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Research Article

Interactive Brain Edema Tumor Segmentation In Different Modality Images With A Combined Novel Neural Network

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ABSTRACT

MR/CT images are facing the difficulties during investigation of tumours in brain part especially in edema portions. Different modalities has lot of information to measure and find out the exact boundary range. MRI and CT images are playing a vital role in medical field to find out and curing the tumour in any area. If the image has big in size and has high amount of information of the MRI AND CT images, then it takes the time to register, filter and segment that images. This research article represents a programmed brain tumour detection technique to expand the exactness and yield and reduction the finding time. An essential role in the investigation of tumours is played by precise identification of the location and size of the brain tumour. The three stages of the analytic strategy are pre-handling of the MRI images, extraction, and grouping. The highlights are segregated based on Dual-Tree Complex wavelet modification following image histogram balance (DTCWT). At the very end, Back Propagation Neural Networks (BPN) is employed to explain the normal and dysfunctional brains. The Spatial Fuzzy K-Means Clustering effectively estimates tumour detection.

Keywords: DT-CWT, GLCM, Neural Network

1. INTRODUCTION

It is possible that image processing algorithms, such as commotion evacuation, would be used to detect lines, regions, and possibly places with specified surfaces before moving on to (low-level) highlight extraction. Prior to properly processing an image, it is crucial to reduce the image to a series of numbers that the system can manage. Each number speaking to the splendor estimation of the image at a specific area is known as an image component,

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or pixel. An average digitized image may have 512 × 512 or about 250,000 pixels, albeit a lot bigger images are getting to be normal.

After the image has been digitized, the PC can be used to execute three basic actions on it. For a particular task, the yield image's single pixel value is dependent upon the information image's single pixel value. For nearby tasks, a few neighbor activities, ring pixels in the information image decide the estimation of a yield image pixel. In a worldwide the information image pixels add to yield image pixel esteem. Noise smoothing is a precedent. Median filtering can be linked to a 3 * 3 pixel window to smooth a noisy picture. This means that the estimate of each pixel is recorded in the uproarious picture along with the estimates of its nearest eight neighbours. Then these nine numbers are organized by size, and in the fresh picture the center is selected as the pixel incentive. As the 3 rollover 3 window moves one pixel over the uproarious picture at any specified time, the sifted picture is framed.

2. LITERATURE SURVEY

Ramin et. al., [1] introduced a novel Distance-Wise Attention (NDWA) mechanism. Stelios Krinidis et. al., [2] described that image clustering is attained through effective Fuzzy C-means (FCM) algorithm. The developed approach incorporated spatial information in local values and information about gray level through aim of adopting fuzzy approach. The proposed approach is stated as Fuzzy Local Information C-Means approach (FLICM) [19]. This proposed algorithm completely involves parameters for empirically involves other fuzzy c-means algorithm those available in literature. Experimental analysis is performed through synthesizes of images related to real-world. Results expressed that FLICM provides effective and efficient performance in terms of provision of robustness for noisy images.

JiashengHaoet. al., [3] stated that several segmentation approaches are developed for images processing in last decades. However, segmentation approach utilizes several processing steps using visual and qualitatively or indirect with consideration of effectiveness of segmentation approach. This concept involved in development of concept for entropy based on the consideration of evaluating segmentation approach in with consideration of effectiveness approach. Those approach involves evaluation of entropy of image with evaluation of uniformity of pixel characteristics located within segmented region and segmentation involves the fundamental characteristics of various segmentation techniques.

Jianzhong Wang et. al., [4] Developed a technique for adopting segmentation approach with increased accuracy for images corrupted with pixel intensity for homogeneity this is considered as major problem hence many researchers focused their attention in this domain. Initially, this research adopted clustering context based approach which involves distributing disciplines of anatomy with gray matter surrounding which has been located between white matter (WM) and brain cerebro spinal fluid [20] this exhibits location of three tissues located each other. The location of image context is optimized using minimal entropy criteria optimization. At last, individual context is evaluated using independent FCM algorithm this involved in calculation of image pixel intensity with consideration of tissues. Evaluation of results stated that proposed approach exhibited significant performance and better results.

