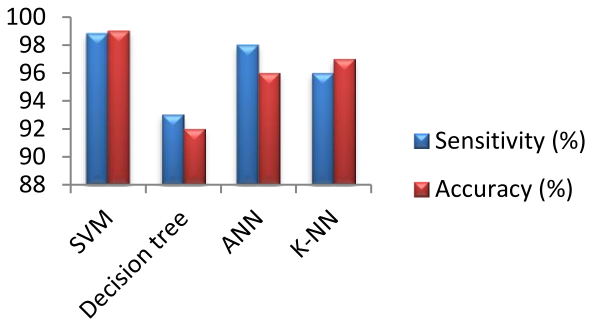

Figure.4 Classification results

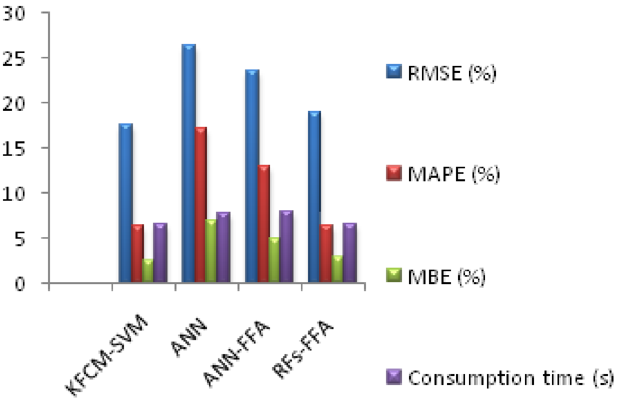

Figure.5 RMSE, MBE, MAPE estimation and time consumption of ischemic stroke techniques

the ANN and the K-NN method because these classifications take place on three factors linear kernel, polynomial kernel, RBF, sigmoid kernel function. The parameter such as sensitivity and accuracy improves on our SVM classification method. It demonstrates, if the sensitivity value is true positive, the patient is affected by the ischemic stroke. If the specificity value is true negative, that means the patient is does not affected by the ischemic stroke. In our method, the sensitivity and the accuracy are 98.8% and 99% respectively.

4.2 Performance evaluation

The performance of the hybrid KFCM and the SVM classifier is tested based on the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Bias Error (MBE). The efficiency of the classification process is evaluated based on the RMSE. The accuracy of the classification process is evaluated based on the MAPE rate. MBE is an average deviation indicator; a negative value means that the classification is under forecasted and vice versa. The RMSE, MBE, and MAPE is estimated in the following ways,

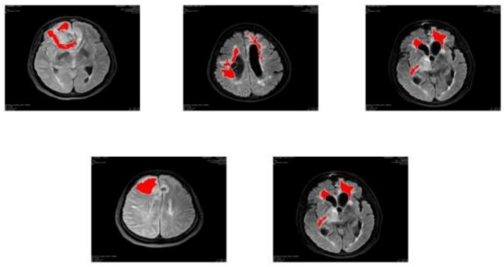

Figure.6 Detection of acute stroke

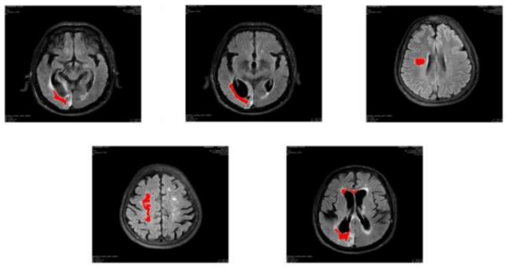

Figure.7 Detection of sub-acute stroke lesions

$$RMSE = \sqrt{\frac{1}{Y}\sum_{t=1}^{Y}(X_t - X_{dt})} \qquad (31)$$

$$MAPE = \frac{1}{Y}\sum_{t=1}^{Y}\left|\frac{X_t - X_{dt}}{X_t}\right| a \qquad (32)$$

$$MBE = \frac{1}{Y}\sum_{m=1}^{t} X_{dt} - X_t \qquad (33)$$

Where, X_t - Target value, X_{dt} - Classified value, Y - Total number of samples.

Fig. 5 shows the statistical result of our proposed method. In our method, the SVM classification technique is utilized for the classification process. The RMSE, MBE and MAPE of our method are compared with the existing ANN [18], ANN-FFA [19] and RF-FFA [25]. Compared with the existing method, our proposed method has 17.64% RMSE, 6.24% MAPE and 2.55% MBE and the consumption time is 6.45 (s).

4.3 Detection of acute and sub-acute stroke lesions

By and large, the results revealed that the SVM classifier reliably and basically beat all other non-tuned classifiers for all ground truth sets and circumstances. Fig. 6 demonstrates the acute stroke lesion segmentation for case 01-case 05. Fig. 7 demonstrates the sub-acute stroke lesion segmentation for case 06-case 10. Here, the KFCM-SVM classifiers fail to segment the exact stroke lesions; it distinguishes both stroke and non-stroke regions, in light of the way that the dice metric values are more imperative than zero for this circumstance. Contrasted and the existing method, the proposed method recognizes the acute and sub-acute stroke precisely.

5. Conclusion

In this research, the classification performance of the proposed SVM classifier with KFCM segmentation technique is compared with existing classifier techniques. From the simulation result the proposed method has better performance in classification of Ischemic stroke lesions and provides the accurate segmentation of the lesion region (i.e.acute and sub-acute phases) than the existing segmentation techniques. The accuracy of the classifier is increased to 99%, by using a soft clustering technique (Kernalized Fuzzy clustering) instead of hard clustering technique (C – Means clustering) as mention in the evaluation report. When compared to the classical approach the proposed SVM classifier gives good performance. By using this technique, the accurate region of the stroke is identified and detected and also it is utilized to classify the types of the stroke (that means acute stroke or sub-acute stroke). By considering the dataset with scattering lesion tissues, the accuracy of the classifier has to be further improved.

In future, the segmentation and classification requires more improvement, so the improved segmentation and classification algorithm can be made possible in the future.

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