

Performance Comparison of Radial Basis Function Networks and Probabilistic Neural Networks for Telugu Character Recognition

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Abstract

The research on recognition of hand written scanned images of documents has witnessed several problems, some of which include recognition of almost similar characters. Therefore it received attention from the fields of image processing and pattern recognition. The system of pattern recognition comprises a two step process. The first stage is the feature extraction and the second stage is the classification. In this paper, the authors propose two classification methods, both of which are based on artificial neural networks as a means to recognize hand written characters of Telugu, a language spoken by more than 100 million people of south India(Negi et al. ,2001). In this model, the authors used Radial Basis Function (RBF) networks and Probabilistic Neural Networks (PNN) for classification. These classifiers were further evaluated using performance metrics such as accuracy, sensitivity, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV) and F measure. This paper is a comparison of results obtained with both the methods. The values of F measure are quite satisfactory and this is a good indication of the suitability of the methods for classification of characters. The values of F-Measure for both the methods approach the value of 1, which is a good indication and out of the two, RBF is a better method than PNN.

Index terms— Classification, sensitivity, specification, F-measure, PPV, NPV.

1 Introduction

Character recognition is a form of pattern recognition [2]. Any pattern feature recognition system consists of two major steps, extraction and classification. The main focus in this paper is on classification. Classification is one of the important decision making factor for many real world problems. In this model authors used the classification techniques for identifying similar shaped Telugu characters.

classifiers. RBF neural networks have fast training and learning rate because of their locally tuned neurons. They also exhibit a universal approximation property and good generalization ability. Probabilistic neural network integrates the characteristics of statistical pattern recognition and Back Propagation Neural Network (BPNN) and it has the ability to identify boundaries between the categories of patterns. In this research work the aforementioned two classifiers have been chosen for identification of Telugu script and then compared their performance.

2 II. Literature Review

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In the present work, authors used radial basis function network and probabilistic neural network as Considerable amount of research has occurred in identifying methods suitable for character recognition Nawaz et al. [3] developed a system for recognition of Arabic characters with RBF network and Hu invariant moments are used as predictor variables. Ashok and Rajan, [4] designed a system for writer identification with handwriting

42 using Radial Basis function. The efforts published by Vijay and Ramakrishnan, [5] described a system for the
43 recognition of Kannada text where they used the wavelet features as attributes and RBFN as a classifier. Birijesh
44 , [6] designed the system for the hand written Hindi characters and in this work the performance of Multi Layer
45 Perceptron (MLP) and RBF networks were compared and it was shown that RBF is superior to MLP. Kunte
46 and Samuel [7] developed a neural network classifier with Hu invariant moments, Zernike moments as predictor
47 variables and RBF network as a classifier. Vatkin and Selinger [8] used RBF neural network for the classification
48 of hand written Arabic numerals using Legendre moments as predictor variables. Romera et al. [9] described
49 an advanced system of classification using probabilistic neural networks and they used the classifier for optical
50 Chinese character recognition. Khatatneh et al. [10] proposed a new technique in developing a recognition
51 system for handling Arabic hand written characters with probalistic neural networks, which yields a significant
52 improvement. The work published by Koche [11] compared the classification results of template matching,
53 probabilistic neural network, and feed forward back propagation neural network where the performance of PNN
54 was superior. Jeatrakul and Wong [12] compared the ©2011 Global Journals Inc. (US)

55 3 III. Problem Statement

56 Application of neural networks for optical character recognition is the problem domain. The goal of this paper
57 is to construct classifiers with radial basis function networks, probabilistic neural networks and to compare the
58 performance.

59 4 IV. Proposed System

60 The model proposed in this paper builds a pattern recognition system. Any pattern recognition comprises of two
61 steps, feature extraction and classification. As the main aim of the paper is for classification a brief review of
62 feature extraction is given.

63 5 1) Feature Extraction

64 As predictor variables used in the classification play a major role in increasing the accuracy of the classifier,
65 the feature extraction is an important step. The system proposed by us is for the classification of Telugu hand
66 written letters. The Telugu characters are neither available commercially nor available on the net. So the authors
67 collected images from 60 people covering different educational back grounds and different age groups. Sample
68 set of characters collected from one person and the corresponding Telugu alphabet and the class label are shown
69 in figure ??.

70 6 Figure1: Sample set of Characters

71 As handwriting varies from person to person and from time to time with the same person, the following
72 preprocessing steps are required before extracting the features.

