



# **PERFORMANCE ANALYSIS OF SUPPORT VECTOR MACHINE FOR PREDICT RAINFALL AND HEART DISEASES**

Kolluru Venkata Nagendra<sup>1</sup>, Dr.M.Ussneiah<sup>2</sup>

**Abstract-** The goal of this paper is to find the challenging pattern of Rain Fall Forecasting and Heart Diseases. The study dealt with two applications one is rainfall forecasting and another one is heart diseases prediction. SVM is good for predicting the Rain Fall Forecasting. Support vector machine (SVM) was applied for Rain Fall forecasting data using Linear kernel model. In this research by using SVM classification method to classify the rainfall datasets and shall be comparing its performance with Multi Layer Perceptron, Naïve Bayes, and Decision Tree classification methods.

In this research SVM classification method is also used to build a classification model for a TIFF dataset. The dataset used herein is of Andhra Pradesh rainfall map. The map comprises of Rain fall coverage for various districts. The methodology used classifies the map based on Rain fall coverage. The performance of SVM is calculated using kappa statistics and accuracy parameters and it is established that for the given data set SVM classifies the raster image dataset with great accuracy.

Finally, A hybrid classification method encompasses the advantages of the individual classification approaches that it is built upon. In this research we will be examining few popular algorithms used for classifying medical diagnosis data with a hybrid of support vector machines and neural networks. After that we will discuss the performance of these algorithms depending on different parameters and comparing their correct rate in different categories.

**Keywords –** Classification, Data Mining, Support Vector Machine, classifier, Neural Networks, Bagging

## **1. INTRODUCTION**

Data mining (DM) is a process of nontrivial extraction of implicit, previously unknown and potentially useful knowledge from a large amount of incomplete, noisy, fuzzy and random data. Data Mining is away to discover unknown knowledge and summarize data in a new way that was previously unseen.

Classification is one of main tasks of data mining. Classification means to analyze the pattern of data in a training set to find out an accurate description model of each category and generalize a known structure to apply it to new data. Classification procedure includes data acquisition, feature selection, model selection, training and evaluation. The data that is to be used for training and testing should be collected in advance. The feature selection is affected by previous feature description of data sets. The classifier should be trained to determine system parameters. Usually there will be some repetitions of former procedures based on previous evaluation results to create a better result [1].

In this paper we shall be investigating various classification methods. The remote sensed data that we shall be using in this paper is the Andhra Pradesh rainfall data set collected from the Indian Institute of Tropical Metrology portal. Over the last decade, advances in species predictive distribution modeling, have been paralleled by the evolution and the development of geographical information systems (GIS), remote sensing, statistical modeling and database management [2]. Statistical models to predict the occurrence or the distribution of species are becoming increasingly important tools in conservation planning and wildlife management[3].Marine species classification like the rainfall dataset classification we shall discuss in this paper is of interest to many disciplines, including physical, biological, and fisheries oceanography, marine geology, and coastal ecology, leading to a plethora of approaches[4][5].

## **2. PROPOSED ALGORITHM**

Study pertaining to classification and prediction of rainfall has gained a lot of significance due to frequent recurrence of hurricanes and floods in the recent past. There is a large amount of data that has been accumulated pertaining to rainfall over a period of time. This huge voluminous data is tossing challenges to the research community in terms of processing and active analysis. Current methods and algorithms are insufficient to do effective analysis. Hence advanced data mining techniques like machine learning algorithms and their hybridization techniques are suitable for processing and effective analysis.

Classification is a data mining technique that is used to construct a model and allocate class labels to data instances. It is also used to predict class labels for unlabelled data. In this research work different classification techniques like Naive Baye's, Decision Tree, KNearest Neighbor and Linear Kernel based Support Vector Machines are used for classifying spatial data.

<sup>1</sup> Research Scholar, Department of ComputerScience, VS University,SPSRNellore,AP,INDIA.

<sup>2</sup> Assistant Professor, Department of ComputerScience, VS University,SPSRNellore,AP,INDIA.

Performance Analysis of these algorithms based on various parameters is carried out and it is found that performance of SVM based classification is very good for the variety of datasets used.

