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A Novel Feature Extraction Method for The Detection of CMBs

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ABSTRACT

CMBs are deposits found in the brains of elderly people and stroke victims. This can lead to dementia as well as a variety of other issues with everyday activities like remembering, driving, and so on. In this paper, an effective feature extraction technique to detect cerebral microbleeds (CMB) has been proposed. In the feature extraction stage, weber local descriptor is applied which extracts two components. In these components Gray-level Co-occurance Matrix (GLCM) and Histogram of Oriented Gradient (HOG) are applied. Thus, two sets of features are extracted. In the classification stage, Artificial Neural Network is used to identify the CMB and non- CMBs areas. This method gives the sensitivity of 83.3%, specificity of 76.9% and an accuracy of 80%. The result of this technique is free from human errors.

I. INTRODUCTION

Cerebral microbleeds (CMBs) are small chronic brain haemorrhages that occur in a variety of diseases including cerebral amyloid angiopathy [1], stroke and neurodegenerative disorders. Susceptibility-weighted magnetic resonance imaging is the most widely used medical imaging modality for detecting CMBs (SWI). SWI senses paramagnetic tissues very well. Hemosiderin, for example, is found in most CMBs. As a result, there is a strong distinction between average and abnormal brain. CMB detection necessitates not only intensive human labour but also domain-specific knowledge, which makes the job time-consuming and laborious, lowering detection accuracy and efficiency [8].

In medical image processing algorithms, image denoising methods are important [2]. Noise, inhomogeneity, and sometimes variance are all present in a brain picture. Filters are used in the preprocessing stage for this reason. Spatial filters, boost filters, and wiener filters are among the filters used. Wiener filters are basic, but they strip the image's edges and blur the image.

Back Propagation Neural Network (BPNN) [3], Forward Back Propagation Artificial Neural Network (FP-ANN) and k-Nearest Neighbor (k-NN) [4], Generalized Eigenvalue Proximal SVM (GEPSVM) classifier [5], and AdaBoost algorithm with random forests [6] are some of the techniques used previously for classification.

The objective of this paper is the accuracy of the detection. For noise removal, two simple filters such as median filter and Gaussian filter are used. Next, Region of Interest (ROI) is selected based on size, roundness and various other basic parameters. Then, a new technique based on the combination of Weber Local Descriptor (WLD), Gray Level Co-occurrence Matrix (GLCM) and Histogram Of Gradient (HOG) is proposed for feature extraction. This extracts two components namely the differential excitation and gradient orientation. After which two sets of features are extracted by applying Gray Level Co-occurrence Matrix (GLCM) [7] in the differential excitation component, that gives the first set of features and then the Histogram Of Gradient (HOG) is applied in both the components of WLD. For the classification stage, Artificial Neural Network (ANN) is used. This classifies the selected region into either CMB or non-CMB.

This paper is organized as follows: Section II explains the proposed method. The results and discussions are made in section III. Finally section IV concludes the work with its ideas on future enhancement.

II. PROPOSED METHOD

The proposed work consists of three stages. They are, 1. Preprocessing stage, 2. Feature extraction stage and 3. Classification stage. Each of the stages is explained as follows and the block diagram is shown in the fig.2.

2.1 FEATURE EXTRACTION STAGE

The feature extraction techniques used here extracts two types of features: feature 1 and feature 2. Feature 1 is the resultant of applying gray-level co-occurrence matrix (GLCM) in differential excitation that was extracted by weber local descriptors. The feature 2 is obtained by applying Histogram of Gradient (HOG) in the combination of both the differential excitation and gradient orientation. The brief explanation of the feature extraction methods are described as follows.

2.1.1 WEBER LOCAL DESCRIPTORS (WLD)

It's a psychological principle. It states that the shift in a stimulus that we only observe (such as lighting or sound) is a constant ratio of the original stimulus.
If the shift is smaller than this constant ratio of the original stimulus, a person will perceive it as background noise rather than a true signal.

For each pixel, the differential excitation portion of the proposed Weber Local Descriptor (WLD) is computed. It's the ratio of two terms: the first is the current pixel's intensity, and the second is the relative intensity differences between a current pixel and its neighbours. In addition, the gradient orientation of the current pixel is computed.

2.1.2 GRAY-LEVEL CO-OCCURRENCE MATRIX (GLCM)

The other name for GLCM is gray-level spatial dependence matrix. It is one of the statistical methods of finding the spatial relationship between the pixels in an image. ie, it checks or considers how often a pixel with a specified gray-level value i occurs in a spatial relationship with the pixel value j within the same image and then measuring the statistical parameters from that matrix. The statistical parameters may be of many types some of them are energy or uniformity, contrast, correlation, homogeneity, shade, prominence, standard deviation, mean, variance, entropy, etc. In our paper, we are going to find only five statistical parameters. The parameters used here are energy, contrast, correlation, homogeneity and variance.

