Analysis of Ensemble Models for Handwriting Recognition

M. Govindarajan
Assistant Professor, Department of Computer Science and Engineering,
Annamalai University, Annamalai Nagar – 608002, Tamil Nadu, India.
e-mail: govind_aucse@yahoo.com

Abstract-Combining complementary classifier is common practice in pattern recognition that improves recognition rates and system reliability. In this research work, new ensemble classification methods are proposed with homogeneous ensemble classifier using bagging and heterogeneous ensemble classifier using arcing and their performances are analyzed in terms of accuracy. A Classifier ensemble is designed using Radial Basis Function (RBF) and Support Vector Machine (SVM) as base classifiers. The feasibility and the benefits of the proposed approaches are demonstrated by the means of standard datasets of recognizing totally unconstrained handwritten numerals. The main originality of the proposed approach is based on three main parts: preprocessing phase, classification phase and combining phase. A wide range of comparative experiments are conducted for standard datasets of recognizing totally unconstrained handwritten numerals. The performance of the proposed homogeneous and heterogeneous ensemble classifiers are compared to the performance of other standard homogeneous and heterogeneous ensemble methods. The standard homogeneous ensemble methods include Error correcting output codes, Dagging and heterogeneous ensemble methods include majority voting, stacking. The proposed ensemble methods provide significant improvement of accuracy compared to individual classifiers and the proposed bagged RBF and SVM performs significantly better than ECOC and Dagging and the proposed hybrid RBF-SVM performs significantly better than voting and stacking. Also heterogeneous models exhibit better results than homogeneous models for standard datasets of recognizing totally unconstrained handwritten numerals.

Keywords: Accuracy, Arcing, Bagging, Ensemble, Radial Basis Function, Support Vector Machine.

1. INTRODUCTION

Handwriting recognition is a branch of image processing with many uses such as machine reading of postal addresses, checks and banknotes, old documents, barcodes, polls and tax forms (Bagheri Noaparast, et al., 2009). Optical Character Recognition (OCR) is a field of research in pattern recognition, artificial intelligence and machine vision. It refers to the mechanical or electronic translation of images of handwritten, typewritten or printed text into machine-editable text. Nowadays, the accurate recognition of machine printed characters is considered largely a solved problem. However, handwritten character recognition is comparatively difficult, as different people have different handwriting styles. So, handwritten OCR is still a subject of active research (Vamvakas, G., et al., 2010).

The hand written signature has also an adequate importance in online banking applications, credit cards, and cheque processing mechanism (K. Harika, and T.C.S. Ready, 2013). For the authentication and validation of passports, biometrics systems can be used; specifically for the signature verification (S. Odeh, and M. Khalil, 2011). The Gaussian noise caused by scanning of the document, the difference between the positions of signature in the document, the stamps and other typed texts which are mixed with the signature that creates some difficulties during the extraction of original signature from the image (R. Anjali, and M.R. Mathew, 2013). There are two main tasks of signature recognition and verification one of them is the correct identification of the owner of signature, and the other is correct classification of signature whether it is a genuine or a forded (V.M. Deshmukh, and S.A. Murab, 2012).

The handwritten signatures are the most authentic and realistic use of a person's identification in legal and commercial transactions (G.P. Patil, and R.S.Hegadi, 2013). In hand written signature verification used many methods for verification of a signature such as Support Vector Machines (SVMs) (Alaei, et al., 2009 and Sadri, J., et al., 2003), Neural Networks (NNs) (Bagheri Noaparast, et al., 2009), K-Nearest-Neighbours (KNNs), Decision Trees, Hidden Markov Model (HMM), Fuzzy logic (Hanmandlu, M. et al., 2003), Genetic algorithm, Bagging, Statistical Classifiers, Fisher linear discriminant, Hybrid Classifiers (Xiao-Xiao Niu, et al., 2012), Bayesian decision theory. Instead of simply training one classifier for the task, some authors have adopted strategies to train multiple classifiers, and combine their predictions when classifying a new sample. For instance, Chergui et al., (2012) using ensemble learning for handwriting recognition, the performance had increased compared to the individual classifier.