73 7 1.1) Normalization

74 All the scanned images are brought to a common size by identifying the tight fit rectangular boundary around
75 the image and they are scaled to 32x32 image.

76 8 1.2) Binarization and Thinning

77 The aim of this process is to separate the character from the back ground in the grey image color to black and
78 white and then the image is thinned down to skeleton of unitary thickness.

79 After preprocessing a set of 41 features are extracted from the skeletal images covering the local, global and
80 statistical features. A brief description of the features is given in Table ??.

81 Table ??: Description of Features

82 9 V1

83 The number of pixels in skeletal image that are in excited state V2

84 The number of pixels in skeletal image that have one excited neighbor V3

85 The number of pixels in skeletal image that have two excited neighbors V4

86 The number of pixels in the skeletal image that have three excited neighbors V5

87 The number of pixels in the skeletal image that have two excited neighbors which are 180 degrees apart V6 ,V7
88 ,V8

89 The densities of pixels in the excited state when the image is divided into three regions horizontally V9,v10.v11

90 The densities of the pixels in the excited state when the image is divided into three regions vertically V12

91 Total number of crossings i.e., changes from 1's to 0's and from 0's to 1's as the image scanned horizontally
92 V13

93 Total change in the horizontal crossings V14

94 Total number of crossings i.e., changes from 0's to 1's and from 1's to 0's as the image is scanned in the vertical
95 direction V15

96 Total change in the vertical crossings V16

97 The number of connected components in the image V17 Euler number the binary matrix i.e., the skeletal
98 image V18 entropy: is a statistical measure of the randomness that can be used to characterize the texture of
99 the input image Entropy= $-\sum (p \cdot \log_2(p))$; V19 Energy: is the sum of squared elements in the grey level co
100 occurrence matrix. Energy= $\sum p(I)^2$ for all i and j V20 Contrast: returns a measure of the intensity contrast
101 between a pixel and its neighbor over the whole image Contrast = $\sum |i-j| \cdot 2 \cdot p(i,j)$ for all I and j V21

102 Correlation: is measure of how correlated a pixel to its neighbor over the whole image. Correlation= $\sum ((i-\mu_i)(j-$
103 $\mu_j)p(I,j)) / \sum i \cdot j$

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108 performance of classifiers developed using RBF and PNN and according to them the performance of RBF was
109 found to be superior.

110 From the literature survey it has been observed that the recognition systems were developed for Arabic and
111 Kannada and Chinese script using RBF and probabilistic work. Not much work had been reported for Telugu
112 script using RBF and PNN. This literature review reveals a dearth in information regarding recognition of Telugu
113 hand-written characters. It inspired us to develop a classifier for Telugu script using RBF and PNN and compare
114 the performance of the networks.

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116 **11 V22**

117 Cluster tendency: Measure of the grouping of the pixels that have similar gray level values. Cluster tendency=
118 $\sum (I+j - 2\mu) \cdot k \cdot p(I,j)$ V23

119 Standard deviation of the binary matrix V24 Maximum value of the gray level co occurrence matrix V25,V26

120 Co ordinates of the centroid of the binary skeletal image V27 ,V28

121 Number of crossings at the centroid in horizontal and vertical directions V29 Eccentricity: scalar that specifies
122 the eccentricity of an ellipse that has same second moments as the region of the image V30 Orientation: scalar
123 (in degrees) between the x axis and the major axis of the ellipse ,that has the same second moments as the image
124 V31 Scalar that specifies the number of pixels in the convex area of the image V32 Diameter: scalar that specifies
125 the diameter of the circle as the region of the image V33 Solidity: scalar specifying the proportion of pixels that
126 are in the region of the image.

127 **12 V34**

128 Extent: scalar that specifies the ratio of pixels to the total in the bounding box V 35 to v41 Hu invariant moments:
129 seven moment based features which are invariant to size and orientation of the character As the data obtained
130 for different features are with different scales, standardization of the data is required before proceeding with any
131 classification task. The standardization is performed with $X = \frac{X - \mu}{\sigma}$ 2) Classification

132 Classification is a data mining technique used to predict group membership for data instances. The objective
133 of the data classification is to analyze the input data and to develop an accurate description or model for each
134 class using the features present in the data. The model is used to predict the class label of unknown records and
135 such modeling is referred as predictive modeling. The methodology used in the paper uses predictive modeling
136 and developed using neural networks. As the goal of this work is to compare the performance of a classification
137 model and is based on the counts of test samples correctly and incorrectly predicted by the model.

