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GFF CLASSIFIER BASED COMPARATIVE ANALYSIS OF DIFFERENT FEATURE EXTRACTION METHODS FOR DETECTION OF DIABETIC RETINOPATHY

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Abstract:
Diabetic retinopathy is becoming the major cause of blindness in today's world. Early detection of diabetic retinopathy is very essential to avoid further evidences. Retinal images are digital images of the eye fundus is sensitive and specific for early signs of diabetic retinopathy. An automated image analysis method to detect early signs of diabetic retinopathy is greatly desired for testing. This paper focuses on Generalized Feed Forward Neural Network (GFFNN) method to detect diabetic retinopathy in retinal images. In this paper the authors used GFFNN classifier to classify the retinal images into normal and abnormal. Discrete Cosine Transform (DCT), Fast Fourier Transform (FFT), Singular Value decomposition (SVD) with 9 different statistical parameters form three different feature vectors. These feature vectors are used to train GFFNN. The % classification accuracy is 95.45%, 100% and 95.83% for DCT, FFT and SVD feature vectors designed GFFNN classifier.

Keywords: Generalized Feed Forward neural network (GFFNN), Retinal images database DIARETDB0, Discrete Cosine Transform (DCT), Fast Fourier Transform (FFT), Singular Value decomposition (SVD).

Introduction

Diabetes is a disease that affects blood vessels throughout the body, particularly in the kidneys and eyes. When blood vessels in the eye are affected, the condition is referred to as diabetic retinopathy (DR). Diabetic retinopathy is a major public health problem and a leading cause of blindness in the World[1,2,3]. Therefore early detection of diabetic retinopathy is very important to avoid vision loss. Ophthalmologist can obtain retinal images from patients to be diagnosed by using a fundus camera. From the image, symptoms will be identified manually by an ophthalmologist. Therefore more time is required to diagnose number of patients. Automatic detection of clinical signs of DR can help ophthalmologists in the diagnosis of the disease, with the subsequent cost and time saving[4,5,6]. In this paper we have proposed GFFNN classifier for the detection of diabetic retinopathy. Three feature vectors are formed with the help of DCT, FFT, SVD and 9 statistical parameters. The GFFNN is trained separately for these three feature vectors and their performance is compared. Fig.1 shows the architecture for proposed GFFNN based classifier. It consists of modules: Retinal Fundus Image input, Preprocessing, Feature Extraction, Formation of feature vectors, Generalized Feed Forward Neural Network (GFFNN), Designing of optimal GFFNN and testing on CV/test dataset.

Related Work

A computerized screening system can be used for fully automated mass screening [7].Such systems screen a large number of retinal images and identify abnormal images, which are then further examined by an ophthalmologist. This would save a significant amount of workload and time for ophthalmologists, allowing them to concentrate on their resources on surgery and treatment.

G. G. Gardner, D. Keating [8] proposed a MLP NN to detect the presence of red lesions in image regions of size30 × 30 pixels. They achieved 73.8 % image-based accuracy. In 2001, Hayashi et al [9] presented computer aided diagnosis (CAD) system which assist physician in detecting abnormalities associated with fundus images of the retina. X. Zhang and O. Chutatape [10] proposed Support Vector Machine. They reported a true positive rate of 90.6% with 2 false positives per image. The use of cross validation is not mentioned in these works. E. Grisan and A. Rugger [11] presented image-based results. They obtained Sensitivity 75% and Specificity 99% for a database of 200 images and Sensitivity 83% and Specificity 98% for different database of 60 images. Claudio A. Perez Daniel A. Schulz, Carlos M Aravena [12] proposed new cascade classifier based method for online optic disc detection. The method extracts Haar features from rectangular windows that are used to scan the digital image of the eye fundus. María García, María I. López, Jesús Poza [13] proposed lesion based and image-based criteria. The results achieved mean sensitivity of 95.9% for MLP and a mean positive predictive value of 85.7% for RBF. With an image-based criterion, the results achieved 100% mean sensitivity, 87.5% mean specificity

for MLP and RBF respectively. Prof. G. U. Kharat and Dr. S.V. Dudul [14] MLPNN and GFFNN were employed to recognize six fundamental human emotions. DCT and Statistical Parameters are used for feature extraction. They achieved 100% recognition rate on training data set (Seen examples) and test data set (Unseen examples). Carla Agurto, Vinayak Joshi, *et al.* [15] presented the system to automatically classify subjects with hypertensive retinopathy (HR) using digital color fundus images. This approach was tested on 74 digital color fundus photographs taken with TOPCON and CANON retinal cameras using leave-one out cross validation. An area under the ROC curve (AUC) of 0.84was achieved with sensitivity and specificity of 90% and 67%, respectively.

Database Acquisition

A necessary tool for the reliable evaluation and comparison of medical image processing algorithms is a database including a selected set of high quality medical images. The images are representatives of normal as well as diabetic retinopathy patients and have been verified by experts. In order to conduct the experiment for detection of retinal images as normal or abnormal, DIARETDB0 database is used, which consists of 130 colour fundus images.