This paper proposes new ensemble classification methods to improve the classification accuracy. The main purpose of this paper is to apply homogeneous and heterogeneous ensemble classifiers for standard datasets of recognizing totally unconstrained handwritten numerals to improve classification accuracy.

Organization of this paper is as follows. Section 2 describes the related work. Section 3 presents proposed methodology and Section 4 explains the performance evaluation measures. Section 5 focuses on the experimental results and discussion. Finally, results are summarized and concluded in section 6.

2. RELATED WORK

In the field of handwriting recognition lot of research has been done in which many techniques are covered and still many remains to be covered. Signature is divided into two halves and for each half a position of the centre of gravity is calculated with reference to the horizontal axis. The structure features from modified direction feature and other features as surface area, length skew and centroid feature are considered. For classification, two approaches are compared: the Resilient Backpropagation (RBP) neural network and Radial Basic Function (RBF) using a database of 2106 signatures containing 936 genuine and 1170 forgeries (Surabhi Garhawal and Neeraj Shukla, 2013). These two classifiers register 91.21% and 88 % true verification respectively.

Deshmukh et al., (2012) have proposed a method for verification and recognition of offline signatures based on neural networks in which the signature has been captured and examined in the form of an image. This model is also writer independent and the pattern recognition process is divided into two major classes of problems which make it possible for the building of robust model, which can be best for the small data sets in which it gives the best result even if the numbers of signatures are small from a signer. There are various successful classifiers for verification of offline signatures, like the Support Vector Machines (SVM) and Hidden Markov Model HMM and they are overall better in the performance than the HMM approaches.

Patil et al. (2013) have used the support vector machine which has the fast learning capability and separating the hyper plans in the high dimensional feature spaces. Main goal of this technique is to optimize the simplification bounds.

R. Ebrahimpur, et al., (2010) proposed a new classifier combination model for Farsi handwritten digit recognition. The model is consisted of four RBF neural networks as the experts and another RBF network as the gating network which learns to split the input space between the experts. Considering the input data, which is an 81-element vector extracted using the loci characterization method, the gating network assigns a competence coefficient to each expert. The final output is computed as the weighted sum of the outputs of the experts. The recognition rate of the proposed model is 93.5% which is 3.75% more than the rate of the mixture of MLPs experts previously ran on the same database.

Maziar Kazemi et al., (2015) aims to improve the results of identifying the Persian handwritten letters using Error Correcting Output Coding (ECOC) ensemble method. Firstly, the image features are extracted by Principal Components Analysis (PCA).After that, ECOC is used for identification the Persian handwritten letters which it uses Support Vector Machine (SVM) as the base classifier. The empirical results of applying this ensemble method using 10 real world data sets of Persian handwritten letters indicate that this method has better results in identifying the Persian handwritten letters than other ensemble methods and also single classifications.

Le Hoang Thai et al. (2012) focuses on image classification using SVM and ANN. The k-NN classifier, a conventional non-parametric, calculates the distance between the feature vector of the input image (unknown class image) and the feature vector of training image dataset. In this paper, SVM and ANN are used to identify optimal weights.SVM need to be trained first, the parameter of SVM is adjusted to suitable for the training data in the specific problem. The training dataset contains 322 matrixes of images of Roman numerals. The average classification rate is 86%.

S. Adebayo Daramola et al. (2010) proposed combination of DCT signature features and HMM are incorporated to develop a robust model framework and signature classification algorithm. It gives recognition performance of the system is 99.2%. Kumar et al., (2012) have applied four different approaches like 'Linear SVM', 'Polynomial SVM', 'k-NN' and 'RBF-SVM' to experiment with handwritten Gurmukhi characters. A total of 7000 samples have been collected and used. Features extraction methods like 'zoning feature', 'diagonal feature', 'directional feature', and 'transition feature' have been used. An accuracy of 94.8% without PCA and 97.7% with PCA application is reported.