Johannes R. Sveinssonet. al., [5] focused on synthetic aperture radar (SAR) those corrupted by speckle noise corrupted by electromagnetic wave random interference. In contrast, it is observed that homogeneous codes of wavelet transform exhibits better performance rather than curvelet transform. This research uses two combination for analysis for SAR images denoising with time invariant wavelet and curvelet transform. By use of total segmentation variation segmentation between edges area and homogeneous area were evaluated. Simulation results stated that denoised schemes provides good and clear images.

Vahid Ezzati Chahar Ghaleh et. al., [6] Extraction of lip contour is considered as major challenge for visual speech recognition system or lip reading. Hence it put forth the requirement for development of effective segmentation approach. Comparison of previous methods express extraction of RGB component with consideration of simple lip region this act as input for C-means clustering for extraction of lip region. Application of different C-means clustering for different images results demonstrated excellent segmentation characteristics for various illumination specifically for speakers [20].

Haibo Wang et. al., [7] Expressed breast cancer highly relies on mitotic count which act as key component this has been involved in division of number of cell quantifying since it undergoes mitosis process at certain point of time. In existing CNN approach certain drawbacks has been observed such as complex and higher label data required. Through application of light CNN model, it involved in provision of minimal complexity and adopts cascade strategy with strategy of handcrafted approach and features derived with CNN which involved in maximization of overall performance using leverage of feature sets.

Kevin Jarrett et. al., [8] Adopted two stage extraction for obtaining effective accuracy rather than other techniques. This developed approach utilizes random filter with recognition rate of 63% in the Caltech-101, along with provision of non-linearities which has been used in pooling layer of network. Results expressed that supervised refinement approach provides state of art performance for NORB datasets at 5.6%. This approach involved in pre-training of unsupervised technique followed by supervised refinement which offers higher accuracy in Caltech-101 (>65%) with minimal distortion and error rate. The MNSIT offers value of 0.53%. The drawback observed for this approach is non-linearity.

Xavier Glorotet. al., [9] Evaluated the influence of non-linear activation function in an cancer identification. The evaluation of cancer is performed through consideration of logistic sigmoid activation function with unsuited activation function involves initialization of random value consideration of mean value, which is derived using saturation at top hidden layer of network. Saturation values moves from its saturated unites within them and slowly with explanation of plateaus observed in training datasets in neural network.

Mohak Shah et. al., [10] Tissue intensity standardization is one of the majaor process of dealing with the preprocessing phases study and analysis of MRI images of human brain. Sources of variations in the intensity ranges across different MRI volumes, even after intensity in homogeneity correction, can result from heterogeneity of data due to difference in scanners. The method of Nyulet. al. [18] has become a widely used standard for intensity normalization. An extensive validation of this approach on multi-site multi-scanner data in the presence of MS has yet not been performed. We aim to undertake this validation in this work and show the effectiveness of this procedure on standardizing tissue intensities in the MRI volumes.

Karen Simonyanet. al., [11] investigated the effect of depth conventional network for improving accuracy of image recognition for large-scale applications. The representations perform effectively over datasets which exhibits significant state-of-art performance. Evaluation of performance provides ConvNet model for facilitating effective performance for computer vision deep representation visually. The drawback observed with this approach is Spatial Pooling.

Pavel Dvorak et. al., [12] evaluated the 3D image segmentation through performance of predicting local structure. Different parameters are evaluated using consideration of various anatomical structure of dense annotation. Convolution neural network act as learning algorithm which significantly performed for evaluating feature correlation among different points. The developed approach is evaluated for consideration of public dataset of BRATS2014 with 3 different segmentation task with consideration of multi-modality. Results expressed the state-of-art factor for segmentation of brain tumor where data set consists of 254 multi-modal volumes with computation time of 13 seconds for the obtained volume. The drawback observed in this approach is subtasks multi-modal segmentation.