A novel approach to classify remote sensed data using a Hybrid SVM classifier is proposed. Support Vector machines and bagging methodologies are used to construct the hybrid classifier for effective spatial data analysis. This method is evaluated and the results compared with that of Support Vector machine classifiers and neural network classification methods. The proposed hybrid method when applied to classify the rainfall data in a region in India and it is found that it gives better results when compared to traditional neural network and support vector machine classification methods used individually without any compromise in classification accuracy.

### 3. BACKGROUND KNOWLEDGE

#### 3.1 Overview of SVM Classifier

Support vector machine (SVM) is a promising methodology which is used in various applications. They have a strong mathematical foundation. They are used to solve both two class and multi class classification problem [6] [7]. In a two class problem the input data has to be categorized as two diverse categories wherein each category is assigned a unique class label [8]. A multi class classification problem can be divided it into multiple two class classification problems and solved by aggregating the individual results to get the final result of the multi class problem.

Success of SVM depends on their strong mathematical foundation that conveys several significant properties:

Margin maximization: The classification boundary functions of SVMs maximize the margins, which leads to maximizing generalization performance.

Systematic nonlinear classification via kernel tricks: SVMs effectively handle non-linear classifications using kernel tricks.

One of the major advantages of SVM is that feature selection is automatically taken care by it and one need not separately derive features.

#### 3.2 Overview of Naive Bayes:

The Naïve Bayes method of classifying data is based on Bayes rule with an assumption that the attributes viz.  $X_1, X_2 \dots, X_n$ , given an attribute  $Y$  are all conditionally independent of the other. This notion shortens the depiction of  $P(X/Y)$  and the problem of appraising it from the training data set [9][10].

Given a data item  $X$ , the naïve bayes classifier predicts that data item  $X$  belongs to the class having utmost posterior probability conditioned on  $X$ . It predicts that tuple  $X$  belongs to class  $C_i$  only if Equation (7) mentioned below is satisfied.

$$P(C_i/X) > P(C_j/X) \text{ for } 1 \leq j \leq m, j \neq i \quad (1)$$

Maximize  $P(C_i|X)$ : find the maximum posteriori hypothesis using equation (2).

$$P(C_i/X) = \frac{P(X/C_i)P(C_i)}{P(X)} \quad (2)$$

$P(X)$  remains constant for all classes, thus, maximize  $P(X|C_i)P(C_i)$

To maximize  $P(X|C_i)P(C_i)$ , we need to know class prior probabilities. If the probabilities mentioned herein are not known, assume that

$$P(C_1) = P(C_2) = \dots = P(C_n) \Rightarrow \text{maximize } P(X|C_i) \quad (3)$$

Class prior probabilities can be estimated by  $P(C_i) = |C_i, D| / |D|$

Assume that there is Class Conditional Independence to reduce computational cost of  $P(X|C_i)$  given  $X(x_1, \dots, x_n)$ ,  $P(X|C_i)$  is:

$$P(X/C_i) = \prod_{k=1}^n P(x_k/C_i) = P(x_1/C_i) \times P(x_2/C_i) \dots \times P(x_n/C_i) \quad (4)$$

The probabilities  $P(x_1|C_i), \dots, P(x_n|C_i)$  can be estimated from the training tuples [11][12].

#### 3.3 Overview of MLP Classifier

In this work we used Multi-Layer Perceptron (MLP) neural networks. The architecture for the said MLP neural networks is composed of a layered architecture of neurons, such that output from one layer feeds as an input to the subsequent neurons layer. This neural network assigns a pattern vector  $x$  to a class  $\omega_m$  if the  $m$ th output neuron achieves the highest value .

The learning algorithm of MLP classifier uses the Euclidean norm in order to lessen the said error function defined on the learning set  $(x_i, d_i)$  for  $i = 1, 2, \dots, N$ , Nasin Equation(5)

$$E(w) = \frac{1}{2} \sum_{i=1}^N \|y(x_i, w) - d_i\|^2 \quad (5)$$

where  $x_i$  is an input vector with  $N$  dimensions for  $i=1, 2, \dots, N$ ,  $y$  is  $M$ -dimensional output signal vector,  $w$  is the vector with adapted weights,  $d$  is the desired  $M$ - dimensional desired output vector [13].