In this paper, a hybrid handwriting recognition system is proposed using radial basis function and support vector machine and the effectiveness of the proposed bagged RBF, bagged SVM and RBF-SVM hybrid system is evaluated by conducting several experiments on standard datasets of handwriting recognition. The performance of the proposed bagged RBF, bagged SVM, and RBF-SVM hybrid classifiers are examined in comparison with standalone RBF and standalone SVM classifier and also heterogeneous models exhibits better results than homogeneous models for standard datasets of handwriting recognition.

3. PROPOSED METHODOLOGY

3.1 Preprocessing

Before performing any classification method the data has to be preprocessed. In the data preprocessing stage it has been observed that the datasets consist of many missing value attributes. By eliminating the missing attribute records may lead to misclassification because the dropped records may contain some useful pattern for Classification. The dataset is preprocessed by removing missing values using supervised filters.

3.2 Existing Classification Methods

3.2.1 Radial Basis Function Neural Network

The Radial Basis Function Network (RBF) is in its simplest form a three layered feed forward neural network with one input layer, one hidden layer and one output layer (R. Callan, 1998). It differs from an MLP in the way the hidden layer performs its computation. The connection between the input layer and the output layer is nonlinear, while the connection between the hidden layer and the output layer is linear. RBF networks are instance based, meaning that it will compare and evaluate each training case to the previous examined training cases. In an MLP all instances are evaluated once while in an RBF network the instances are evaluated locally (Tom M, 1997). Instance based methods use nearest neighbor and locally weighted regression methods. An RBF network can be trained more efficiently than a neural net using backpropagation since the input and output layer are trained separately.

3.2.2 Support Vector Machine

Support Vector Machines has been introduced by Vapnik and his colleagues (C. Cortes and V. Vapnik, 1995), SVM models are very similar to classical multilayer perceptron neural networks used for classification (R. Hua, Dai liankui, 2010), but recently they have been extended to solve regression problems (V. Vapnik et al., 1997). Moreover, SVM has been shown a success use in some areas such as; Handwritten Recognition (O. Rashnodi et al., 2011), Face Detection (J. Ruan and J. Yin, 2009), Time Series Prediction (N. Sapankevych and R. Sankar, 2009) and others. SVM is very similar to an ANN since both receive input data and provide output data. For regression, the input and output of SVM are identical to the ANN. However, what makes the SVM primarily better is that the SVM does not suffer from over fitting like ANN does. So, the ANN memorizes the input data on the training stage and will not perform well at the testing data.

3.3 Homogeneous Ensemble Classifiers

3.3.1 Dagging

This Meta classifier (Gupta, S. and Singh, H., 1996) creates a number of disjoint, stratified folds out of the data and feeds each chunk of data to a copy of the supplied base classifier. Predictions are made via majority vote, since all the generated base classifiers are put into the Vote meta classifier. It is useful for base classifiers that are quadratic or worse in time behavior, regarding number of instances in the training data.

3.3.2 ECOC

Error correcting output codes (ECOC) are commonly used in information theory for correcting bit reversals caused by noisy communication channels, or in machine learning for converting binary classifiers, such as support vector machines, to multi-class classifiers by decomposing a multi-class problem into several two-class problems (E. Allwein, R.E., 2000). Dietterich and Bakiri introduced ECOC to be used within the ensemble setting. The idea is to use a different class encoding for each member of the ensemble.

3.3.3 Proposed Bagged RBF and SVM Classifiers

Given a set D, of d tuples, bagging (Breiman, L. 1996a) works as follows. For iteration i (i =1, 2,…..k), a training set, D_i, of d tuples is sampled with replacement from the original set of tuples, D. The bootstrap sample, D_i, created by sampling D with replacement, from the given training data set D repeatedly. Each example in the given training set D may appear repeatedly or not at all in any particular replicate training data set D_i. A classifier model, M_i, is learned for each training set, D_i. To classify an unknown tuple, X, each classifier, M_i, returns its class prediction, which counts as one vote. The bagged RBF and SVM, M^*, counts the votes and assigns the class with the most votes to X.