The fig.2 shows the samples for abnormal and normal retinal images. The images are pre-processed by resized and converted in gray scale before the feature extraction. The samples of pre-processed images are shown in fig.3.

Generalised Feed Forward Neural Network

Generalized feed forward networks are a generalization of the MLP such that connections can jump over one or more layers. In theory, MLPNN can solve any problem that a generalized feed forward network can solve. generalized feed forward networks(GFFNN) often solve the problem much more efficiently. Each layer in this neural network has an associated learning rule and learning parameters. The transfer functions those are available within the various Axon components. Each one of these axon components applies a static map to the data it receives. The map can be linear or nonlinear, or it can normalize the input to the PE. In this neural network for learning back propagation is most common form. Fig.4 shows generalized feed forward network with 73 inputs, 01hidden layer and 02 output layers.

Feature Extraction

For detection of diabetic retinopathy we have extracted transform domain and statistical features. In transform domain features we used 64-point DCT, 64-point FFT, Singular Value Decomposition(SVD) and for statistical parameters we used Entropy, mean, standard deviation, average, Euler number, contrast, correlation, energy, homogeneity. Such features can contribute to classify images into normal and abnormal images by using GFF neural network [16,17,18]. Based on above feature extraction techniques we formed three different feature vectors as below:

Feature vector I: DCT with statistical parameters

Feature vector II: FFT with statistical parameters

Feature vector III: SVD with statistical parameters

Design I: 64- point DCT feature vector designed GFFNN

In this design we have used feature vector I as an input to GFFNN. The different parameters like number of hidden layers (HLs), number of processing elements (PEs), learning rule, transfer function and percentage of tagging for optimized MLP classifier are varied and tested on CV/test dataset. It is observed that single hidden layer gives satisfactory results. The graphical results are as shown in fig.5 to 13. As shown in fig. 5, the minimum Mean Square Error (MSE) is obtained at 03 PEs.

Final minimum MSE on variations of training and CV data along with average classification accuracy is calculated and shown in fig.6 and 7 respectively. Optimal results are obtained when 10% exemplars are used for cross validation (CV) and 90% for training neural network.

Various transfer functions are used for training the network and final minimum MSE on training and CV data is measured is shown in fig.8. Percentage of average classification accuracy for different transfer functions is also shown in fig.9. It is observed that tanh is the most suitable transfer function.

With tanh transfer function the GFF NN neural network is trained using different learning rules namely Momentum, Conjugate-Gradient (CG), Quick Propagation (QP) and Delta Bar Delta (DBD). For different learning rules final minimum MSE on training and CV data set is measured and is indicated in fig. 10 and percentage average classification accuracy is shown in fig. 11. It is observed that momentum is the most suitable learning rule for GFFNN.

Various step size are used for training the network and final minimum MSE on training and CV data is measured is shown in fig.12. Percentage of average classification accuracy for different step size is also shown in

fig.13. It is observed that 0.1 is the most suitable step size for designing GFF neural network.

The designed parameters are as follows for **design I:**

Tag data CV = 10% and train = 90%
Input PEs. = 73
Output PEs. = 02
Exemplars =117
Hidden layers = 01
Hidden layer 1
Number of PEs. = 03
Transfer function = tanhAxon
Learning rule = Momentum
Step size = 0.1
Momentum = 0.7
Output layer PEs. = 02
Transfer function = tanhAxon
Learning rule = Momentum
Step size = 0.1,Momentum = 0.7
Supervised learning control
Maximum epochs = 5000
Termination – MSE increase, CV set
Weight update = Batch
Number of epochs = 5000
Number of runs = 03
Used Cross validation
CV termination is after 500 epochs without improvement in MSE.
For classification problems, make classes evenly weighted.
Time elapsed per epoch per exemplar = 0.070 ms.

From table 1 to table 4, the overall accuracy of detection of diabetic retinopathy by using GFFNN with design I is 100% and 95.45% for normal and abnormal retinal images on train data and cross validation data respectively.

Design II: 64- point FFT feature vector designed GFFNN

In this design we have used feature vector II as an input to GFFNN by varying number of hidden layers (HL), number of processing elements (PEs), learning rule, transfer function and percentage of tagging for optimized GFFNN classifier design and tested on CV/test dataset. The graphical results are as shown in fig.14 to 22.

The designed parameters are as follows for **design II:**

Tag data CV = 10% and train = 90%
Input PEs. = 73
Output PEs. = 02
Exemplars =117
Hidden layers = 01
Hidden layer 1
Number of PEs. = 06
Transfer function = tanhAxon
Learning rule = Momentum
Step size = 0.3
Momentum = 0.7
Output layer PEs. = 02
Transfer function = tanhAxon
Learning rule = Momentum
Step size = 0.1,Momentum = 0.7
Supervised learning control
Maximum epochs = 5000
Termination – MSE increase, CV set
Weight update = Batch
Number of epochs = 5000
Number of runs = 03
Used Cross validation
CV termination is after 500 epochs without improvement
in MSE.
For classification problems, make classes evenly weighted.
Time elapsed per epoch per exemplar = 0.095 ms.

