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Classification of Rainfall Data Using Linear Kernel Based Support Vector Machines

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Abstract

Classification is a data mining technique used to predict group membership for data instances.Exploration of satellite imagery has become increasingly important in several application domains such as change detections, fire risk mapping etc... There are many algorithms used for image classification these days. In this paper we will be examiningfew popular algorithms used for classifying remote sensed data like decision tree classifier, Multi-layer perceptron classifier, Support Vector machines and Naïve Bayes classifier. To optimize the classification accuracy of support vector machines an algorithm will be proposed. 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, classifier, Support Vector Machines, SVM.

INTRODUCTION

Eliciting vital information from huge amounts of repositories of data in any organization is a very important component of building organization strategy. The process of accomplishing the same is known as data mining. It encapsulates the process of amalgamating variety of data from diverse sources and eliciting information from the same [1].

Information can be elicited from data in two main ways. The first one is called supervised learning. This approach is used when data can be categorized into two or more categories. Data is first separated into training and test sets. Using training set the model is trained and the same is validated against the test set. Once the model is thus built the same can be used to predict the category of any new data set. Another approach is used when the data cannot be categorized into two or more categories. It is called unsupervised learning. In this paper the approach is restricted to discussing supervised learning [2].

In this paper we shall be investigating Naïve bayes, decision tree, MLP and SVM algorithms. The remote sensed data that we shall be using in this collected from the IMD portal. The rainfall dataset classification we shall discuss in this paper is useful in fisheries oceanography, biological, physical, marine geology and coastal ecology.[3-4].

In this research paper the classification of rainfall data is done using SVM for which diverse characteristics are exploited to portray the evidence level confined in the data set. The suggested technique is then matched with Naïve bayes, decision tree, multi-layer perceptron classifiers. Various statistical parameters are used to compare these methods. The result of comparing these methods is that we lead to the conclusion that the SVM method is the best compared to the other used methods on the said data set[5].

Our next section presents the proposed methodology. Section III describes Background Knowledge about various classifiers discussed and in section IV discussion of results is carried out. Section V summarizes the work and in section VI data source is acknowledged and in the final section references are given.

PROPOSED METHODOLOGY

The approach used in this paper has many steps as illustrated in the below mentioned diagram:

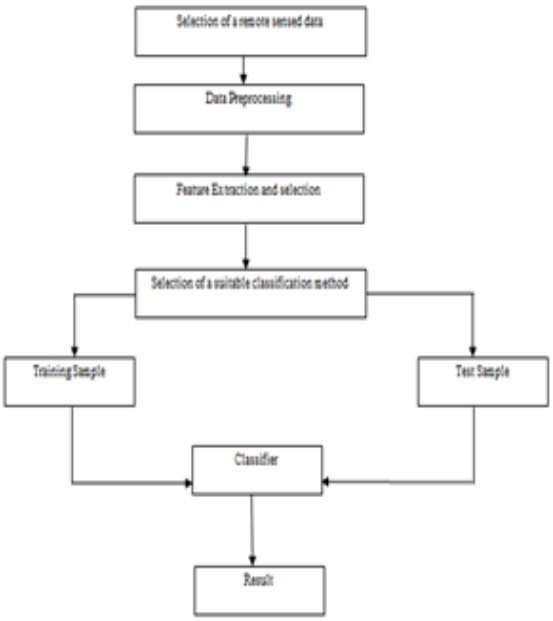


FIGURE 1: PROPOSED MODEL

Data Selection

The first obvious step in any data mining procedure is data selection. Hence in this paper data is selected from the IMD portal.

Processing of data

The data thus collected shall have many erroneous entries like missing values, duplicate values etc. The same is first cleaned for removing data anomalies.

Feature Extraction and Selection

Feature selection happens to be an important step in a supervised learning process that shall be used in this paper.

Supervised classification approach selection

Different supervised classification approaches have diverse merits and demerits[8]. The selection of an appropriate classification approach is an art rather than a science[17-18].

In this paper we shall be 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.

Background Knowledge the mentioned classification methods are given in Section III.

Training and Testing

The obtained model from the previous method is validated against the test set[19].

BACKGROUND KNOWLEDGE

Naive Bayes

This classification method is grounded on the famous concept called Bayes rule. It has an underlying assumption that attributes x and y are conditionally independent. [6-7].

In this approach a data item x is classified into a class with maximum posterior probability and also if it satisfies the below equations[8].

$$P(P_i/Q)>P(P_j/Q) \text{ for } 1<=j<=m, j\neq i \quad (7)$$

$$P(P_i/Q) = \frac{P(Q/Pi)P(Pi)}{P(Q)} \quad (8)$$

If the probabilities cited herein are unknown, then,

$$P(P_1)=P(P_2)=\ldots=P(P_n) \Rightarrow \text{maximize } P(Q|P_i) \quad (9)$$

Class prior likelihoods can be assessed by $P(P_i)=|P_i,M|/|M|$

Given $Q(q_1,\ldots,q_n)$, $P(Q|P_i)$ is:

$$P(Q/P_i) = \prod_{k=1}^{n} P(\frac{qk}{Pi})$$

$$= P(q1/P_i)qP(q_2/P_i).....xP(q_n/P_i) \quad (10)$$

The probabilities $P(q_1|P_i)$, $\ldots P(q_n|P_i)$ can be estimated from the training tuples[9-11].

MLP Classifier Over View

This approach makes use of a layer of neurons wherein output from one layer is supplied as input to another layer of neurons and Euclidean distance is used to minimize the cost as in Equation(11)

$$E(w) = \frac{1}{2}\sum_{i=1}^{N} ||y(ai,b) - di||^2 \quad (11)$$

Where a is input and b is output vector [7].