Algorithm: RBF and SVM ensemble classifiers using bagging

Input:

- D, a set of d tuples.
- *k* = 2, the number of models in the ensemble.
- Base Classifiers (Radial Basis Function, Support Vector Machine)

Output: Bagged RBF and SVM, M^*

Method:

(1) for *i* = 1 to *k* do // create k models

(2) Create a bootstrap sample, D_i, by sampling D with replacement, from the given training data set D repeatedly. Each example in the given training set D may appear repeated times or not at all in any particular replicate training data set D_i

(3) Use D_i to derive a model, M_i;

(4) Classify each example d in training data D_i and initialized the weight, W_i for the model, M_i, based on the accuracies of percentage of correctly classified example in training data D_i.

(5) endfor

To use the bagged RBF and SVM models on a tuple, X:

1. if classification then
2. let each of the k models classify X and return the majority vote;
3. if prediction then
4. let each of the k models predict a value for X and return the average predicted value;

3.4 Heterogeneous Ensemble Classifiers

3.4.1 Weighted Majority Algorithm

The weighted majority algorithm corrects the trivial algorithm. It maintains a weighting of the experts. Initially all have equal weight. As time goes on, some experts are seen as making better predictions than others, and the algorithm increases their weight proportionately. The algorithm's prediction of up/down for each day is computed by going with the opinion of the weighted majority of the experts for that day.

Weighted majority algorithm

Initialization: Fix an $\eta \leq 1/2$. For each expert i, associate the weight $w_i^{(1)} := 1$.

For t = 1,2,…,T:

1. Make the prediction that is the weighted majority of the experts' predictions based on the weights $w_1^{(t)}, \ldots, w_n^{(t)}$. That is, predict "up" or "down" depending on which prediction has a higher total weight of experts advising it (breaking ties arbitrarily).

2. For every expert i who predicts wrongly, decrease his weight for the next round by multiplying it by a factor of (1 - η):

$$w_i^{(t+1)} = (1 - \eta) w_i^{(t)} \qquad \text{(update rule).}$$

3.4.2 Stacking

Stacking is the combining process of multiple classifiers generated by different learning algorithms $L_1 \ldots L_n$ on a single dataset. In the first phase a set of base level classifiers $C_1, C_2 \ldots C_n$ is generated. In the second phase a meta level classifier is developed by combining the base level classifier.

3.4.3 Proposed RBF-SVM Hybrid System

Given a set D, of d tuples, arcing (Breiman. L, 1996) works as follows; For iteration i (i =1, 2,…..k), a training set, D_i, of d tuples is sampled with replacement from the original set of tuples, D. some of the examples from the dataset *D* will occur more than once in the training dataset D_i. The examples that did not make it into the training dataset end up forming the test dataset. Then a classifier model, M_i, is learned for each training examples *d* from training dataset D_i. A classifier model, M_i, is learned for each training set, D_i. To classify an unknown tuple, X, each classifier, M_i, returns its class prediction, which counts as one vote. The hybrid classifier (RBF-SVM), M^*, counts the votes and assigns the class with the most votes to X.

Algorithm: Hybrid RBF-SVM using Arcing Classifier

Input:

- D, a set of d tuples.
- *k* = 2, the number of models in the ensemble.
- Base Classifiers (Radial Basis Function, Support Vector Machine)

Output: Hybrid RBF-SVM model, M^*.

Procedure:

1. For i = 1 to k do // Create k models
2. Create a new training dataset, D_i, by sampling D with replacement. Same example from given dataset *D* may occur more than once in the training dataset D_i.
3. Use D_i to derive a model, M_i
4. Classify each example d in training data D_i and initialized the weight, W_i for the model, M_i, based on the accuracies of percentage of correctly classified example in training data D_i.
5. endfor

To use the hybrid model on a tuple, X:

1. if classification then
2. let each of the k models classify X and return the majority vote;
3. if prediction then
4. let each of the k models predict a value for X and return the average predicted value;

The basic idea in Arcing is like bagging, but some of the original tuples of D may not be included in Di, where as others may occur more than once.

4 PERFORMANCE EVALUATION MEASURES

4.1 Cross Validation Technique

Cross-validation (Jiawei Han and Micheline Kamber, 2003) sometimes called rotation estimation, is a technique for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice. 10-fold cross validation is commonly used. In stratified K-fold cross-validation, the folds are selected so that the mean response value is approximately equal in all the folds.

