Global Journal of Computer Science and Technology
Volume 11 Issue 4 Version 1.0 March 2011
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 0975-4172 & Print ISSN: 0975-4350

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Keywords: Classification, sensitivity, specification, F-measure, PPV, NPV.

Classification: GJCST Classification: I.5.1, I.2.7

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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 [1] . 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.

Keywords: Classification, sensitivity, specification, F-measure, PPV, NPV.

I. 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.

In the present work, authors used radial basis function network and probabilistic neural network as 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 identity 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.

II. Literature Review

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

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

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

III. Problem Statement

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

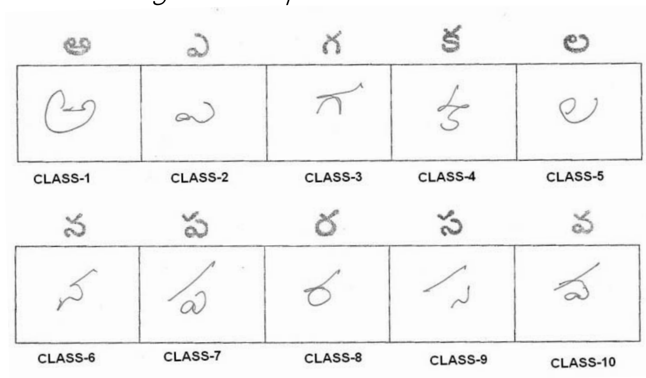
IV. Proposed System

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

1) *Feature Extraction*

As predictor variables used in the classification play a major role in increasing the accuracy of the classifier, the feature extraction is an important step. The system proposed by us is for the classification of Telugu hand written letters. The Telugu characters are neither available commercially nor available on the net. So the authors collected images from 60 people covering different educational back grounds and different age groups. Sample set of characters collected from one person and the corresponding Telugu alphabet and the class label are shown in figure 1.

Figure1: Sample set of Characters



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

1.1) *Normalization*

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

1.2) *Binarization and Thinning*

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

After preprocessing a set of 41 features are extracted from the skeletal images covering the local, global and statistical features. A brief description of the features is given in Table 1.

Table 1: Description of Features

V1	The number of pixels in skeletal image that are in excited state
V2	The number of pixels in skeletal image that have one exited neighbor
V3	The number of pixels in skeletal image that have two excited neighbors
V4	The number of pixels in the skeletal image that have three excited neighbors
V5	The number of pixels in the skeletal image that have two exited neighbors which are 180 degrees apart
V6 ,V7 ,V8	The densities of pixels in the exited state when the image is divided into three regions horizontally
V9,v10.v11	The densities of the pixels in the exited state when the image is divided into three regions vertically
V12	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
V13	Total change in the horizontal crossings
V14	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 direction
V15	Total change in the vertical crossings
V16	The number of connected components in the image
V17	Euler number the binary matrix i,e., the skeletal image
V18	entropy: is a statistical measure of the randomness that can be used to characterize the texture of the input image Entropy=-sum $(p*\log_2 (p))$;
V19	Energy: is the sum of squared elements in the grey level co occurrence matrix. $Energy=\sum p(I)^2$ for all i and j
V20	Contrast: returns a measure of the intensity contrast between a pixel and its neighbor over the whole image Contrast $= \sum \mid i-j \mid^2 p(i,j)$ for all I and j
V21	Correlation: is measure of how correlated a pixel to its neighbor over the whole image. $Correlation=\sum((i-\mu i)(j-\mu j)p(I,j))/\sigma_i \sigma_j$

V22	Cluster tendency: Measure of the grouping of the pixels that have similar gray level values. Cluster tendency= $\sum \sum (I+j-2\mu)^k p(I,j)$
V23	Standard deviation of the binary matrix
V24	Maximum value of the gray level co occurrence matrix
V25,V26	Co ordinates of the centroid of the binary skeletal image
V27 ,V28	Number of crossings at the centroid in horizontal and vertical directions
V29	Eccentricity: scalar that specifies the eccentricity of an ellipse that has same second moments as the region of the image
V30	Orientation: scalar (in degrees) between the x axis and the major axis of the ellipse ,that has the same second moments as the image
V31	Scalar that specifies the number of pixels in the convex area of the image
V32	Diameter: scalar that specifies the diameter of the circle as the region of the image
V33	Solidity: scalar specifying the proportion of pixels that are in the region of the image.
V34	Extent: scalar that specifies the ratio of pixels to the total in the bounding box
V 35 to v41	Hu invariant moments: seven moment based features which are invariant to size and orientation of the character