Bjoern H. Menzeet. al., [13] represented a method for appearance of tumor with sequence in multi-dimensional scenario with provision of tumor segmentation based on channel-specific scenario. Through use of generative model information are shared about spatial location with channel lesions through using multi-modal signal at higher specific range class of healthy tissues for segmentation of normal tissues in brain. Apart from tissue types, the developed model includes encoding of voxel for latent variable based on this probability of tumor is identified in voxel. However, this research exhibits complex computational time.

3. RELATED WORK

The primary objective this research is to identify tumor in MRI/CT medical images using modeling of multi-clustering approach and process of morphology. Generally, segmentation is stated as partitioning an image in to multiple segments. The MRI of brain is taken and using filter noises in the images are removed. In next step, filtered image is processed with k-means clustering for segmentation of brain images. In the noisy background morphological characteristics of tumor is obtained using smoothing of tumor region. For telemedicine applications through hybrid technique both primary and secondary regions of images are compressed. The methods used here are 1. DT-CWT, 2. GLCM Features Extraction and 3. NN Training and classification.

BLOCK DIAGRAM:

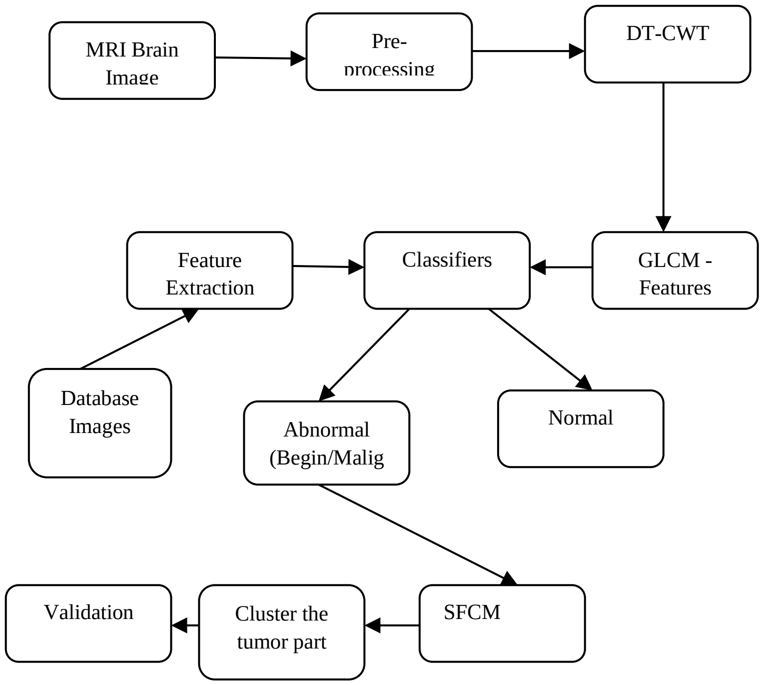


Fig. 1: Edema Tumor Segmentation Process - Block Diagram

Steps involved in Edema Tumor Segmentation Process

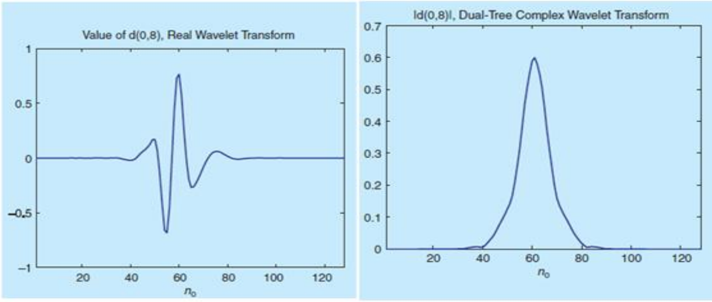
3.1. Preprocessing

Image restoration is stated as achieving clean and original image from noise or corrupted using estimation. Normally, corruption in image is occurred due to several factors such as blur, camera miscues, motion and noise. Both terms restoration and enhancement of image are varied on their own context in this image restoration involved in image emphasizes pleasing vision for observer, but this will not generate realistic view in terms of scientific view of images.