2.1.3 HISTOGRAM OF GRADIENT (HOG)

The Histogram of gradient (HOG) is the one which is mainly used for object detection and recognition. By using this both the differential excitation and gradient orientation components a histogram of gradient can be constructed. So as to compute the histogram of gradient (HOG), {WLD(£(x), $\varphi_q{}^*(x)$)} , the representation of £(x) varies from 0 to N-1 and the value of $\varphi_q{}^*(x)$ is from 0 to T-1. Here N represents the dimentionality of the image and T represents the dominant orientation. With these parameters, a 2D histogram with each column representing gradient orientation ($\varphi_q{}^*(x)$) and each row representing the differential excitation (£(x)) is constructed. To obtain the features more in detail, a 2D histogram can be encoded to two 1-D histogram.

Each pixel value is plotted in the histogram channel based on the values of $\varphi_q{}^*(x)$. The histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees, depending unsigned and signed integer values. Usually, 9 histogram channels are said to be the best performed one in the detection experiments.

At the result, a comparison can be made for the classification by the first feature, classification by the second feature and the combination of two features.

2.2 CLASSIFICATION STAGE

In classification stage, Artificial Neural Network (ANN) is used. ANN is also referred as connectionist systems. This is mainly used to label the sub image as CMB or non CMB based on all the features that are extracted from the feature extraction stage.

Neural networks are a set of algorithms that are used to recognize patterns, cluster it and classify them. They help to group unlabeled data according to the similarities among the features that are extracted from the previous section and then classify the data. It is one of the mathematical models that consist of a number of highly interconnected processing elements that are organized into several layers, geometry and functionality that resembles as like the human brain [5].

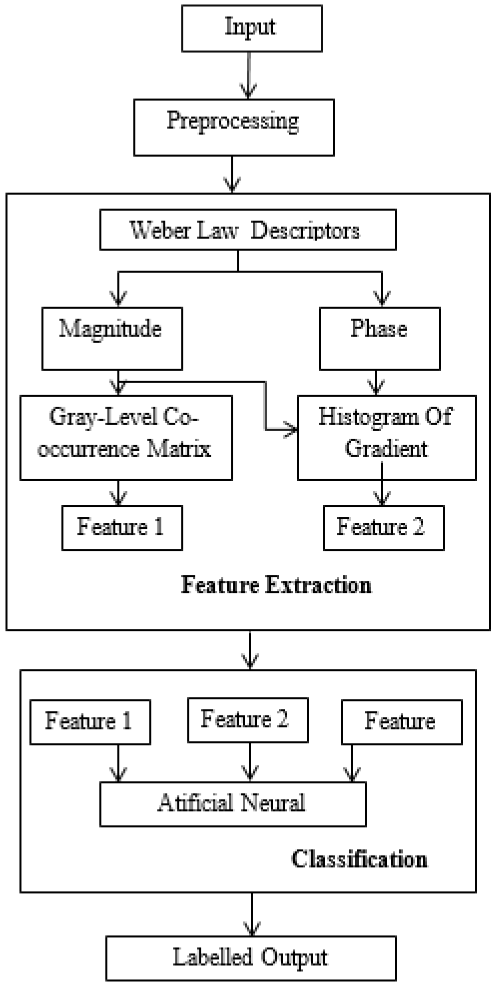


Fig.1 : Block diagram of the proposed method

The feed forward neural network is used as the classifier which has three layers such as the input layer, hidden layer and the output layer. The Back Propagation Network (BPN) is used for MRI image analysis and the feed forward neural network is used to demonstrate the capability of ANNs to classify the MRI images as normal or CMB affected. Thus, at first the Back Propagation Network was created with three layers input, hidden and output layer and the training were done with sigmoid transfer function. The weights in an ANN express the relative strengths (or mathematical values) of the various connections that transfer data from layer to layer.