4.2 Criteria for Evaluation

The primary metric for evaluating classifier performance is classification Accuracy: the percentage of test samples that the ability of a given classifier to correctly predict the label of new or previously unseen data (i.e. tuples without class label information). Similarly, the accuracy of a predictor refers to how well a given predictor can guess the value of the predicted attribute for new or previously unseen data.

5. EXPERIMENTAL RESULTS AND DISCUSSION

5.1 U.S Zip Code Dataset Descriptions

The data used in classification is 10 % U.S. Zip code, which consists of selected records of the complete U.S. Zip code database. The database used to train and test the hybrid system consists of 4253 segmented numerals digitized from handwritten zip codes that appeared on U.S. mail passing through the Buffalo, NY post office. The digits were written by many different people, using a great variety of sizes, writing styles, and instruments, with widely varying amounts of care.

5.2 NIST Dataset Description

The dataset used to train and test the systems described in this paper was constructed from NIST's Special Database 3 and Special Database 1 which contain binary images of handwritten digits. NIST originally designated SD-3 as their training set and SD-1 as their test set. However, SD-3 is much cleaner and easier to recognize than SD-1. The reason for this can be found on the fact that SD-3 was collected among Census Bureau employees, while SD-1 was collected among high-school students. Drawing sensible conclusions from learning experiments requires that the result be independent of the choice of training set and test among the complete set of samples. Therefore it was necessary to build a new database by mixing NIST's datasets.

5.3 Experiments and Analysis

In this section, new ensemble classification methods are proposed using classifiers in both homogeneous ensembles using bagging and heterogeneous ensembles using arcing classifier and their performances are analyzed in terms of accuracy. The performance of the proposed homogeneous and heterogeneous ensemble classifiers are compared to the performance of other standard homogeneous and heterogeneous ensemble methods.

5.3.1 Homogeneous Ensemble Classifiers

The U.S Zip Code and NIST datasets are taken to evaluate the base and homogeneous ensemble classifiers.

Table 1: The Performance of base classifiers and Homogeneous Ensemble Classifiers for U.S Zip Code Dataset

Dataset	Classifiers	Classification Accuracy
U.S Zip Code	RBF	86.46 %
	Proposed Bagged RBF	97.74 %
	ECOC RBF	95.48 %
	Dagged RBF	90.97 %
	SVM	93.98 %
	Proposed Bagged SVM	95.45 %
	ECOC SVM	94.20 %
	Dagged SVM	87.21 %

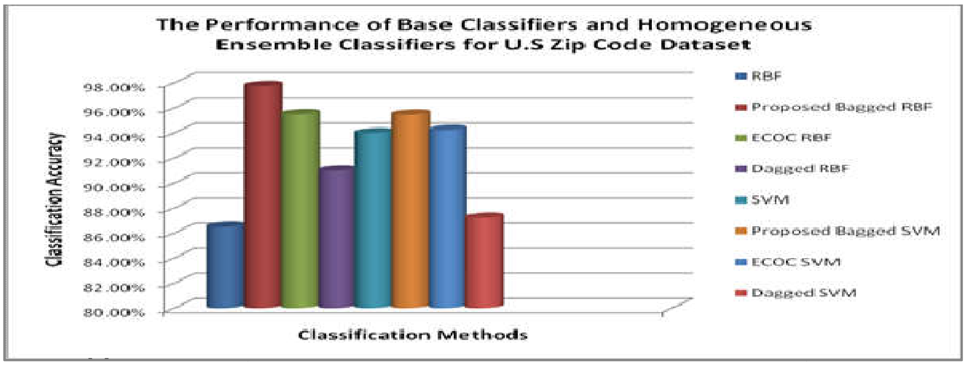

Fig.1: Accuracy for Homogeneous Ensemble Classifiers in U.S Zip Code dataset

Table 2: The Performance of base classifiers and Homogeneous Ensemble Classifiers for NIST Dataset