Finally, designed GFF NN is tested on training and CV dataset and results are shown in table 5 to 8.

From table 5 to table 8, the overall accuracy of detection of diabetic retinopathy is 100% for normal and abnormal retinal images on train data as well as cross validation data sets.

Design III: 64- point SVD feature vector designed GFFNN

In this design we have used feature vector III as an input to GFFNN by varying number of hidden layers (HL), number of processing elements (PEs), learning rule, transfer function and percentage of tagging for optimized GFFNN classifier design and tested on CV/test dataset. The graphical results are as shown in fig.23 to 31.

The designed parameters are as follows for **design III:**

Tag data CV = 10% and train = 90%
Input PEs. = 73
Output PEs. = 02
Exemplars =117
Hidden layers = 01
Hidden layer 1
Number of PEs. = 15
Transfer function = tanhAxon
Learning rule = Momentum
Step size = 0.1
Momentum = 0.7
Output layer PEs. = 02
Transfer function = tanhAxon
Learning rule = Momentum
Step size = 0.1,Momentum = 0.7
Supervised learning control

Maximum epochs = 5000
Termination – MSE increase, CV set
Weight update = Batch
Number of epochs = 3000
Number of runs = 03
Used Cross validation
CV termination is after 300 epochs without improvement
in MSE.
For classification problems, make classes evenly weighted.
Time elapsed per epoch per exemplar = 0.091ms.
Finally, designed GFF NN is tested on training and CV dataset and results are shown in table 5 to 8.
From table 9 to table 12 for design III the overall accuracy of detection of diabetic retinopathy is 98.97% and 95.83% for normal and abnormal retinal images on train data and cross validation data respectively.

Table1*: Confusion matrix on training data using GFF*

Output / Desired	*o1(Abnormal)*	*o2(Normal)*
o1(Abnormal)	99	0
o2(Normal)	0	18

Table2*: Performance parameters for training data using GFF*

Performance	***o1***	***o2***
MSE	0.00078275	0.00080599
NMSE	0.006012942	0.006191472
MAE	0.020048299	0.020156657
Min Abs Error	1.1093E-05	9.3374E-05
Max Abs Error	0.0555492	0.055547759
r	0.997831718	0.997818887
Percent Correct	100	100

The overall accuracy is = 100%

Table 3 & 4 show that on Cross Validation data, the classification accuracy is 95.45%.

Table3*: Confusion matrix for CV data using GFF*

Output / Desired	*o1(Abnormal)*	*o2(normal)*
o1(Abnormal)	10	0
o2(normal)	1	2

Table 4*: Performance parameters for CV data using GFF*

Performance	***o1***	***o2***
MSE	0.043584561	0.04800291
NMSE	0.334808674	0.368749627
MAE	0.13885197	0.127054878
Min Abs Error	0.005363616	0.008494312
Max Abs Error	0.509371244	0.655460425
r	0.818011051	0.818251707
Percent Correct	90.90909091	100

The overall accuracy is = 95.45%

Finally, designed GFF NN is tested on training and CV dataset and results are shown in table 1 to 4.

Table5: *Confusion matrix on training data using GFF*

Output / Desired	*o1(Abnormal)*	*o2(normal)*
o1(Abnormal)	98	0
o2(normal)	0	19

Table6*: Performance parameters for training data using GFF*

Performance	***o1***	***o2***
MSE	0.000839201	0.000865656
NMSE	0.006169618	0.006364107
MAE	0.021812382	0.021953294
Min Abs Error	0.000356678	5.64917E-05
Max Abs Error	0.055463204	0.055461738
r	0.997817659	0.997770886
Percent Correct	100	100

The overall accuracy is = 100%

Table7: *Confusion* matrix for CV data using GFF

Output / Desired	*o1*	*o2*
o1	12	0
o2	0	1

Table8*: Performance parameters for CV data using GFF*

Performance	***o1***	***o2***
MSE	0.034319778	0.033321902
NMSE	0.48333688	0.469283449
MAE	0.120474793	0.117922573
Min Abs Error	0.013990083	0.010651076
Max Abs Error	0.417664353	0.484133295
r	0.721990803	0.773903493
Percent Correct	100	100

The overall accuracy is = 100%

Table9*: Confusion matrix on training data using GFF*

Output / Desired	*o1(Abnormal)*	*o2(normal)*
o1(Abnormal)	96	0
o2(normal)	2	19

Table10*: Performance parameters for training data using GFF*

Performance	***o1***	***o2***
MSE	0.019623531	0.019773949
NMSE	0.144267733	0.145373568
MAE	0.084792226	0.085399597
Min Abs Error	2.30005E-05	0.000195629
Max Abs Error	0.620714181	0.605107823
r	0.928351893	0.927517954
Percent Correct	97.95918367	100