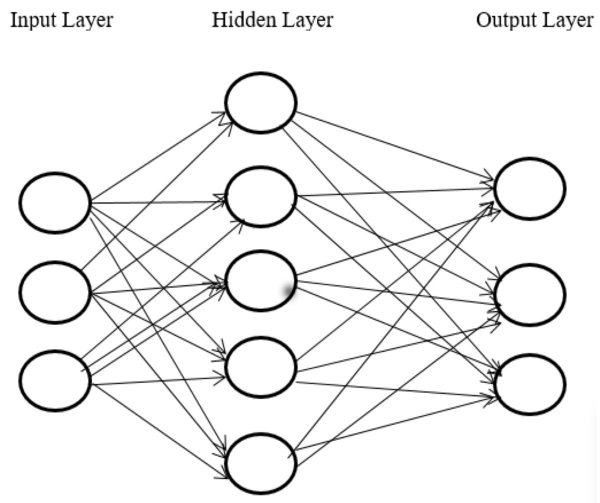
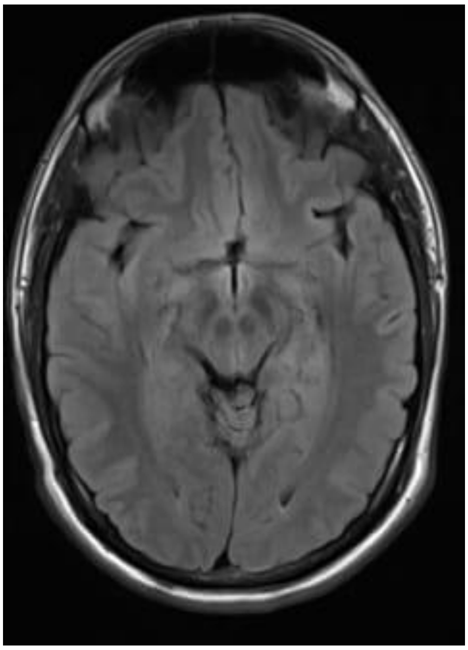


Fig.2: Architecture of Artificial Neural Network (ANN)

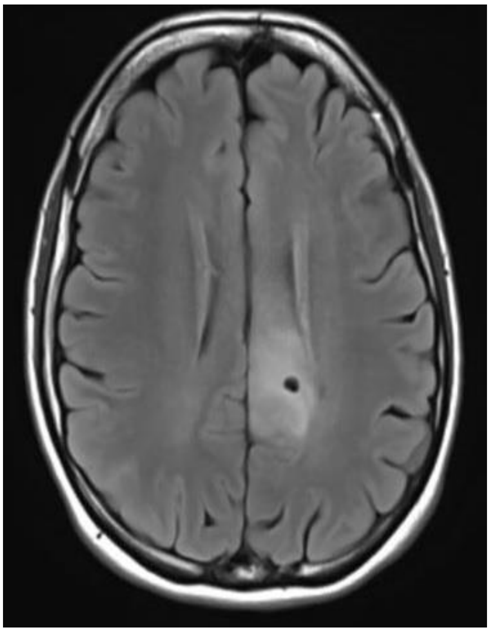
III. RESULTS AND DISCUSSION

A. EXPERIMENTATION

The experiment is done in the training dataset (i.e) in the 70 images from 30 subjects.



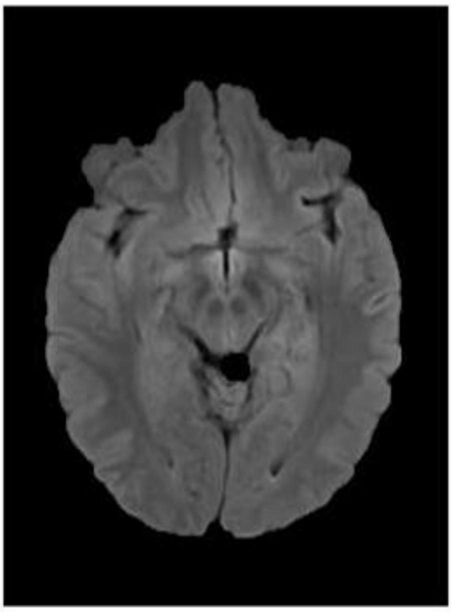
(a)



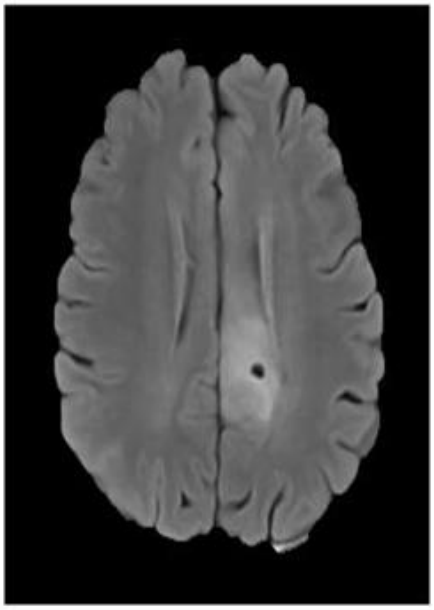
(b)

Fig.3 : Inputs with score volume projection onto the axial plane. (a) Normal MRI brain image (b) Raw data with true CMB

Fig.3 shows the comparison of normal MRI image and CMB affected MRI brain image. Since all MRI images are in three dimensions, they are converted to grayscale. The noise reduction filter and smoothing filter are then added. The binary image is extracted after the input image is improved. There may be some noise and holes in the binary picture. Thus, simple morphological operations are used to clear it, and the result is a skull stripped brain image. The morphologically corrected image is used as a mask in the skull stripping process, which is then applied to the original image. The skull stripped image of a regular MRI image and a CMB affected human MRI brain image are shown in Figure 4.