138 3) Performance Metrics of records from class i predicted to be of class j.

139 Although confusion matrix provides the information needed to determine how well a classification model
140 performs, summarizing this information with a single number would make it convenient to compare the
141 performance of different models. This can be done by using the performance metrics such as sensitivity or
142 recall, specificity, precision or positive predictive value, negative predictive value, F-measure and accuracy.

143 **13 3.5) F-measure**

144 It can be used as a single measure of performance of the test. The F measure is the harmonic mean of precision
145 and recall

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147 Where X is the median and Sx is the standard deviation. To ensure accurate classification a large number
148 of features are extracted in our models, which are to be characteristic of each individual character. Different
149 researchers used different number of variables to suit their purposes like Huette et al. [13] who used about 124
150 and Patra et al. [14] who used only 17 and the authors used 41 variables. As the number of features increases,

151 the complexity of the pattern recognition system increases, so we reduced the dimensions by using factor analysis.
 152 Predictor variables are reduced to 18 variables from a total of 41 variables.

153 Several criteria may be used to evaluate the performance of a classification algorithm in supervised learning.
 154 A confusion matrix is a useful tool for analyzing how well a classifier can identify test samples of different classes
 155 [15], which tabulates the records correctly and incorrectly predicted by the model. Each entry C_{ij} in the confusion
 156 matrix denotes the number 4) Radial Basis Function Approach Radial basis function network which is a feed
 157 forward network consists of three layers input layer, hidden layer and the output layer. The architecture of
 158 RBF is shown in Figure ???. The RBF is different from the ordinary feed forward networks in calculating the
 159 activations of hidden neurons. The activations at the hidden neurons are computed by using the exponential of
 160 distance measures.

161 Each node in the input layer corresponds to a component of the input vector x . The second layer, the only
 162 hidden layer in the neural network applies non linear transformation from input space into hidden space by
 163 employing non-linear activation function such as Gaussian kernel. A linear node at the output layer corresponds
 164 to the classes of the problem. A simple way to choose the number of radial basis functions is to create a hidden
 165 neuron centered on each training pattern. However, this method is computationally very costly and takes up
 166 huge amount of memory. In our model, the training patterns are clustered into a reasonable number of groups
 167 using K-means clustering algorithm.

168 15 INPUT LAYER HIDDEN LAYER OUTPUT LAYER Fig- 169 ure 2: Radial Basis Function Network

170 Then a neuron is assigned to each cluster centre. The output of each hidden neuron is calculated by using the
 171 Gaussian radial basis function? ? ? ? ? ? ? ? ? = $2 \cdot 2 \cdot \exp(-\frac{2}{\sigma^2} \|\mu_i - x\|^2)$ (? G

172 Where, x is the training sample, μ_i is the centre of the hidden i th neuron and σ is the width of the neuron. The
 173 width of the basic functions are set to a value which is a multiple of the average distance between the centers.
 174 This value governs the amount of smoothing.

175 The activation at the output neurons is defined by the summation() ? + = $\sum_i G_{ij} \exp(-\frac{2}{\sigma^2} \|\mu_i - x\|^2)$
 176 1 ?

177 In our model, we fixed the number of centers as 100 and width as 2.4 which is a multiple of the average
 178 width 0.6 of the hidden neuron. The percentages of characters correctly classified for different number of centers
 179 and for different widths (σ values) are shown in Table 2 and table 3 respectively. With the above results, the
 180 authors fixed the parameters, the number of hidden neurons as 100 and width of the basis function as 2.4. With
 181 these parameters the confusion matrix obtained as shown in Figure ??. The input layer does not perform any
 182 computation and simply distribute the input to the neurons in the pattern layer which has one node for each
 183 training example. On receiving the pattern x from the input layer, the neuron x_{ij} of the pattern layer computes
 184 its output as

185 16 Number of Centers

186 $() () () ? ? ? ? ? ? ? ? ? = \frac{2 \cdot 2}{\sigma^2} \exp(-\frac{2}{\sigma^2} \|\mu_i - x\|^2)$ $\sum_{ij} T_{ij} d_{ij} x x x x$

187 Where, d denotes the dimension of the pattern vector x , σ is the smoothening parameter and x_{ij} is the neuron
 188 vector. The summation layer neurons compute the maximum likelihood of pattern x being classified into C_i by
 189 summarizing and averaging the output of all the neurons that belong to the same class,

190 17 Results and Discussions

191 In this paper the authors compared the classification models developed using radial basis function network and
 192 probabilistic neural network. The summary of the confusion matrix for both the methods is shown in table 5
 193 and table 6 respectively.