The overall accuracy is = 98.97%

***Table11**: Confusion matrix for CV data using GFF*

Output / Desired	*o1(Abnormal)*	*o2(normal)*
o1(Abnormal)	11	0
o2(normal)	1	1

***Table12**: Performance parameters for CV data using GFF*

Performance	***o1***	***o2***
MSE	0.065743582	0.059608355
NMSE	0.925888779	0.839484336
MAE	0.17064458	0.170960062
Min Abs Error	0.030673248	0.031369892
Max Abs Error	0.70364556	0.607845059
r	0.598880893	0.621010275
Percent Correct	91.66666667	100

The overall accuracy is = 95.83%

***Table13**: Comparison of % of classification accuracy for GFFNN with different given designs*

Designs	Percentage(%) of classification accuracy	
	On Train Data	On CV Data
Design I	100	95.45
Design II	100	100
Design III	98.97	95.83

***Table14**: Accuracy, sensitivity and specificity percentages using GFFNN*

Designs	Accuracy (%)	Sensitivity (%)	Specificity (%)
Design I	92.30	90.90	100
Design II	100	100	100
Design III	92.30	91.67	100

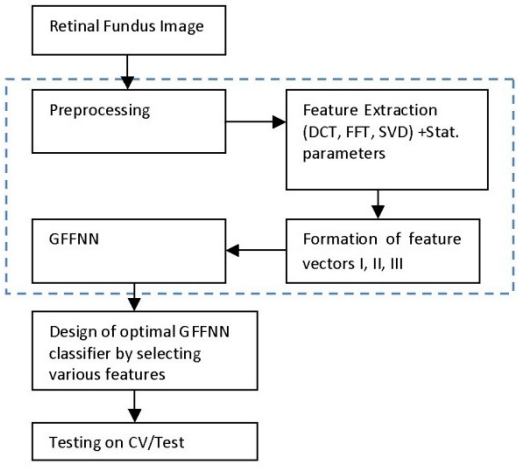

Figure 1 Overview of classifier system.

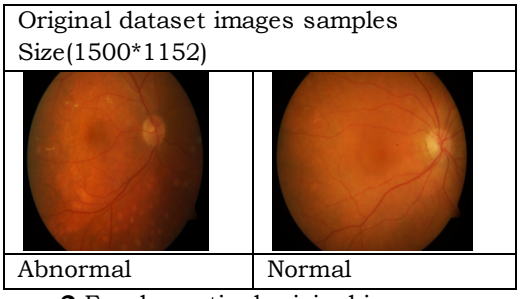

Figure 2 Fundus retinal original images

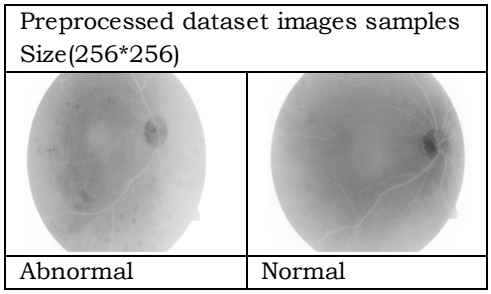

Figure 3 Preprocessed retinal images for feature extraction

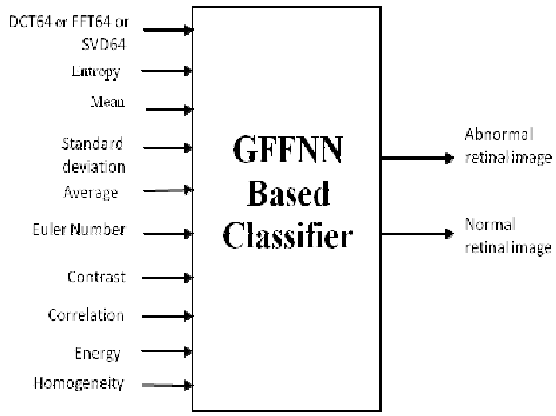

Figure 4 Generalized feed forward network with two hidden layers & one output layer.

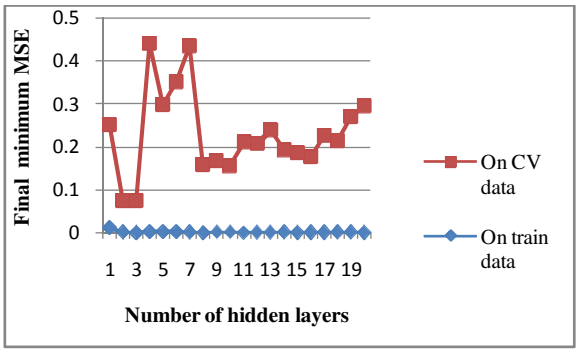

Figure 5 Graph showing variation of final minimum MSE with number of processing elements

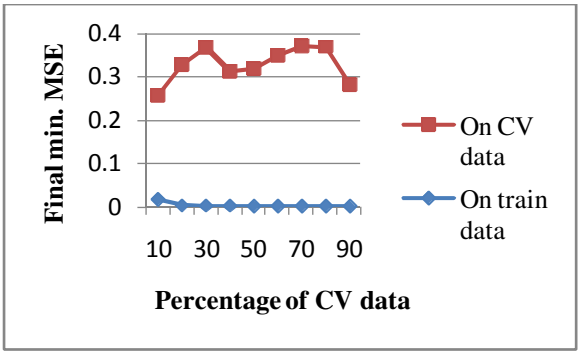

Figure 6: Graph indicating variation of final minimum MSE with % of CV data.