Dataset	Classifiers	Classification Accuracy
NIST	RBF	76.50 %
	Proposed Bagged RBF	91.80 %
	ECOC RBF	69.90 %
	Dagged RBF	79.10 %
	SVM	89.20 %
	Proposed Bagged SVM	98.00 %
	ECOC SVM	92.40 %
	Dagged SVM	86.00 %

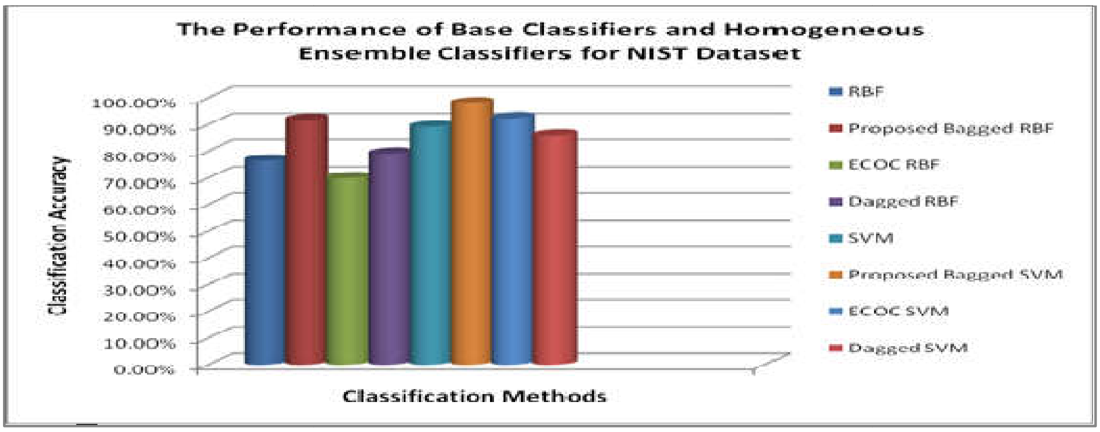

Fig.2: Accuracy for Homogeneous Ensemble Classifiers in NIST dataset

5.3.2 Heterogeneous Ensemble Classifiers

The U.S Zip Code and NIST datasets are taken to evaluate the base and heterogeneous ensemble classifiers.

Table 3: The Performance of Base and Heterogeneous Ensemble Classifiers for U.S Zip Code dataset

Dataset	Classifiers	Classification Accuracy
U.S Zip Code	RBF	86.46 %
	SVM	93.98 %
	Proposed Hybrid RBF-SVM	99.13 %
	Voted RBF-SVM	96.24 %
	Stacked RBF-SVM	93.23 %