Enhancement of image deals with several process like contrast stretching, procedure for nearest neighborhood and de-blurring through processing of prior model for the created image. Noises are removed effectively in image enhancement with offering significant resolution; even this technique is not acceptable for several applications. Even for Fluorescence Microscopic process observed images are not effective and significant. Several image processing techniques are involved in recovering of objects. For image restoration De-Convolution is adopted which able to increase the increase the image resolution in direction of axial with removal of noise for contrast enhancement.

3.2. Dual-tree complex wavelet transforms (DT-CWT)

Recently DT - CWT is emerged image enhancement technique which has been considered as enhancement of DWT with fewer additional characteristics. This technique composes of selective image direction with consideration of two or higher image dimensions combined with shift invariant approach. This can be achieved through consideration of redundancy factor of 2-D images for signals with d-dimensional characteristics, this can be substantially minimal than the undecimated DWT approach. Dual-tree CWT with characteristics of multidimensional (M-D) factor is not separable but it is based on the efficient computation and separable filter bank (FB). In dual-tree transformation complex wavelets with excellent characteristics are made and this can be widely used in image and signal processing techniques.



(a) (b)

Fig. 2:(a) Real wavelet Transform, (b) Dual-Tree Wavelet Transform

Fig.2(a): The value of the wavelet coefficient in "Real-Valued Discrete Wavelet Transform and Filter Banks

At the edges of neighborhood conventional DWT approach develops both wavelet coefficients at small and large scale. In this contrast, CWT coefficient analytics provides image magnitude is directly related to image proximity. Here, test signal value at edge is defined as $n = n0$, $x(n) = u(n - n0)$.

The above figure illustrated that value obtained for wavelet coefficient value of *d(0, 8)* (i.e stage 3 of eighth coefficients involved in "Real Value discrete wavelet transform and filter bank with function of n0. Here both ends are used to compute the dual –tree CWT complex co-efficient.

Wavelet transform and Multi-scale analysis

Wavelet transformation displays notable performance as a state-of-the-art performance presentation in signal processing applications. In this, DWT process sinusoidal oscillating basic function are replaced with Fourier transform function which act as local oscillating function known as wavelets. In this scenario, wavelet is defined as wavelet is stated as stretched and shifted version of real-value band pass filter illustrated as $\Psi(t)$. This wavelet function is carefully selected and combined with scaling-function of low pass filter defined as $\varphi(t)$, for ortho - normal basic expansion of 1-D continuous time signal of real-value. This can be a finite energy analog signal $x(t)$ which can be decomposed in to scaling and wavelet function which is represented as:

$$x(t) = \sum_{n=-\infty}^{\infty} c(n)\,\varphi(t-n) + \sum_{j=0}^{\infty} \sum_{n=-\infty}^{\infty} d(j,n)^{2j/2}\, \aleph(2^j t - n). \quad (1)$$

The scaling coefficients $c(n)$ and wavelet coefficients $d(j, n)$ are computed via the inner products,

$$c(n) = \int_{-\infty}^{\infty} x(t)\varphi(t-n)dt, \quad (2)$$

$$d(j,n) = 2^{j/2}\int_{-\infty}^{\infty} x(t)\aleph(2^j t - n)dt. \quad (3)$$

The signal time-frequency analysis is performed by measuring content of frequency measured at various instances of time. Their avail a linear time, efficient computational algorithm for computing coefficient such as c(n) and d(j,n) with final-scale representation of signal for N samples for two octave band with recrusive low-pass filter application h0(n), high pass filter h1(n) and operation of up and down sampling process. This filter involved in effective parameterization of designing scaling and wavelet function through desirable properties like fast frequency decay and compact time (analysis of local possibility for time frequency) and orthogonality with consideration of lower-order polynomials.