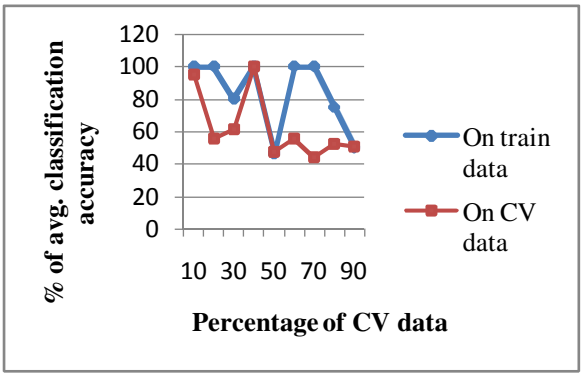

Figure 7: Graph showing variation of % average classification accuracy with % of CV data

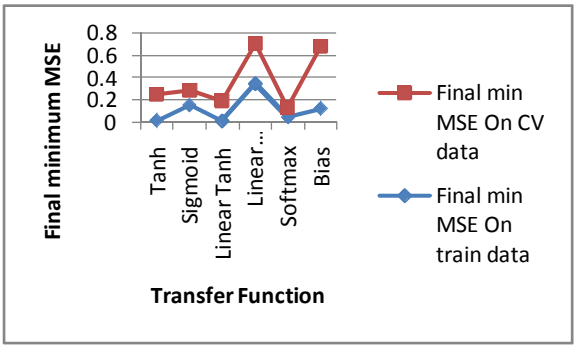

Figure 8: Graph showing variation of Final minimum MSE with different transfer functions

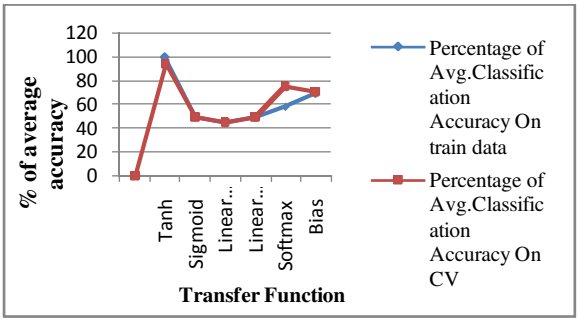

Figure 9: Graph showing variation of % of average classification accuracy with different transfer functions

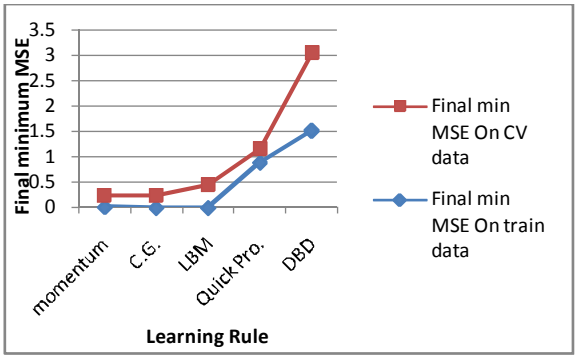

Figure 10: Graph showing variation of Final minimum MSE with learning rule

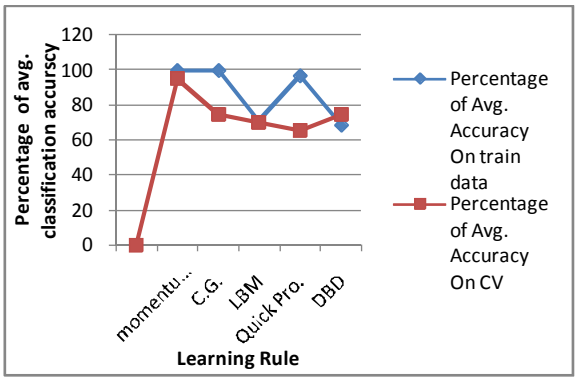

Figure 11: Graph showing variation of % of average classification accuracy with learning rule