(a)



(b)

Fig.4 : Skull Stripped images. (a) Skull stripped Normal MRI brain image (b) Skull stripped CMB affected image

For the construction of ROI, the size of each image is reduced to 420x376. This image is divided into subimages of 36x36 [19]. Thus, 12x11 subimages are obtained each will be in a size of 36x36. The below figure shows few sub images for the normal MRI brain image, which are 36x36 in size. Fig.5 shows the few subimages of a normal MRI brain image.

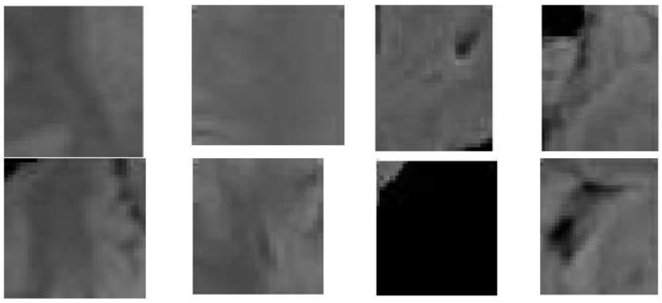


Fig.5 : SubImages for the normal MRI brain image

The below figure shows few subimages for the CMB affected MRI brain image, which are 36x36 in size. Fig.6 shows the few subimages of a CMB affected MRI brain image.

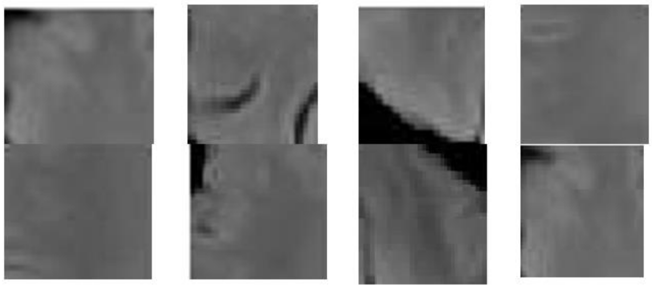


Fig.6 : SubImages for the CMB MRI brain image

These individual subimages are given as the input to the feature extraction stage. In this stage, Weber Local Descriptor (WLD) is applied to each of the subimages. Afterwhich, the Gray-level cooccurance matrix and Histogram Of Gradient are applied. Now, two sets of features are extracted. They are FEATURE 1and FEATURE 2.

FEATURE 1

After the application of WLD, the first component extracted is differential excitation by the eqn (4). In this component, Gray Level Co-occurance Matrix (GLCM) is applied. Here, five parameters are computed such as contrast by the eqn (8), correlation by the eqn (9), energy by the eqn (11), homogeneity by the eqn (12) and variance by the eqn (13). Thus the features are extracted as set 1.

GLCM Parameters	CMB Affected Image					Normal Image				
	SubImage 1	SubImage 2	SubImage 3	SubImage 4	SubImage 5	SubImage 1	SubImage 2	SubImage 3	SubImage 4	SubImage 5
Contrast	11.28603	12.18934	12.07092	12.26931	12.54989	12.06389	12.07295	12.07829	11.21347	10.52384
Correlation	-0.09494	-0.06733	-0.02285	0.011745	0.00697	10.52384	-0.00938	0.001493	0.025403	0.032386
Energy	0.003634	0.003529	0.003479	0.003468	0.0035	0.003473	0.003479	0.003484	0.00352	0.003522
Homogenity	0.137398	0.147753	0.157838	0.158699	0.149932	0.154802	0.155598	0.153201	0.159226	0.170879
Variance	231.7324	221.0009	211.3031	208.2466	211.7512	210.852	212.8629	212.3099	215.7915	209.962

Table 1 : GLCM values for its various parameters

- FEATURE 2

After the application of WLD, the second component extracted is gradient orientation by the eqns (5 to 7). Then, Histogram Of Gradient (HOG) is applied. Thus another set of features are extracted as set 2.

The table 2 shows the features which are obtained from the subimages of a CMB affected MRI human brain in which when Histogram Of Gradient is applied.