As the data obtained for different features are with different scales, standardization of the data is required before proceeding with any classification task. The standardization is performed with

$$X^1 = \frac{X - \overline{X}}{S_X}$$

Where $\overline{X}$ is the median and Sx is the standard deviation. To ensure accurate classification a large number of features are extracted in our models, which are to be characteristic of each individual character. Different researchers used different number of variables to suit their purposes like Huette et al.[13] who used about 124 and Patra et al.[14] who used only 17 and the authors used 41 variables. As the number of features increases, the complexity of the pattern recognition system increases, so we reduced the dimensions by using factor analysis. Predictor variables are reduced to 18 variables from a total of 41 variables.

2) *Classification*

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

3) *Performance Metrics*

Several criteria may be used to evaluate the performance of a classification algorithm in supervised learning. A confusion matrix is a useful tool for analyzing how well a classifier can identify test samples of different classes [15], which tabulates the records correctly and incorrectly predicted by the model. Each entry Cij in the confusion matrix denotes the number of records from class i predicted to be of class j. Although confusion matrix provides the information needed to determine how well a classification model performs, summarizing this information with a single number would make it convenient to compare the performance of different models. This can be done by using the performance metrics such as sensitivity or recall, specificity, precision or positive predictive value, negative predictive value, F-measure and accuracy.

3.1) *Sensitivity:*

It measures the actual members of the class which are correctly identified as such. It is also referred as True Positive Rate (TPR) or recall. It is defined as the fraction of positive examples predicted correctly by the classification model

$$\text{Sensitivity (recall)} = \frac{TP}{(TP+FN)}$$

3.2) *Specificity*

It is also referred to as true negative rate .It is defined as the fraction of negative examples which are predicted correctly by the model

$$\text{Specificity} = \frac{TN}{(TN+FP)}$$

3.3) *Precision (Positive predictive value)*

It is also called as positive predictive value and determines the fraction of records that actually turns out to be positive in the group which has been declared as positive class by the classifier

$$\text{Precision} = \frac{TP}{(TP+FP)}$$

3.4) *Negative predictive value (NPV)*

It is proportion of the samples which do not belong to the class under consideration and which are correctly identified as non members of the class

$$\text{NPV} = \frac{TN}{(TN+FN)}$$

3.5) *F-measure*

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

$$\text{F Measure} = \frac{2 * precision * recall}{(precision + recall)}$$

3.6) *Accuracy*

Accuracy is used as a statistical measure of how well a binary classification test identifies or excludes a condition. It is a measure of proportion of true results

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

Where TP=true positives, TN =True negatives, FP=false positives, FN=false negatives

In our model we used the following two networks for classification

1. Radial Basis Function Networks
2. Probabilistic Neural Networks

4) *Radial Basis Function Approach*

Radial basis function network which is a feed forward network consists of three layers input layer, hidden layer and the output layer. The architecture of RBF is shown in Figure 2. The RBF is different from the ordinary feed forward networks in calculating the activations of hidden neurons. The activations at the hidden neurons are computed by using the exponential of distance measures.

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

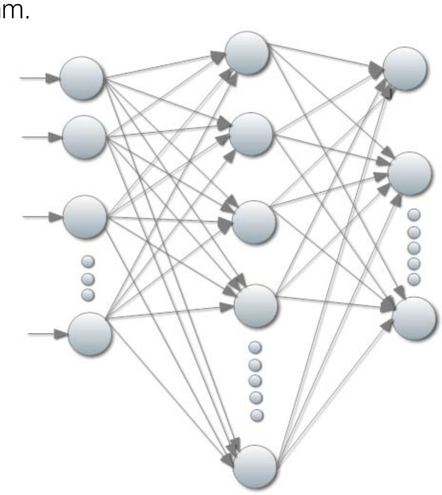


Figure 2: Radial Basis Function Network

Then a neuron is assigned to each cluster centre. The output of each hidden neuron is calculated by using the Gaussian radial basis function

$$G(\| x - \mu_i \|) = \exp\left(- \frac{\| x - \mu_i \|^2}{2\sigma^2} \right)$$

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

The activation at the output neurons is defined by the summation

$$Y(x) = \sum_i w * G(\| x - \mu_i \|) + b$$

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.