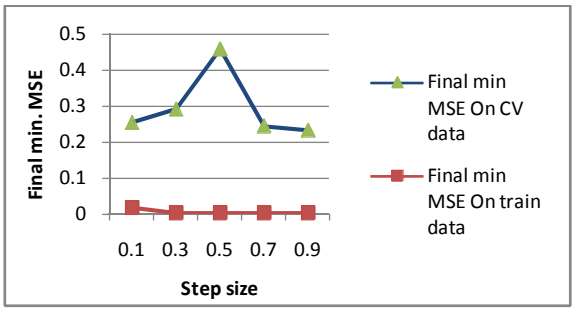

Figure 12: Graph showing variation of Final minimum MSE with different step size

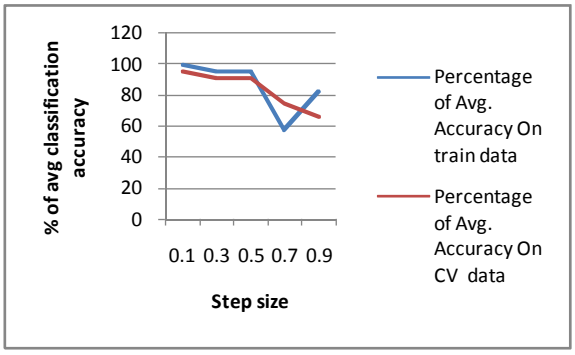

Figure 13: Graph showing variation of % of average classification accuracy with different step size

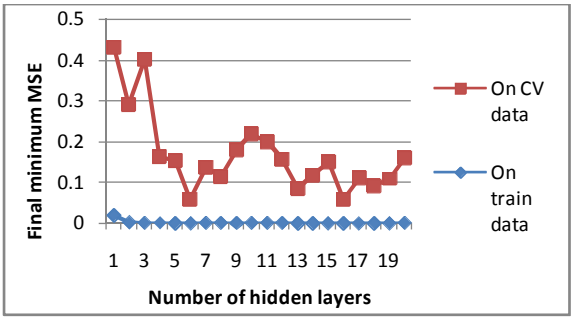

Figure 14: Graph showing variation of final minimum MSE with number of processing elements

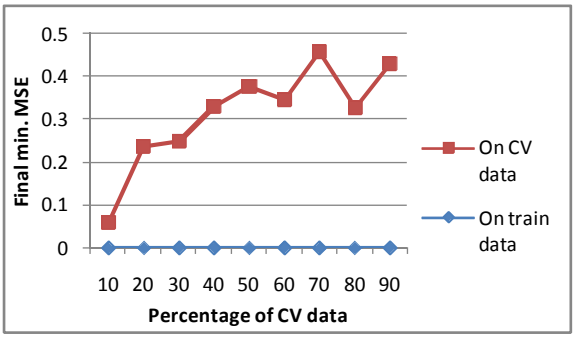

Figure 15: Graph indicating variation of final minimum MSE with % of CV data.

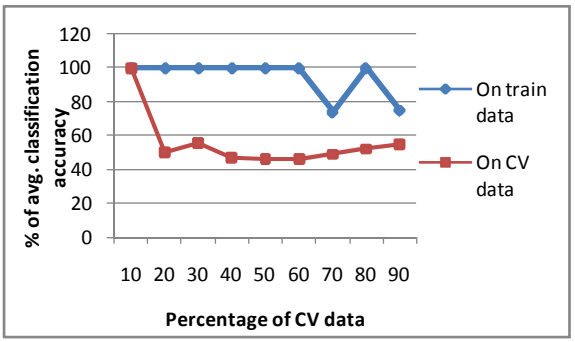

Figure 16: Graph showing variation of % average classification accuracy with % of CV data

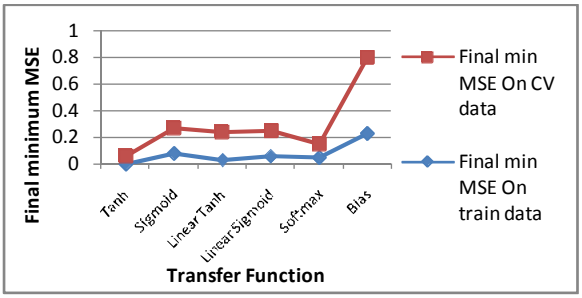

Figure 17: Graph showing variation of Final minimum MSE with different transfer functions

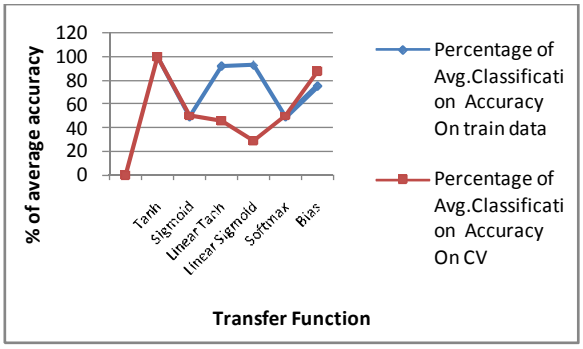

Figure 18: Graph showing variation of % of average classification accuracy with different transfer functions