HOG features	CMB Affected Image									
SubImage 1	0.22074125	0.21011859	0.25034948	0.19304754	0.1534293	0.10765453	0.20569993	0.26488145	0.25909089	0.292142415
	0.039069	0.00853	0.006231	0.029216	0.049992	0.048001	0.025723	0.292142	0.025379	0.036169
	0.058919	0.074669	0.292142	0.069474	0.055104	0.121559	0.069799	0.292142	0.027489	0.007054
	0.07241	0.292142	0.070607	0.128622	0.064707	0.292142				
SubImage 2	0.172229	0.093615	0.056964	0.085246	0.319451	0.15986	0.176233	0.234348	0.240552	0.319451
	0.028407	0.017856	0.030547	0.062655	0.029391	0.049485	0.095637	0.319451	0.031825	0.011871
	0.035724	0.062173	0.319451	0.073237	0.048652	0.047636	0.033101	0.319451	0.011914	0.017986
	0.035354	0.319451	0.018193	0.139696	0.085867	0.319451				

Table 2: HOG features for CMB affected images

The table 3 shows the features which are obtained from the subimages of a Normal MRI human brain in which when Histogram Of Gradient is applied.

HOG features	Normal Image									
SubImage 1	0.038053	0.079382	0.098653	0.095954	0.146461	0.03031	0.033764	0.045244	0.03366	0.369838
	0.022998	0.041076	0.020045	0.079265	0.044849	0.059849	0.055022	0.369838	0.05095	0.373167
	0.029948	0.102533	0.369838	0.058678	0.028193	0.007568	0.005189	0.369838	0.03366	0.369838
	0.072535	0.369838	0.079604	0.25093	0.10359	0.369838				
SubImage 2	0.010419	0.01434	0.038828	0.063879	0.054934	0.021985	0.069738	0.053981	0.040159	0.380967
	0.03038	0.02053	0.012366	0.005313	0.016241	0.068332	0.047488	0.32344	0.115136	0.305761
	0.111091	0.183181	0.32344	0.185226	0.154421	0.242532	0.32344	0.32344	0.002232	0.323159
	0.020991	0.32344	0.044171	0.134218	0.069479	0.32344				

Table 3 : HOG features of Normal images

The feature 1 is first applied to the ANN classifier. The figure below shows various outputs of the classifier when feature 1 was applied independently.

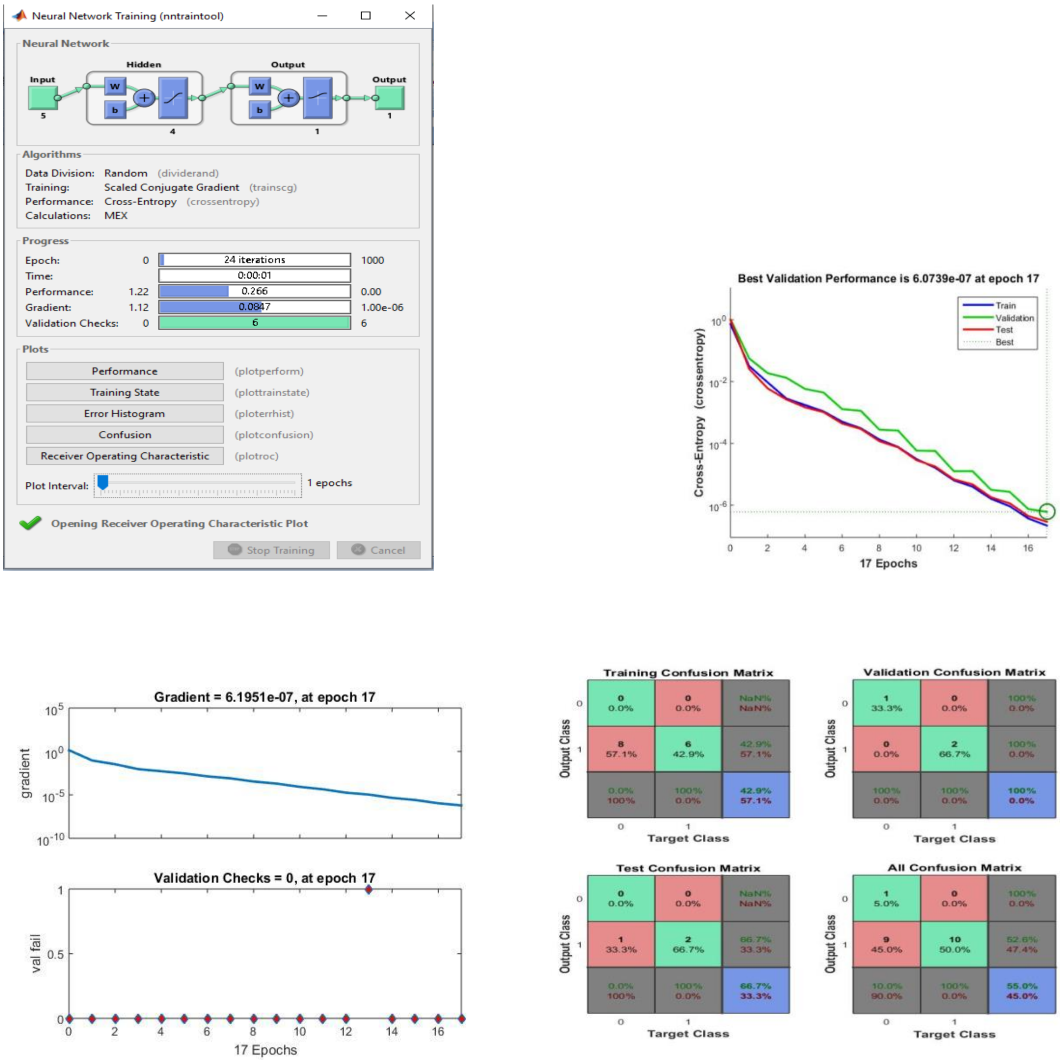
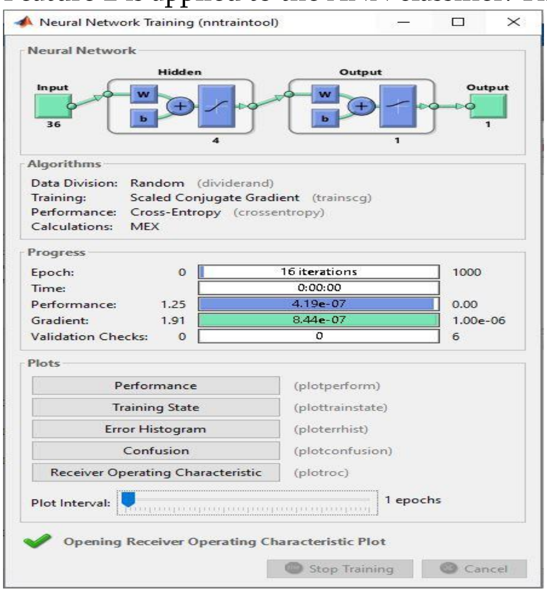
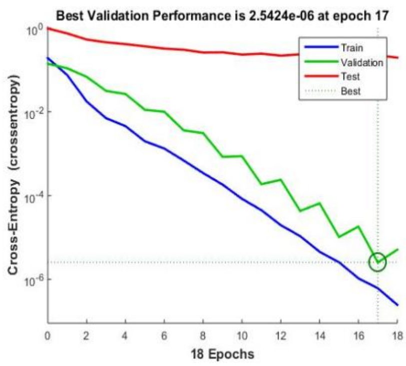