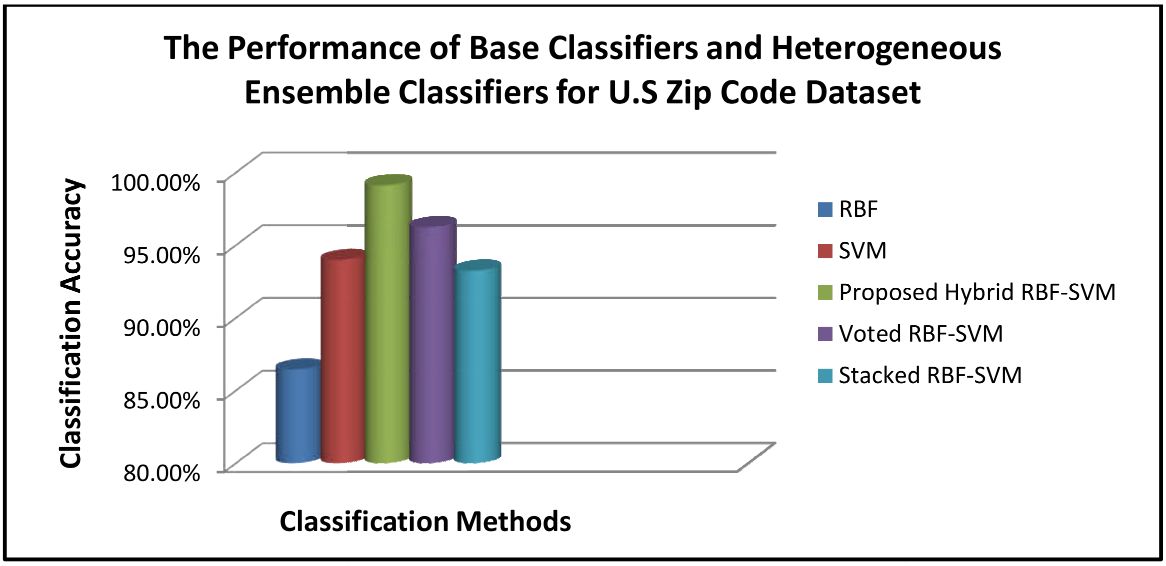

Figure 3: Accuracy for Heterogeneous Ensemble Classifiers in U.S Zip Code dataset

Table 4: The Performance of Base and Heterogeneous Ensemble Classifiers for NIST dataset

Dataset	Classifiers	Classification Accuracy
NIST	RBF	76.50 %
	SVM	91.80 %
	Proposed Hybrid RBF-SVM	99.30 %
	Voted RBF-SVM	90.00 %
	Stacked RBF-SVM	90.20 %

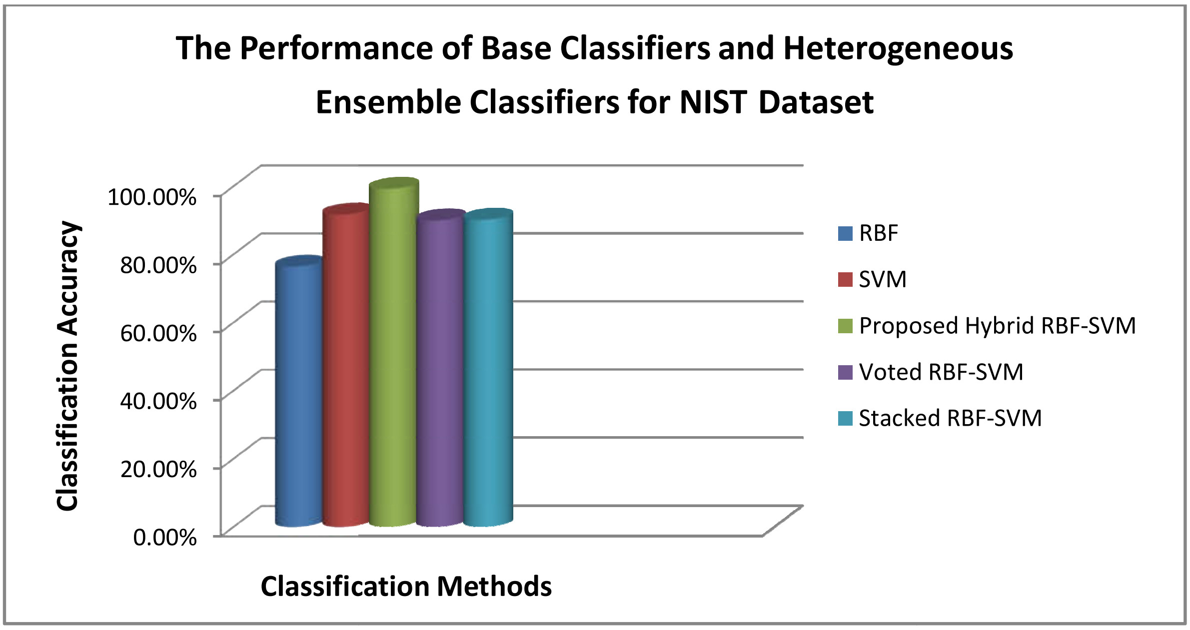

Figure 4: Accuracy for Heterogeneous Ensemble Classifiers in NIST dataset

5.5 Experimental Comparison

5.5.1 Homogeneous Ensemble Classifiers

In this research work, new ensemble classification methods are proposed with homogeneous ensembles using bagging and their performances are analyzed in terms of accuracy. Here, the base classifiers are constructed using radial basis function and Support Vector Machine. Bagging is performed with radial basis function classifier and support vector machine to obtain a very good classification performance. Table 1 and 2 show classification performance for standard datasets of recognizing totally unconstrained handwritten numerals using existing and proposed bagged radial basis function neural network and support vector machine.