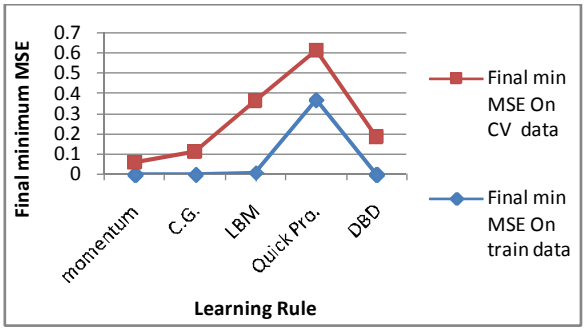

Figure 19: Graph showing variation of Final minimum MSE with learning rule

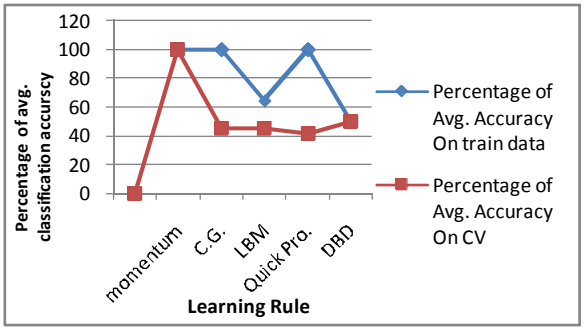

Figure 20: Graph showing variation of % of average classification accuracy with learning rule

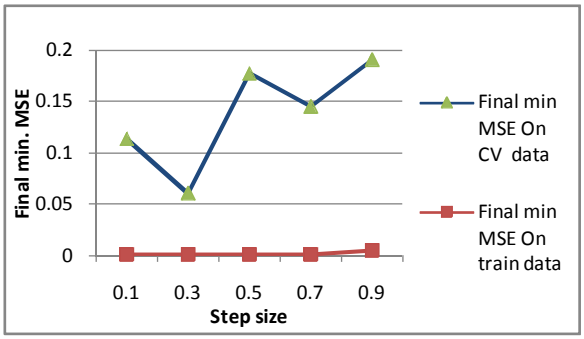

Figure 21: Graph showing variation of Final minimum MSE with different step size

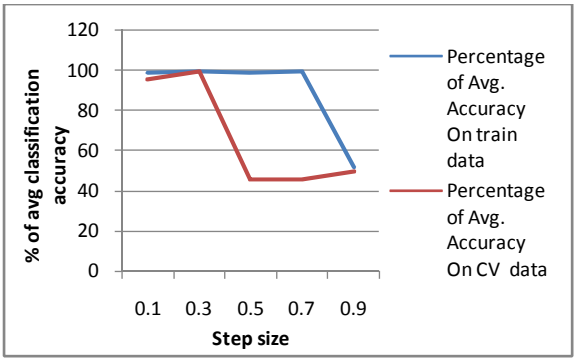

Figure 22: Graph showing variation of % of average classification accuracy with different step size

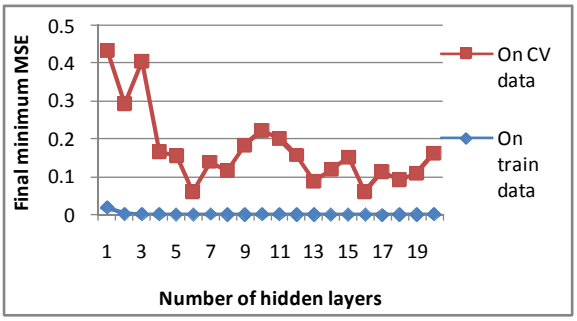

Figure 23: Graph showing variation of final minimum MSE with number of processing elements

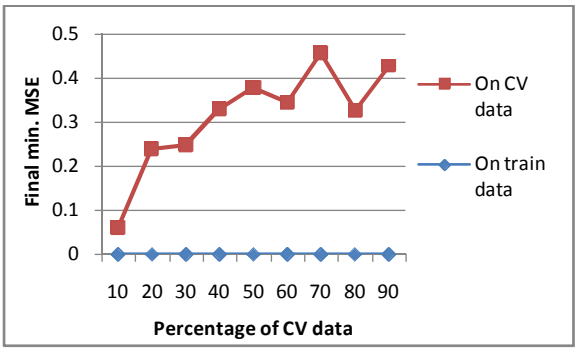

Figure 24: Graph indicating variation of final minimum MSE with % of CV data.

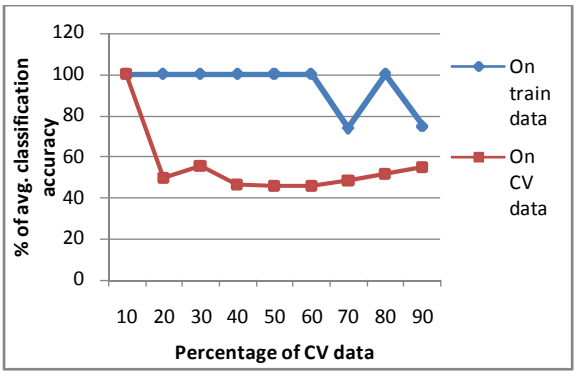

Figure 25: Graph showing variation of % average classification accuracy with % of CV data