Fig 7 : Classifier Output of GLCM feature

Feature 2 is applied to the ANN classifier. Thus, following outputs were obtained.





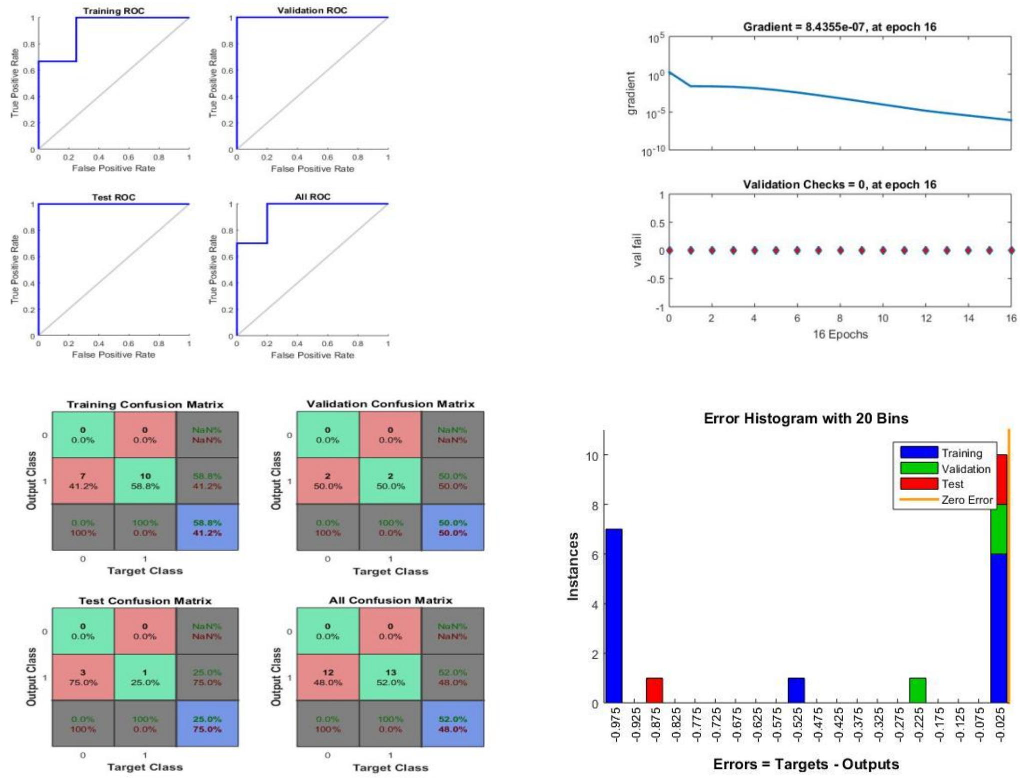
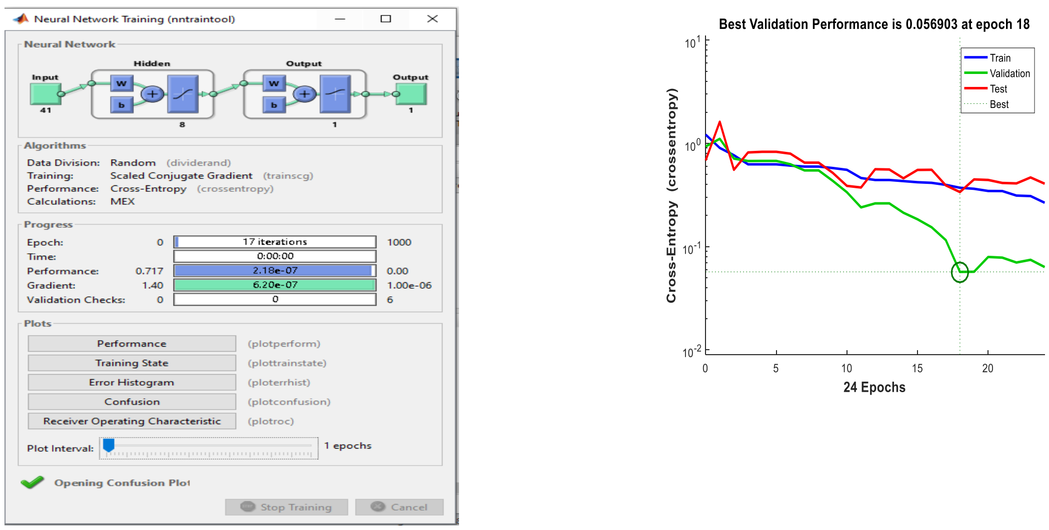


Fig.8 : Classifier Output of HOG feature

At last the features 1 and 2 are combined and it is subjected to the classifier network. Now, the accuracy is increased more when compared to the individual testing of feature 1 and feature 2.