The network builds its predictive model using a set of data samples. The MLP network discussed herein is built with 3 categories of layers viz. one input layer, hidden layers embedded in between and one output layer as shown in Fig. 1. Each and every layer contains neurons which through the weight and bias values are associated with neurons in other layers. The network learns the relationship a mid pairs of inputs (factors) and output (responses) vectors by varying the weight and bias values.

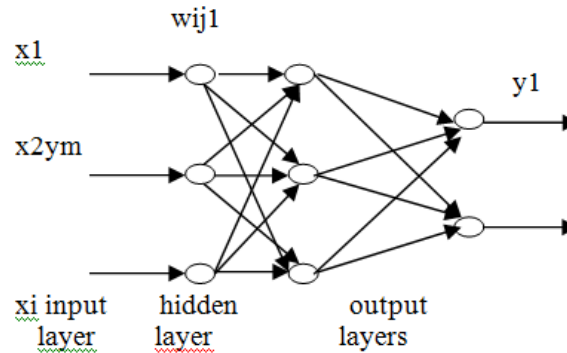


Fig 1: MLP network with one hidden layer.

Each input layer is calculated from the weighted sum of the previous layer. Let  $J-1$  be the previous layer of  $J$ , such that each input  $I_j$  in  $J$  is given by

$$I_j = \sum_{k=1}^{N_k} W_{jk} O_{k-1} \quad (6)$$

and

$$O_{k-1} = \phi(I_{k-1}) \quad (7)$$

where  $j = 1, 2, \dots, N_j$ , being  $N_j$  and  $N_k$  the amount of neurons at the layer  $J$  and  $J-1$ , respectively, and  $w_{jk}$  stands for the weights that modify the  $k$ th output of layer  $J-1$ , i.e.,  $O_{J-1k}$  [6].

In this paper we have used a 5-5-1 neural network with 36 weights.

c). Overview of Bagging: This technique processes samples in parallel is called bagging also known as bootstrap aggregating. It plans to advance the accuracy by constructing enhanced fused classifier, by aggregating the variety of learned classifier outputs into a solitary prediction. The pseudo-code is mentioned below [14-16].

Algorithm Bagging [14]

I:- an inducer

N:-the number of iterations

S:-the training set

Output:  $C_i$ ;  $i = 1, \dots, N$

Step 1:  $i \leftarrow 1$

Step 2: repeat

Step 3:  $S_i \leftarrow$  Sample  $N$  instances from  $S$  with replacement.

Step 4: Construct classifier  $C_i$  using  $I$  on  $S_i$

Step 5:  $i++$

Step 6: until  $i > N$

As sampling with replacement is used, a few original instances of  $S$  might come into view frequently in  $S_i$  and few might not be incorporated at all. So  $S_i$  are dissimilar from each other, however are surely not autonomous. To classify a novel instance, every classifier returns the class forecast for the unidentified instance. The compound bagged classifier,  $I$ , returns the class which was forecasted frequently. The consequence is that this method generates a joint model which often fares superior to the solitary model constructed from the original data. It is true particularly for unsteady inducers as bagging can get rid of their unsteadiness.

In this research we shall be using hybrid model comprising SVM and neural network classification method supplemented by bagging to classify the Framingham datasets and shall be comparing its performance with individual SVM and neural network classification methods. The algorithm for the same is mentioned below:

Algorithm Hybrid SVM

Step 1: Train the SVM classifier for the data set under consideration

Step 2: Construct a new data set with the decision function of the SVM classification approach.

Step 3: Train the ANN with the new data set and validate the same using the test set

Step 4: Repeat the above steps with different samples with replacement approach.