194 18 VI. Conclusion

195 In this paper, the authors presented two classification models, one is radial basis function networks and the other
 196 is probabilistic neural networks and both being implemented using MATLAB. The accuracy of all the classes is
 197 above 90% with both the methods. But the overall accuracy of the RBF network is found to be better from the
 198 results. In

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200 Building a model that maximizes both precision and recall is a key challenge in classification algorithm [16].
 201 Precision and recall can be summarized into another metric known as F measure as explained in performance
 202 metrics. The F measure for both the classes is shown in the form of a graph in figure ??. With the first method



Figure 1: 3. 1 3) 4)

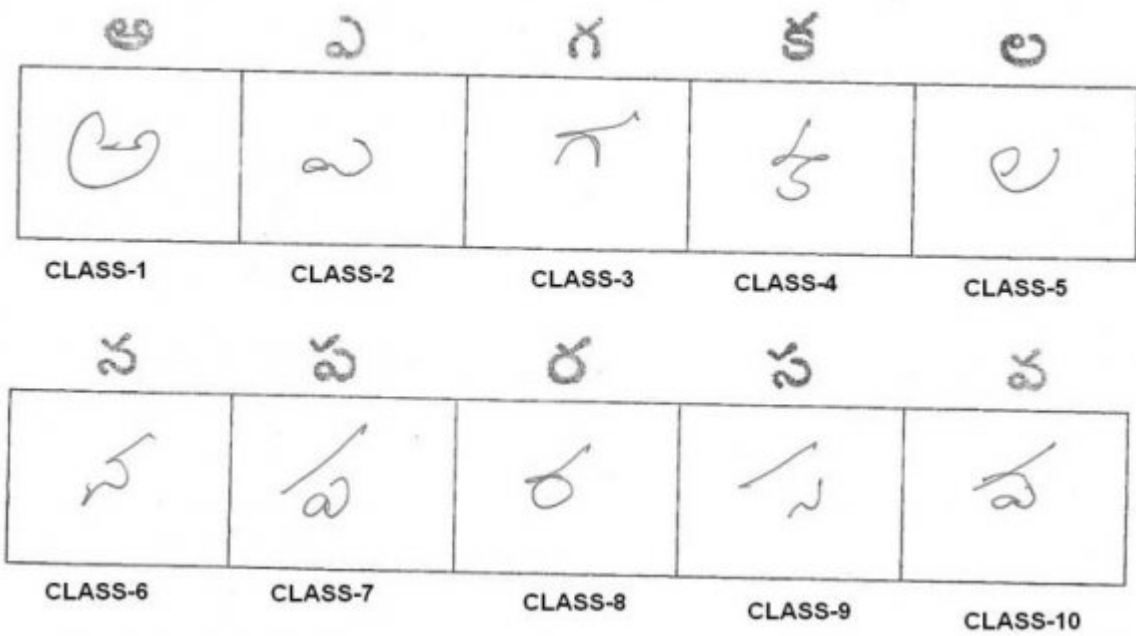
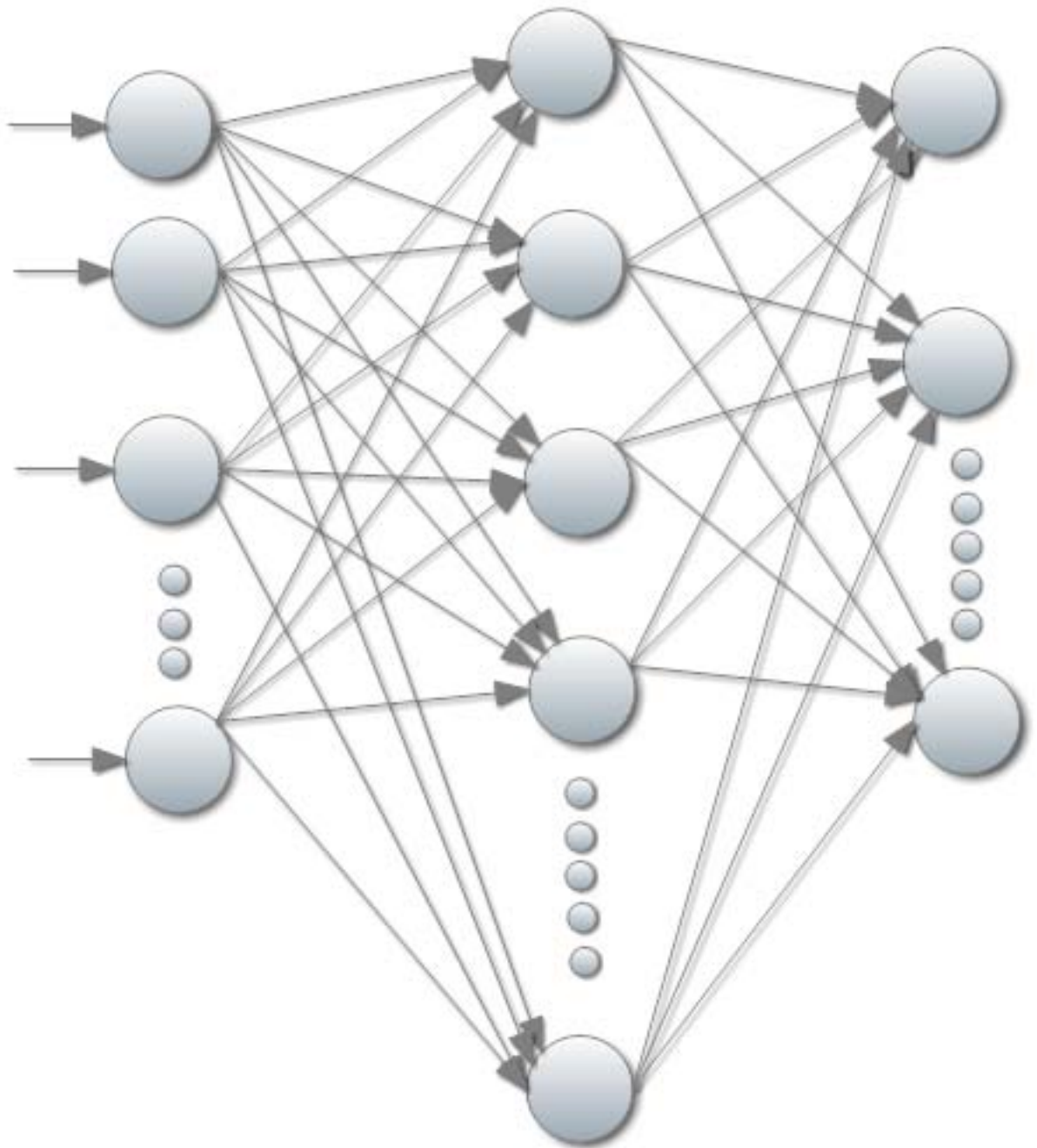