Shift Variance

A little move of the sign enormously bothers the wavelet coefficient wavering example around singularities. Move fluctuation likewise confuses wavelet-area preparing; calculations must be made fit for adapting to the wide scope of conceivable wavelet coefficient examples brought about by moved singularities

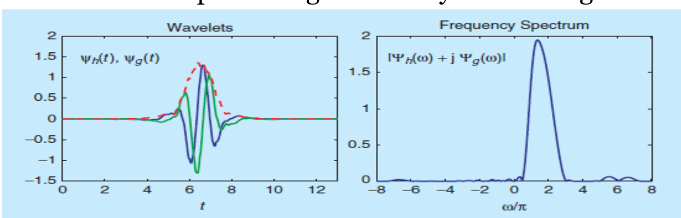


Fig.3: A q-shift complex wavelet corresponding to a set of orthonormal dual-tree filters of length

To better understand Fig.3 wavelet coefficient oscillations and shift variance, consider a piecewise smooth signal $x(t-t0)$ like the step function

$$\mathrm{U(t)} = \begin{cases} 0 & t < 0 \\ 1 & t \geq 0 \end{cases} \quad (4)$$

And its wavelet coefficients consist of samples of the step response of the wavelet

$$d(j,n) \approx 2^{-3j/2}\Delta \int_{-\infty}^{2^j t_0 - n} \aleph(t)dt, \quad (5)$$

3.3. Gray-Level Co-Occurrence Matrix (GLCM) and Feature Extraction

3.3.1. Co-Occurrence Matrix

This has been proposed by R.M.Haralick which represents the feature texture with exploration of spatial dependence texture of gray level [13, 14]. Mathematical expression for co-occurrence matrix is denoted as below [15]:

1. Offering of operator position P(i,j)
2. The A is defined as n*n matrix
3. The elements A[i][j] demonstrate the no. of points in the strength of gray level with occurrence of g[i] with the specification of position P, related to the greylevel points g[j].
4. The C is defined as n*n obtained through division of A for total pairs involved in satisfaction of P. The point C[i][j] provides pairs joint probability involved in satisfaction of P with values of g[i], g [j].
5. The co-occurrence matrix of P is denoted as C.

$$C_t(a,b) = card\{(s, s+t) \in R^2 | A[s] = a, A[s+t] = b\} \quad (6)$$

Table 1: Image example

1	2	1	3	4
2	3	1	2	4
3	3	2	1	1

Table 2: Classical Co-occurrence matrix - Stage I

	0	1	2	3	4	5	6	7
0	0	0	0	0	0	0	0	0
1	0	1	*	0	0	0	0	0
2	0	1	0	*	0	0	0	0
3	0	0	1	1	0	0	0	0
4	0	1	0	0	1	0	0	0
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0

Table 3: Classical Co-occurrence matrix - Stage II

	0	1	2	3	4	5	6	7
0	0	0	0	0	0	0	0	0
1	0	*	1	0	0	0	0	0
2	0	*	0	1	0	0	0	0
3	0	0	*	*	0	0	0	0
4	0	*	0	0	*	0	0	0
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0

Table 4: Classical Co-occurrence matrix - Stage III

	0	1	2	3	4	5	6	7
0	0	0	0	0	0	0	0	0
1	0	*	2	0	0	0	0	0
2	0	*	0	0	2	0	0	0

3	0	0	*	*	0	0	0	0
4	0	*	0	0	*	0	0	0
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0

Table 5: Classical Co-occurrence matrix – Final Stage

	0	1	2	3	4	5	6	7
0	0	0	0	0	0	0	0	0
1	0	1	2	0	0	0	0	0
2	0	1	0	2	0	0	0	0
3	0	0	1	1	0	0	0	0
4	0	1	0	0	1	0	0	0
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0

Consider Case 1:

$$\begin{bmatrix} * & * & 1 & 3 & 4 \\ 2 & 3 & * & * & 4 \\ 3 & 3 & 2 & 1 & 1 \end{bmatrix}$$

P(1,2)=* →**1**
Exclusive for all {(1,3), (1,4), (1,5), (1,6), (1,7)}
P(x)=p(u)
x=u
x=6 (The pixel value ranges from 0 – 6)
Haralick proposed the following texture features :