## 4. RESULTS PERFORMANCE ANALYSIS

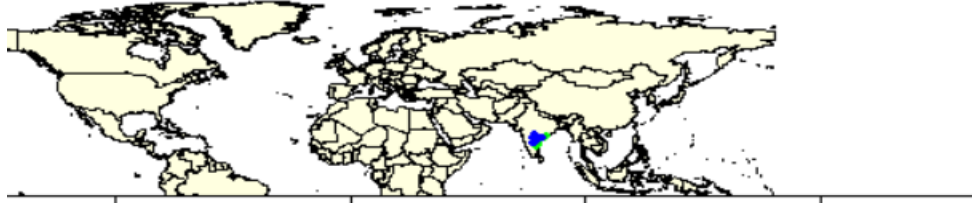
### 4.1 Approach-1 [Rain Fall forecasting- Text data set]

The proposed model is applied in three steps which include image data acquisition, feature extraction and application of classifiers for classifying the rainfall datasets into two groups that is districts with more rainfall and districts with less rainfall while in the end performance of classification is measured using different metrics. However, R software is used to perform the mentioned operations [17].

Classification of the images can lead to four types of results including True positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) where the outcomes of classification are demonstrated in Table-1. And the classified Rain Fall data into two different sets is demonstrated in Figure 2.

Table 1. Possible classification outcomes

Real group	Classification result	
	More	Less
More	TN	FP
Less	FN	TP



Figure(2): Plot of Rainfall data with districts with more rainfall plotted with green and less with blue  
Evaluation metrics

It is observed that the most conventionally utilized evaluation metrics in classification are sensitivity, specificity, prevalence, detection rate and detection prevalence[8][9].The formulae for sensitivity, specificity, prevalence, detection rate and detection prevalence are provided by equations (8), (9), (10), (11) and (12)

$$\text{Sensitivity} = \frac{TN}{(TN+FN)} \times 100 \quad (8)$$

$$\text{Specificity} = \frac{TP}{(TP+FP)} \times 100 \quad (9)$$

$$\text{Prevalence} = \frac{TN+FN}{(TP+FN+FP+TN)} \times 100 \quad (10)$$

$$\text{Detection rate} = \frac{TN}{(TP+FN+FP+TN)} \times 100 \quad (11)$$

$$\text{Detection Prevalence} = \frac{TN+FP}{(TP+FN+FP+TN)} \times 100 \quad (12)$$

Result Analysis: The performance of the proposed classifier SVM with linear kernel is analyzed and compared with Decision tree, MLP, Naïve bayes classifiers. Performance Measures using evaluation metrics are given in Table 2.

Table 2. Performance Measures

Classifier	Sensitivity	Specificity	Prevalence	Detection Rate	Detection Prevalence
SVM	100	100	18.75	12.5	12.5
Decision tree classifier	100	100	18.75	18.75	18.75
MLP Classifier	0	100	18.75	0	0
Naïve bayes classifier	83.3	84.62	18.75	15.62	28.12

Hence, it is identified from the results and findings with the comparative evaluations that SVM approach is better than other classifiers.

#### 4.2 Approach-II [Rain Fall forecasting- TIFF dataset]

Rain fall map of Andhra Pradesh was used as a dataset to perform the said classification. A region of interest (ROI) was extracted from the map that acted as a training data and it was validated against the complete data segment pertaining to a particular Rain fall in the map. The proposed method has been implemented under the environment setting as shown in Table 3 [18][19].

Table.3. Environment Setting

Item	Capacity
CPU	Intel CPU @2 GHz processor
Memory	4GB RAM
OS	Windows 7 32-bit
Tools	Monteverdi tool

Performance of a Classification method can be measured using parameters of a confusion or error matrix view depending on whether the event is correctly classified or no event is correctly classified as shown in Table 4.

Table.4.Confusion / Error Matrix View

Real group	Classification result	
	No Event	Event
No Event	True Negative(TN)	False Positive(FP)
Event	False Negative(FN)	True Positive(TP)

In this paper the parameters used to evaluate the classification is Accuracy and kappa statistics. The formulae for accuracy, specificity, sensitivity and kappa statistics are provided by equations (13), (14), (15) and (16) [20] [21] [22]:

$$\text{Accuracy} = \frac{TP+TN}{(TP+FN+FP+TN)} \times 1 \quad (13)$$

$$\text{Specificity} = \frac{TN}{(TN+FP)} \times 1 \quad (14)$$

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \times 100 \quad (15)$$

$$\text{Kappa statistics} = \text{Sensitivity} + \text{Specificity} - 1 \quad (16)$$

The confusion matrix or error matrix view for SVM Classifier while classifying raster TIFF data set is given in Table 5.