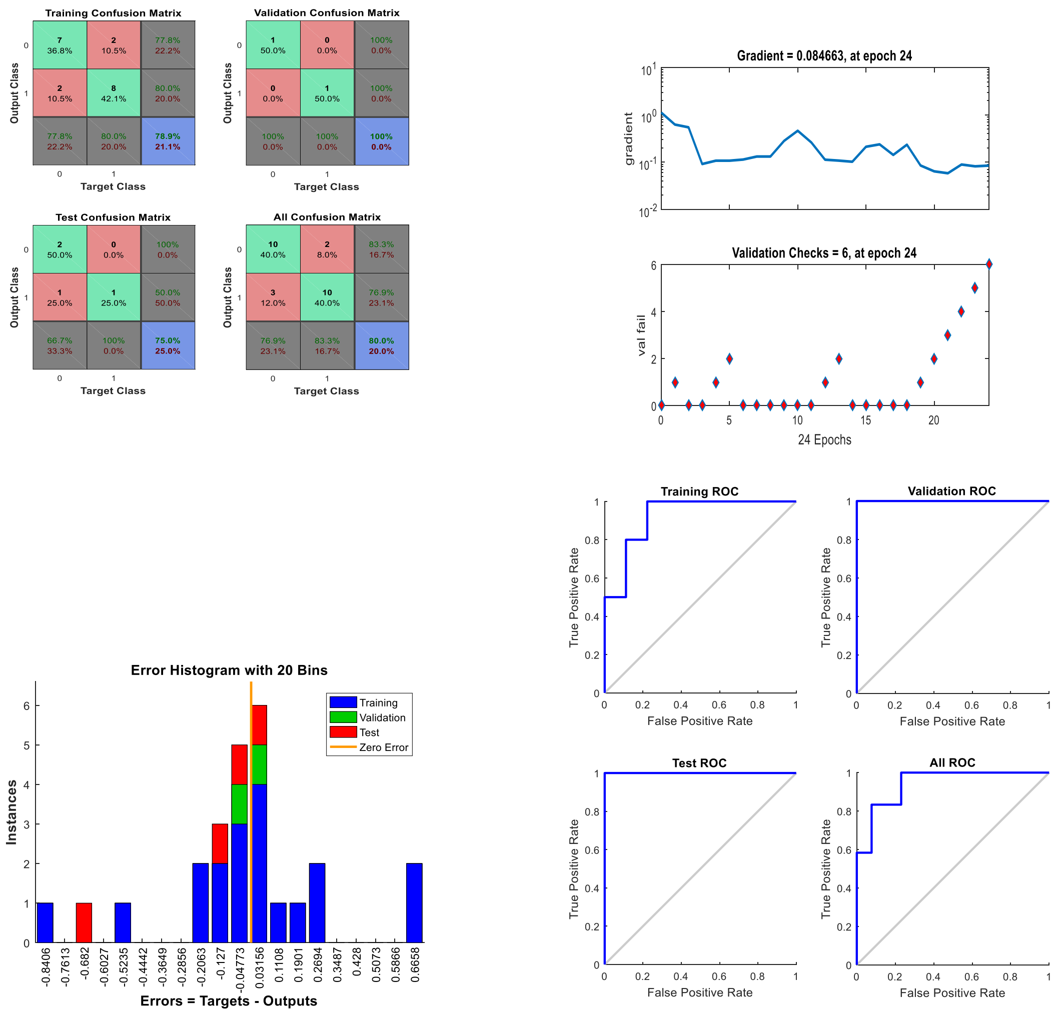


Fig.9 : Classifier Output of combination of GLCM and HOG features

A. EVALUATION PARAMETERS

The performance of our proposed technique is measured by five parameters namely, the sensitivity, precision, average number of false positives per subject, accuracy and specificity. The mathematical representation for the above three parameters are given as follows:

$$\text{S} = \frac{TP}{TP + FN} \tag{1}$$

$$\text{Average number of false positives /subject} = \frac{FP}{Number\ of\ subjects\ in\ testing\ dataset} \tag{2}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{4}$$

In the above equations, True positive represents the sub image which has CMB and True negative represents the presence of CMB mimic which is not a CMB. Whereas, the False positive represents the situation that which is incorrectly classified as CMB and the False negative represents the one which is incorrectly classified as non-CMB.

B. COMPARISON OF FEATURE SETS AND RESULTS

At first the classification step is done by applying the Artificial Neural Network (ANN) in the feature 1 alone. Then, it is applied to the feature 2 alone. Finally, ANN is applied after combining both the features. Now, the combination of both the feature sets gives better performance and higher accuracy thereby detecting the CMBs and non-CMBs more accurately than the existing techniques.

For analysis, 5-fold cross validation procedure is used for dataset-120.

Set of features	True Positive	True Negative	False Positive	False Negative	Sensitivity (%)	Specificity (%)	Accuracy (%)
Feature 1:							
Fold 1	4	11	4	5	44.44	73.33	62.5
Fold 2	6	8	6	5	54.54	57.14	56
Fold 3	4	9	6	5	44.44	60	54.16
Fold 4	5	13	3	3	62.5	81.25	75
Fold 5	3	12	5	4	42.85	70.58	62.5
Average fold					**62.03**		
Feature 2:							
Fold 1	5	15	2	2	71.42857	88.23529	83.33333
Fold 2	6	11	4	3	66.66667	73.33333	70.83333
Fold 3	4	9	6	5	44.44444	60	54.16667
Fold 4	6	12	2	4	60	85.71429	75
Fold 5	3	13	5	3	50	72.22222	66.66667
Average fold:					**70**		
Combination of Feature 1 & 2:							
Fold 1	5	15	0	4	55.55556	100	83.33333
Fold 2	6	14	2	2	75	87.5	83.33333
Fold 3	4	16	2	2	66.66667	88.88889	83.33333
Fold 4	7	15	2	0	100	88.23529	91.66667
Fold 5	3	17	0	4	42.85714	100	83.33333
Average fold:					**85**		

Table 4 : Performance of different sets of features.

From the above table, it can be said that when using the GLCM, the accuracy rate is about 62.03%. This range is worse when compared to the HOG technique. When using the HOG method the accuracy have been increased. But, when both the features are combined together, the accuracy rate, the sensitivity and the specificity are also increased.

IV. CONCLUSION

CMBs in the human brain must be identified because they cause more complications in the elderly's bodies. As a consequence, marking the CMB areas in the brain is important. For CMB performance analysis, the automated detection method for classifying the area of interest is more suitable. The feature extraction technique based on the combination of WLD, GLCM, and HOG is well explained in this paper. When compared to GLCM features, the HOG method extracts more features accurately in MR images, but when used after WLD, it yields even better efficiency and accuracy. In comparison to other methods, this one provides greater precision, sensitivity, and specificity.

As future enhancement, some advanced algorithms can be added to select the Region of Interest automatically. The same method can be done in 3D rather than 2D.

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