- **Energy:**
  It is a measurement of homogeneity in gray-scale images that reflects the distribution of weight and textural uniformity.
  $\sum_x \quad \sum_y p(x,y)^2 \quad p(x,y) is\ the\ GLCM$ (7)
- **Contrast:**
  Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth.
  $CONTRAST \qquad I = \sum \quad \sum (x-y)^2 p(x,y)$ (8)
- **Correlation Coefficient:**
  It measures the joint probability occurrence of the specified pixel pairs.
  Correlation: sum (sum ((x- μx)(y-μy)p(x , y)/$\sigma_x\sigma_y$)) (9)
- **Homogeneity:**
  It measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.
  Homogeneity = sum (sum(p(x , y)/(1 + [x-y]))) (10)

3.4. Neural Network

The Multilayer Perceptron Neural Network Model

The perceptron network structure, which comprises three layers, is depicted in the diagram below:

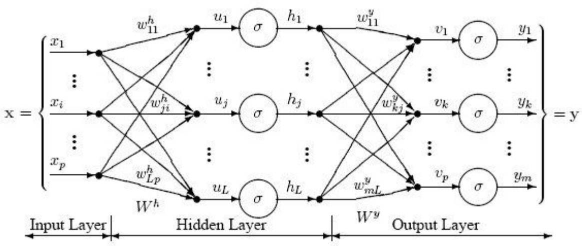


Fig.4: Multilayer Perceptron Neural Network Model

From left, this network has three major layers such, Input layer, Hidden layer and Output layer, all these layer has attached with three neurons effectively for his better performance.

The neuron in the input layer is utilized to predict the variables. . In the case of categorical variables, *N*-1 neurons are meant to denote the *N* categories of the variable.

Architecture of a BPN

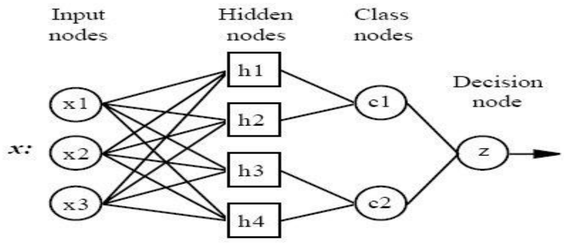


Fig.5: Architecture of a BPN

All BPN networks is made of four layers:

Input layer — For each and every predictor variable only one input is located in input layer. In categorical variable, N-1 neurons are utilized in this number of categories are represented as N. The input fed to neuron (before input layer processing) involves standardized range of values with subtraction of interquartile evaluation of median and division range. Those input values are applied in every neurons located in hidden layer.

Hidden layer — For every training data sets one neuron is located in the system. The predictor values are stored in neurons along with combination of evaluating value of target. The input offered for input layer involved in evaluation of x-vector, the Eucliden distance is computed using for test cases with center point's of neurons after that applied to RBF which is Kernal function through sigma values. The final obtained values is transmitted over pattern layer.

Pattern layer / Summation layer — This pattern layer is completely different for both GRNN and BPN network. In BPN network for target variables one pattern of neurons are presented at each category. Training category of training datasets involved in processing and storing in hidden layer, the weighted values obtained from hidden layers are applied to pattern layer which corresponds to the category of hidden layer. Based on the class of representation pattern neuron values are added.

Decision layer — For both GRNN and BPN decision layers are different. For BPN network, decision layer involves each target category target votes accumulated in pattern layer and largest votes are predicted using category of target.