In our model, we fixed the number of centers as 100 and width as 2.4 which is a multiple of the average width 0.6 of the hidden neuron. The percentages of characters correctly classified for different number of centers and for different widths (σ values) are shown in Table 2 and table 3 respectively.

Table 2: Percentage of Characters Correctly Classified for Different Numbers of Centers

Number of Centers	% Characters Correctly Identified
90	75.8
100	77.7
110	75.8

Table 3: Percentage of Characters Correctly Classified for Different Values of σ

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

With the above results, the authors fixed the parameters, the number of hidden neurons as 100 and width of the basis function as 2.4. With these parameters the confusion matrix obtained as shown in Figure 3.

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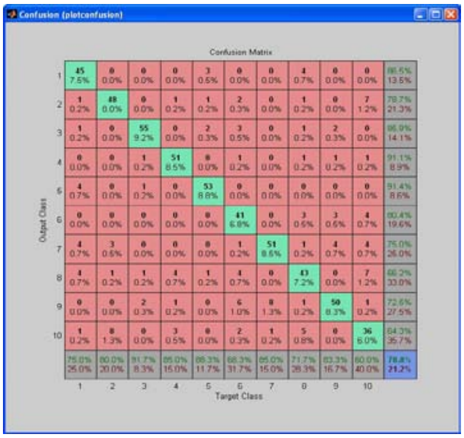

Figure 3: Confusion Matrix

5) *Probabilistic Neural Network Approach*

The PNN as described in Figure 4 consists of input layer, two hidden layers, (one of the example/pattern and class/summation) and an output layer. The process based classification that differentiates PNN and RBF is that PNN works on the estimation of probability density function

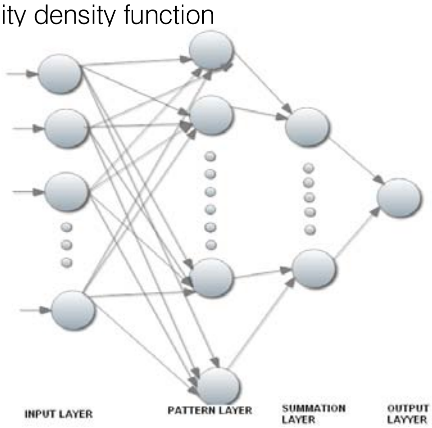

Figure 4: Probabilistic Neural Network

The input layer does not perform any computation and simply distribute the input to the neurons in the pattern layer which has one node for each training example. On receiving the pattern x from the input layer, the neuron xij of the pattern layer computes its output as

$$\phi_{ij}(x) = \frac{1}{(2\pi)^{d/2}\sigma^d} \exp\left[-\frac{(x - x_{ij})^T (x - x_{ij})}{2\sigma^2} \right]$$

Where, d denotes the dimension of the pattern vector x, σ is the smoothening parameter and xij is the neuron vector. The summation layer neurons compute the maximum likelihood of pattern x being classified into Ci by summarizing and averaging the output of all the neurons that belong to the same class,

$$P_i(x) = \frac{1}{(2\pi)^{d/2}\sigma^d} \frac{1}{N_i} \sum_{j=1}^{Ni} \exp\left[-\frac{(x - x_{ij})^T (x - x_{ij})}{2\sigma^2} \right]$$

Where, N_i denotes the total number of samples in a class C_i. If the apriori probabilities for each class are the same, the decision layer classifies pattern x in accordance with the ayes decision rule based on the output of all summation layer neurons.

$$C^{\Lambda}(x) = \arg\ \max\{P_i(x)\}\ \ i = 1,2,.....m$$

Where $C^{\Lambda}(x)$ denotes the estimated class of pattern x and m is the total number of classes in the training samples. In our model we fixed the value of σ as 1.4 and the values of σ and percentage of characters classified for each σ are shown in Table 4 and the best value was found to be at 1.4.