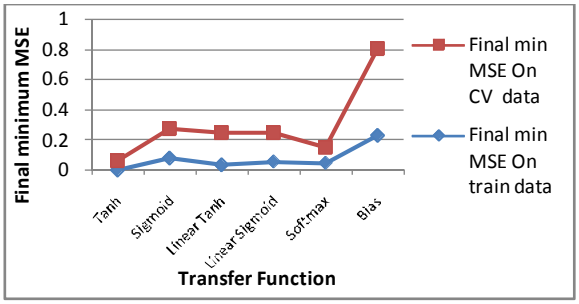

Figure 26: Graph showing variation of Final minimum MSE with different transfer functions

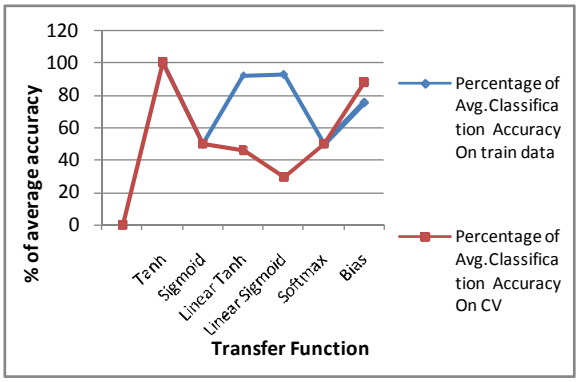

Figure 27: Graph showing variation of % of average classification accuracy with different transfer functions

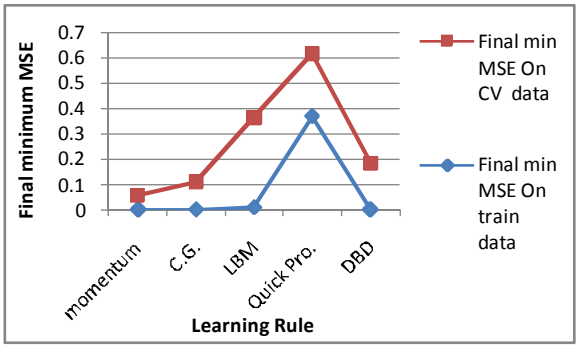

Figure 28: Graph showing variation of Final minimum MSE with learning rule

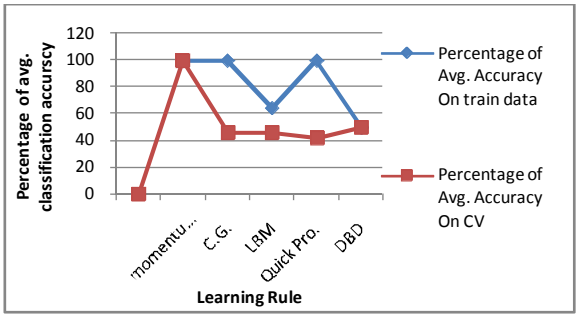

Figure 29: Graph showing variation of % of average classification accuracy with learning rule

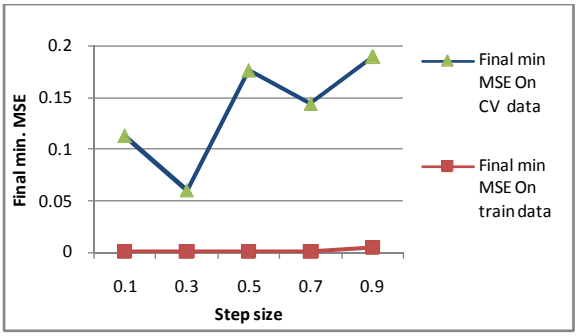

Figure 30: Graph showing variation of Final minimum MSE with different step size

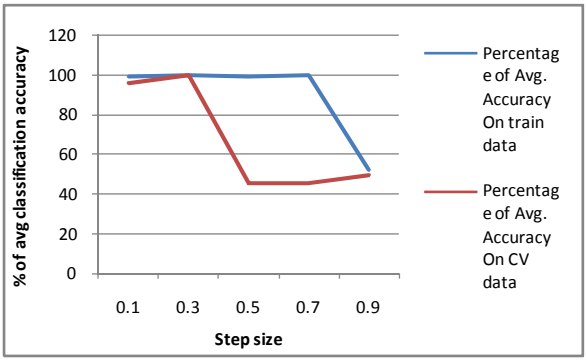

Figure 31: Graph showing variation of % of average classification accuracy with different step size

Discussion and Conclusion

This paper proposed GFFNN classifier system for detection of retinopathy in retinal images. Different feature vectors like DCT, FFT, SVD along with statistical parameters were extracted and used as inputs to the classifier. Percentage of classification accuracy for train and CV data sets for all designs is shown as in table13. Table14 presents comparison of accuracy, sensitivity and specificity for GFF NN with three feature extraction methods. It is observed that with FFT and statistical parameters formed feature vector is best input to design GFF based classifier for detection of diabetic retinopathy in retinal images.

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