Figure 2:



34

Figure 3: Figure 3 :Figure 4 :

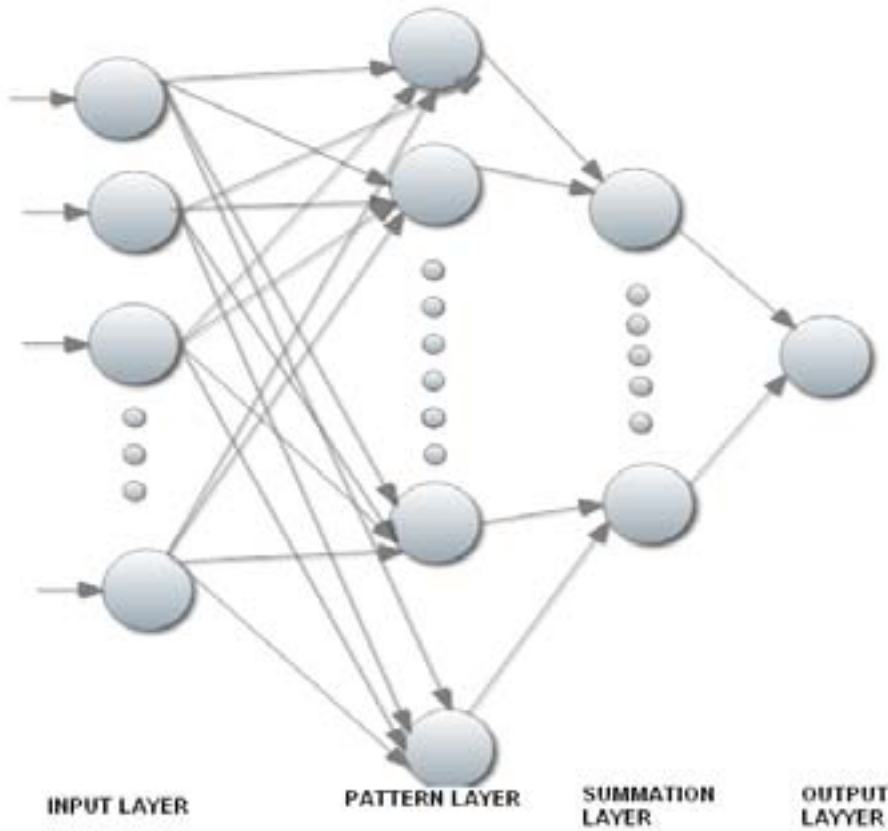


Figure 4:

203 the value of F is less than 0.7 for classes with the labels 8, 10 and with PNN the value is less than 0.7 for classes
 204 with labels 2, 6, 8 and 10. ^{1 2 3}

¹March 2011 Where, w is the weight vector. The weights are computed by $W = (G^T G)^{-1} G^T d$ Where d is the target class matrix. ©2011 Global Journals Inc. (US)

²March 2011 ©2011 Global Journals Inc. (US)

³March 2011 This page is intentionally left blank

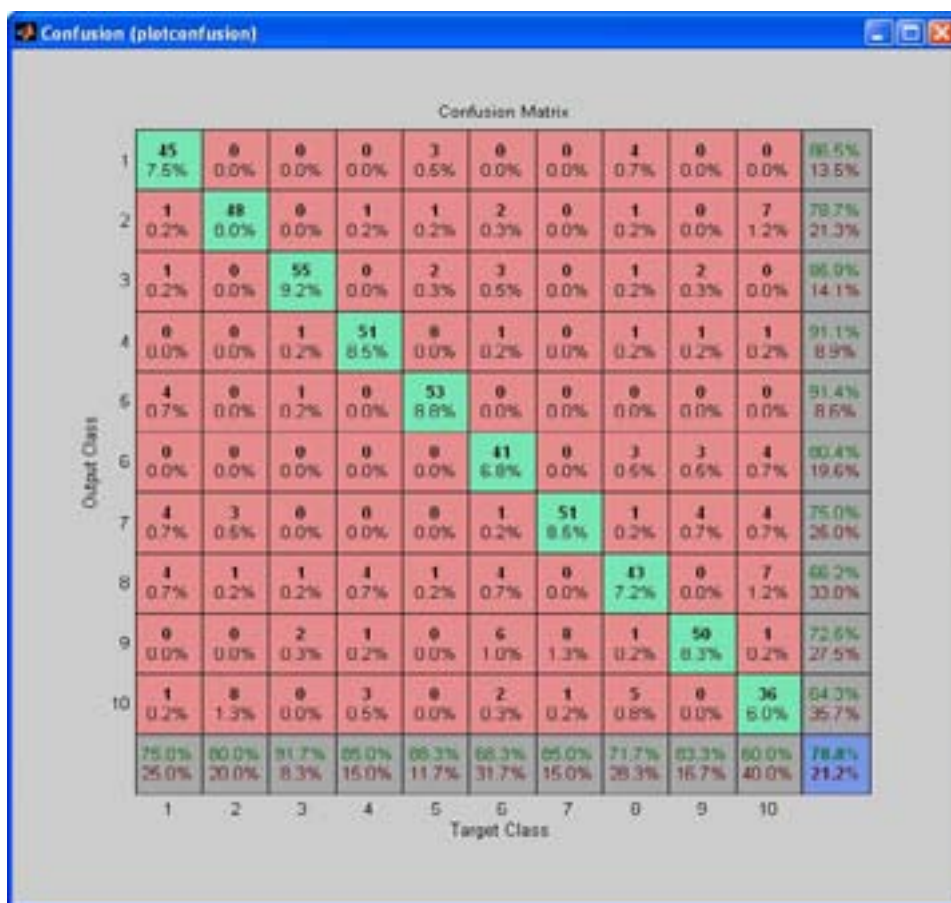


Figure 5:



Figure 6: Figure 4 :

Class	Accuracy	Sensitivity	Specificity	Precision	NPV	F Measure
1	96.33	75	98.70	86.53	97.26	0.8
2	95.83	80	97.59	78.68	97.77	0.79
3	97.66	91.66	98.33	85.93	99.06	0.88
4	97.66	85	99.07	91.07	98.34	0.8793
5	98.00	88.33	99.07	91.38	98.70	0.898
6	95.16	68.33	98.15	80.39	96.54	0.739
7	95.66	85	96.85	75.00	98.30	0.797
8	93.5	71.67	95.93	66.15	96.82	0.688
9	95.166	83.3	96.48	72.46	98.11	0.775
10	92.66	60	92.69	64.28	95.58	0.62

Figure 7: Figure 5 :

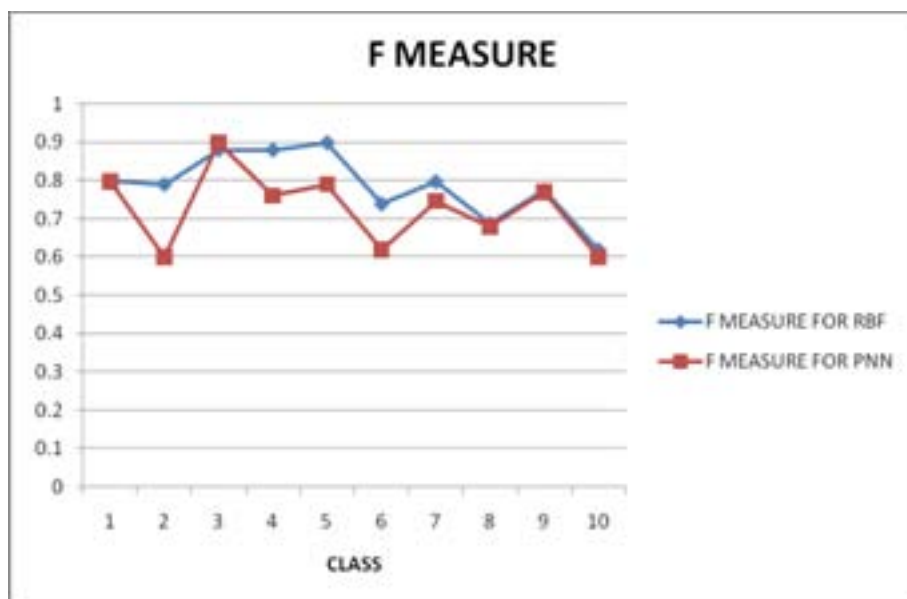


Figure 8:

Class	Accuracy	Sensitivity	Specificity	Precision	NPV	F Measure
1	95.80	81.67	97.40	77.78	97.75	0.796
2	92.10	58.33	96.11	62.50	95.4	0.6
3	98.00	88.33	99.01	91.37	98.70	0.898
4	96.00	61.66	99.80	97.36	95.90	0.76
5	96.00	73.30	98.50	84.62	97.08	0.79
6	93.16	56.67	97.22	69.38	95.28	0.62
7	94.66	78.30	96.48	71.2	95.77	0.746
8	93.33	70.00	95.92	65.62	96.66	0.68
9	94.66	88.33	95.37	67.94	98.65	0.77
10	91.00	68.30	93.52	53.94	96.37	0.6

Figure 9:

2

Figure 10: Table 2 :

3

?	% Characters Correctly Classified
.6	72.5
1.2	78.2
1.8	77.8
2.4	78.8
3.0	78.2

Figure 11: Table 3 :

4

	% Characters Correctly Classified
?	
.9	70.7
1	71.3
1.1	71.7
1.2	72.0
1.3	72.3
1.4	72.5
1.5	72.2
1.6	71.7

Figure 12: Table 4 :

5

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Figure 13: Table 5 :

6

[Note: 1. The Performance metric accuracy which is a function of specificity and sensitivity is a measure for comparing two classifiers. The accuracy of RBF network for all the classes except classes with labels 8 and 10 is above 95% where as with PNN the accuracy for four classes with labels 1, 3, 4, 5 are above 95% and for the remaining is less than 95%. The comparison of accuracy measure is shown in figure5. 2.]

Figure 14: Table 6 :

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