Table 4: Percentage of Characters Correctly Classified for Different Values of σ

σ	% 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

With σ=1.4 the confusion matrix is shown in Figure 4.

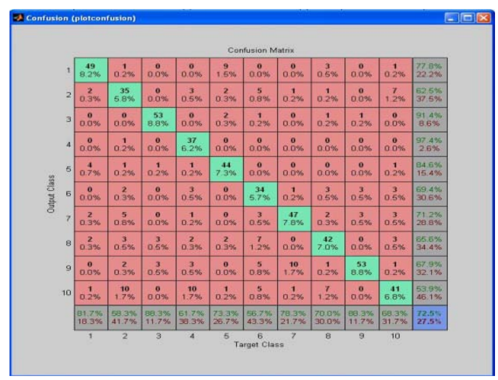

Figure 4: Confusion Matrix

V. Results and Discussions

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

Table 5: Summary of Performance Metrics for RBF Network

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

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Table 6: Summary of Performance Metrics for PNN Network.

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

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 figure 5.
2. Building a model that maximizes both precision and recall is a key challenge in classification algorithm [16]. Precision and recall can be summarized into another metric known as F measure as explained in performance metrics. The F measure for both the classes is shown in the form of a graph in figure 6. With the first method 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 with labels 2, 6, 8 and 10.

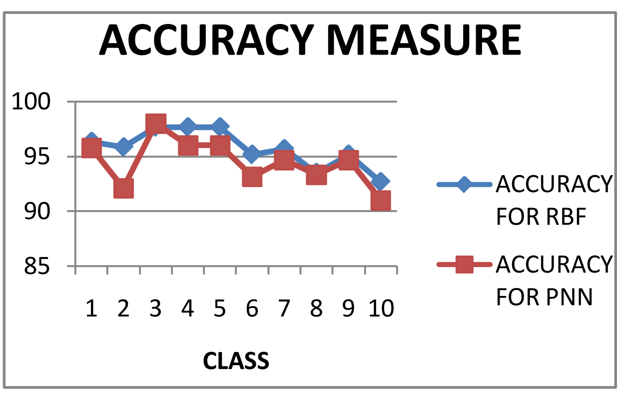
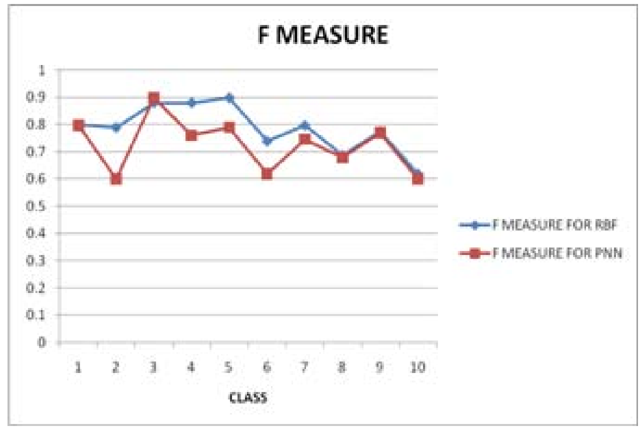


Figure 5: Accuracy Measure



VI. Conclusion

In this paper, the authors presented two classification models, one is radial basis function networks and the other is probabilistic neural networks and both being implemented using MATLAB. The work was carried out with 600 images collected from 60 people and the result is tested with 10 fold cross validation. With RBF network 474 characters are classified correctly while with PNN 435 characters are classified correctly. The following observations are made from the results.

1. Only for class with label 3 the values of accuracy and F measure are found to be good with PNN and for all the remaining classes RBF is showing good results.
2. Percentage of characters classified correctly with RBF network is 78.8% and with PNN the percentage of characters classified correctly is 72.5.
3. Except for class with label 10 the value of F measure is nearer to one, the reason being the character considered for class with label 10 has similar structure with classes with labels 2, 6 and 7.

The accuracy of all the classes is above 90% with both the methods. But the overall accuracy of the RBF network is found to be better from the results. In future we are planning to extend the work to other characters of Telugu script and to use the techniques which are less dependent on the sample size considered for training of the classifier which may reduce the time required for classification

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