Table.5 Confusion Matrix for raster datasets

Prediction	Reference		
	Excess	Normal	Deficient
Excess	14	0	0
Normal	0	16	0
Deficient	0	0	11

Performance Measures using evaluation metrics are specified in Table 6 which are calculated using equations (13), (14), (15) and (16).

Table.6 Performance measures for CSV and raster datasets

Data set type	Accuracy	Kappa Statistics
Raster TIFF data sets	100	100

#### 4.3 Approach-III [Heart Diseases Data Set – Huge Volume data]

The first obvious step in any data mining procedure is data selection. The data being used in this paper is from Framingham heart study. This study began in Framingham with 5209 subjects. Much of the now commonly known heart attack symptoms have come from this study [23]. It consists Gender, age, education, smoker or not, BP status, Whether a person already suffered a heart stroke, Whether a person was diabetic or not, Cholesterol levels of a person, Body Mass index of a person, Heart beat rate of a person and Glucose levels of a person are the attributes. The model tries to predict based on the above mentioned attributes whether a person is prone to suffer a heart attack or not. The performance of the proposed classifier hybrid SVM with neural networks is examined and likened with SVM and neural network and the results are mentioned below.

Table. 7. Performance Measures

Classifier	Accuracy	Specificity	Prevalence	Detection Rate	Detection Prevalence
SVM	86.03	100	98.7	84.7	84.7
Neural Networks	84.7	NA	100	84.7	84.7
Hybrid SVM	94	100	98.9	90.2	90.2

Hence, it is identified from the results and findings with the comparative evaluations that hybrid SVM approach is better than other classifiers.

## 5. CONCLUSION

The research is related to the classification of rainfall data as belonging to various districts of Andhra Pradesh using SVM. Initially, to conduct the research, a methodology has been proposed consisting of several steps along with classification algorithms like SVM, decision tree, MLP and Naïve bayes methods. The research has concluded that the SVM approach of classification is more effective and efficient as compared to other methods because SVM provided higher values for sensitivity, specificity, prevalence, detection rate and detection prevalence. Thus, it can be said that the SVM technique is promising and reliable method of classification. SVM classification method is used to for a TIFF dataset. The dataset used herein is of Andhra Pradesh rainfall map. The methodology used classifies the map based on Rain fall coverage. The performance of SVM is calculated using kappa statistics and accuracy parameters and it is established that for the given data set SVM classifies the raster image dataset with great accuracy. The research is related to the classification of heart patient data from Framingham using hybrid SVM and neural networks. The same is compared with SVM and neural network methods.

Finally we conclude that the SVM is good for Rain fall forecasting, which is a very low volume of data. SVM is also good for predicting less volume of text data and image like TIFF dataset. The volume of dataset is increased the SVM single is not give the good results. So we applied here Hybrid algorithm for huge volume of Framingham heart data. The research has concluded that the hybrid SVM approach of classification is more effective and efficient.

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## BIOGRAPHIES



K.Venkata Nagendra, working as Assistant Professor in the Department of Computer Science Engineering at Geetanjali Institute of Science and Technology, Nellore, Andhra Pradesh, India. He has 6 years of experience in the field of teaching. He is a research scholar in Vikrama Simhapuri University. He did his M.Tech in ANU, Guntur. His areas of interests are Data warehousing and Data Mining and Cloud Computing.



Dr.Maligela Ussneiah, working as Assistant Professor in the Department of Computer Science in Vikrama Simhapuri University, Nellore, Andhra Pradesh, India. He is having 8 years of teaching experience. He did his PhD in computer science from SriKrishna Devaraya Univeristy, Ananthapur, Andhra Pradesh. His areas of interests are Networks, Mobile Wireless Networks, Data warehousing and Data Mining and Image processing.