Steps of the Algorithm

The required modification in the network is applied via back propagation algorithm, through selection of weights in network randomly. The developed algorithm is decomposed in to different categories based on following four steps such as:

1. Computation using feed-forward approach
2. Output layer back propagation
3. Hidden layer back propagation

3.5. GLCMNN Algorithm

```
n=6
file_list = dir('e:\Users\SUMI\Desktop\paper\*.bmp');
no_of_files = length(file_list);
for k = 1 : no_of_files
```

```
l = imread(strcat('e:\Users\SUMI\Desktop\paper\',file_ list(k).name));
if length(size(l))==n
l=rgb2gray(l);
end
if glcm1==n
glcm1 = graycomatrix(l,'Offset',[2 0;0 2]);
stats{k} = graycoprops(glcm1,{'all'}); end
input_nodes glcm1, stats{k}
Input_nodes i, given input xi:
For_each_input node i
        Output i = xi
Compare xi=stats{k}
end
Hidden _layer nodes j
For_each hidden neuron j
        Output j =  ∑i phi(wji·outputi)
Output_ layer neurons k
end
For_eachoutput_neuron k
        Output k =  ∑k phi(wkj·outputj)
ActivateLayer(input,output)
For_each i input_neuron
        calculate_output i
end
output = {output k}
end:
Error() {
For_each_input in InputSet
        Errorinput= ∑k output neuron (targetk-outputk)
return_Average(Errorinput,InputSet)
end
```