The analysis of results shows that the proposed bagged radial basis function and bagged support vector machine classifies are shown to be superior to individual approaches for standard datasets of recognizing totally unconstrained handwritten numerals in terms of classification accuracy. According to figure 1 and 2 proposed combined models show significantly larger improvement of classification accuracy than the base classifiers and the results are found to be statistically significant. This means that the combined methods are more accurate than the individual methods in the field of handwritten recognition.

Tables 1 and 2 compare the performance of proposed bagged RBF and SVM to the performance of ECOC and Dagging with RBF and SVM. The proposed bagged RBF and SVM performs significantly better than ECOC and Dagging on standard datasets of recognizing totally unconstrained handwritten numerals.

5.5.2 Heterogeneous Ensemble Classifiers

In this research work, new hybrid classification method is proposed with heterogeneous ensembles using arcing classifier and their performances are analyzed in terms of accuracy. The data set described in section 5 is being used to test the performance of base classifiers and hybrid classifier. In the proposed approach, first the base classifiers RBF and SVM are constructed individually to obtain a very good generalization performance.

Secondly, the ensemble of RBF and SVM is designed. In the ensemble approach, the final output is decided as follows: base classifier's output is given a weight (0–1 scale) depending on the generalization performance as given in Tables 3 and 4. According to figure 3 and 4, the proposed hybrid models show significantly larger improvement of classification accuracy than the base classifiers and the results are found to be statistically significant. The experimental results show that proposed hybrid RBF-SVM is superior to individual approaches for handwriting recognition in terms of classification accuracy.

The performance comparison between proposed hybrid RBF-SVM and voting, stacking with RBF and SVM can be found in Tables 3 and 4. Both methods use the same base classifiers. The proposed hybrid RBF-SVM performs significantly better on standard datasets of handwriting recognition. The overall relative improvement of accuracy is high.

6. CONCLUSION

In this research work, new combined classification methods are proposed using classifiers in homogeneous ensembles using bagging and the performance comparisons have been demonstrated using standard datasets of handwritten recognition in terms of accuracy. Here, the proposed bagged radial basis function and bagged support vector machine combines the complementary features of the base classifiers. Similarly, new hybrid RBF-SVM models are designed in heterogeneous ensembles involving RBF and SVM models as base classifiers and their performances are analyzed in terms of accuracy. The performance of the proposed homogeneous and heterogeneous ensemble classifiers are compared to the performance of other standard homogeneous and heterogeneous ensemble methods. The standard homogeneous ensemble methods include Error correcting output codes, dagging and heterogeneous ensemble methods include majority voting, stacking.

The experiment results lead to the following observations.

- SVM exhibits better performance than RBF in the important respects of accuracy.
- The proposed bagged methods are shown to be significantly higher improvement of classification accuracy than the base classifiers.
- The hybrid RBF-SVM shows higher percentage of classification accuracy than the base classifiers.
- The proposed ensemble methods provide significant improvement of accuracy compared to individual classifiers and the proposed bagged RBF and SVM performs significantly better than ECOC and Dagging and the proposed hybrid RBF-SVM performs significantly better than voting and stacking.
- The heterogeneous models exhibit better results than homogeneous models for standard datasets of handwriting recognition problem.
- Assessment of performance is based on the calculation of the χ^2 statistic for all the approaches and their critical values are found to be less than 0.455. Hence their corresponding probability is $p < 0.5$. This is smaller than the conventionally accepted significance level of 0.05 or 5%. Thus examining a χ^2 significance table, it is found that this value is significant with a degree of freedom of 1. In general, the result of χ^2 statistic analysis shows that the proposed classifiers are significant at $p < 0.05$ than the existing classifiers.
- The future research will be directed towards developing more accurate base classifiers particularly for the handwriting recognition problem.

ACKNOWLEDGEMENT

Author gratefully acknowledges the authorities of Annamalai University for the facilities offered and encouragement to carry out this work.

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