Experimental Results

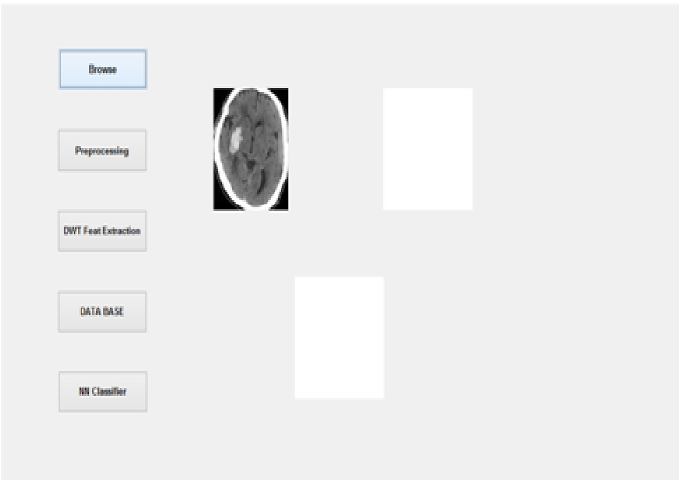


Fig.6: Input Image

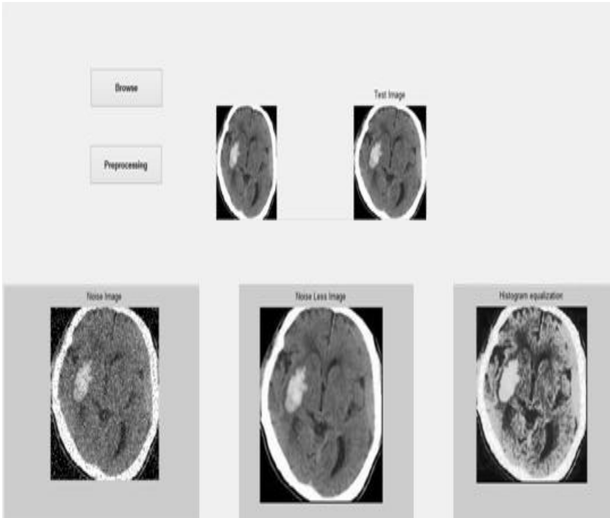


Fig.7: Preprocessing

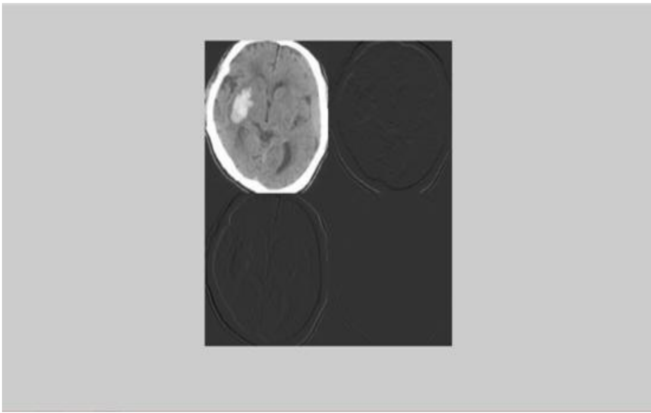


Fig.8: Feature extracting an image

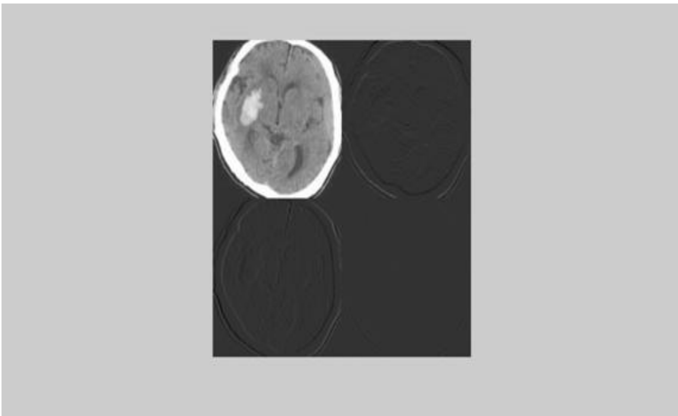


Fig.9: Segmented Results

Fig.10: Neural networks classifier

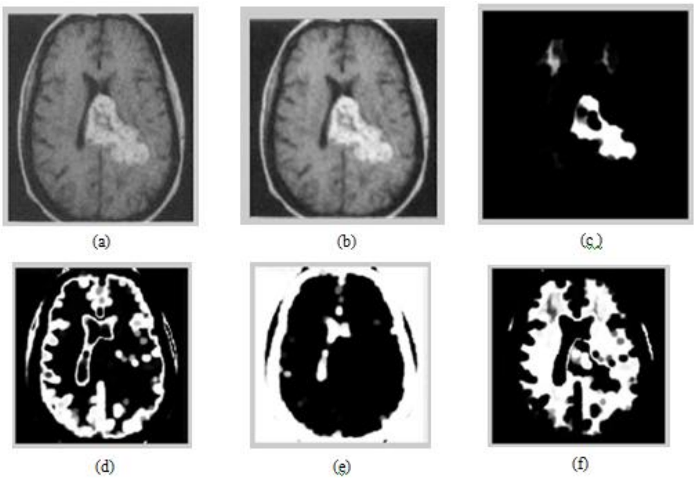


Fig.11: a) Noisy Image, b) Restored Image, c) Fuzzy cluster number1, d) Fuzzy cluster number2, e) Fuzzy cluster number3 and f) Fuzzy cluster number4

5. Conclusion and Future Enhancement

Brain tumor at beginning time is extremely troublesome errand for specialists to distinguish. X-ray images are increasingly inclined to clamor and other ecological obstruction. So it ends up hard for specialists to distinguish tumor and their causes. So here the framework, where framework will recognize mind tumor from images. Here it convert image into grayscale image. Apply channel to image to evacuate commotion and other ecological impedance from image.

Client needs to choose the image. Framework will employ image handling techniques to the image to process it. Then it is to connect the original computation to distinguish the tumor from the image of the brain. Be that as it may, edges of the image are not sharp in beginning period of cerebrum tumor. So apply image division on image to identify edges of the images. In this strategy we connected image division to recognize tumor. Here proposed image segmentation procedure and many image sifting systems for precision. This framework is executed in tangle lab.

The proposed calculation applies on specific instance of tumor for example Hemangiopericytoma. For the future work this calculation can be connected on different cuts of the chose case and different instances of or also. The future extent of this undertaking is to portion a wide range of tumor naturally and a general framework can be proposed with higher precision and lesser time. Volume of the tumor can be determined for neurosurgeries. The examination can be stretched out to identify disease in MRI sections of other body parts.

Future research in the division of restorative images will lead towards improving the precision and computational speed of segmentation approaches, just as limiting the measure of manual connection. These can be improved by joining discrete and persistent based division strategies. Computational adequacy will be significant continuously preparing applications. Division strategies have demonstrated their utility in research zones and are presently underscoring expanded use for robotized analysis and radiotherapy.

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