As shown in Fig. 1. The MLP layer mentioned here is built with 3 layers wherein every neuron has its own weight and bias[9].

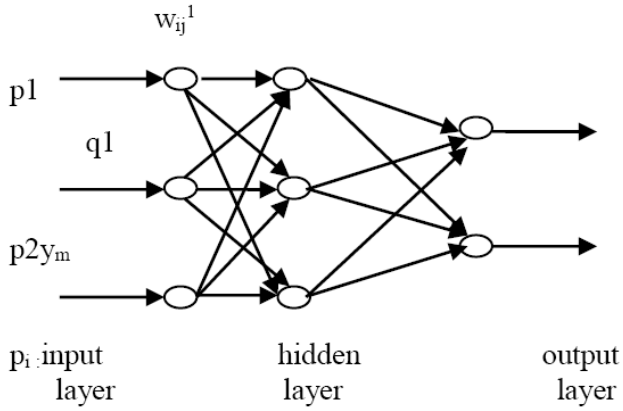


Figure 1: Simple Neural Network.

Any layers input is attained from weighted entirety of preceding layer

$I^J_j=\sum_{k=1}^{Nk} \quad WjkO_k^{J-1}$ (12)

and

$p_k^{J-1}=\phi(Q_k^{J-1})$ (13)

where O is output and P is input and j and k are layer numbers[15-17].

Overview of Decision tree Classifier

Decision trees are classically built recursively, following a top-down approach. The facts attained in the learning process is symbolized as a tree wherein each internal node comprises a query with respect to one precise attribute (with one offspring per potential answer) and each and every leaf is labeled with one of the probable classes. While examining decision tree one initiates at the root node and then follows the replies to the various possible questions in the internal nodes until and unless a leaf node is reached[18]. Classification tree is built in consensus with splitting rule that undertakes the splitting of learning sample into minor parts. A measure for tree splitting t is grounded on a node impurity function I(t)[20-22].In this paper Conditional Inference trees were used to classify the said datasets.

Overview of the SVM

SVM is a supervised technique wherein data is mapped onto a higher order space using a kernel function: $K(x,xj)=\langle\phi(x),\phi(xj)\rangle$. Decision function can be statedas[23-24] (1):

$$f(x) = \sum_{j=1}^{Sv} \alpha jyjK(x, xj) + b \qquad (1)$$

αjisLagrange multipliers, K is kernel function and b is the bias which is calculated using a support vector[25]. Then, the optimum hyper-plane relates to f (x)=0. Henceforth, test data can be dented as (2):

$$x\epsilon\begin{cases} positivecategoryiff(x) > 0 \\ negativecategoryiff(x) < 0 \end{cases} \qquad (2)$$

The specified training set of case label pairs as delivered by equation[26] (3).

$$(x, y) = \{ (x_1,y_1), (x_2,y_2), \ldots\ldots (x_n,y_n)\} \qquad (3)$$

Where $x_n\epsilon R^y$ and $y_n\epsilon$ {-1, +1} and SVM desiresresolution of the optimization problem$\frac{1}{2}W^TW + \sum_{i=1}^{l}\xi_i$C

Subject to as given in equation (4)

$$y_i\ (w^T\Phi(x_i) + b) \geq 1\text{-}\xi_i\xi_i \geq 0 \qquad (4)$$

In this paper 740 support vectors classify rainfall data into two sets. The training error in the said classification process was 0.123109.

RESULTS AND DISCUSSIONS

The algorithms thus discussed is applied 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 by means of diverse metrics. R software is used to perform the mentioned operations [27].

Data Acquisition

Around154 records of rainfall data from various districts from various districts of Andhra Pradesh are obtained.

Features Extraction

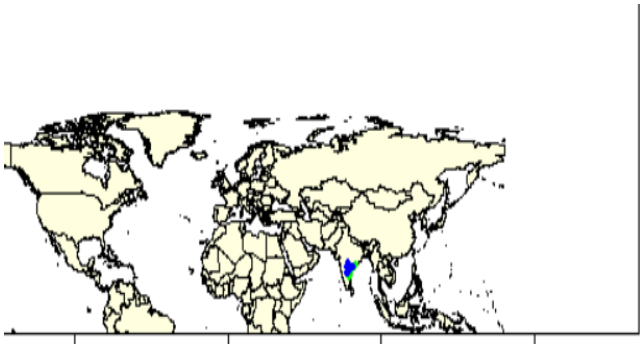
Sixteen features extracted from the data set are fed to the SVM and these are compared with other classifiers.

Image Grouping

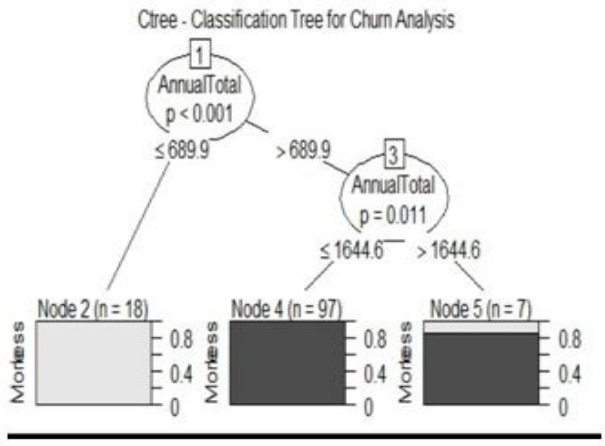
Classification output can be characterized by categorizing the same with a confusion matrix as demonstrated in Table-II.

Table II

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



(a)



(b)

Figure 1a):Plot of Rainfall data with districts with more rainfall plotted with green and less with blue.

b) Decision Tree for Rainfall Data Classification.

Evaluation metrics

Evaluation of the classification models can be carried out using the metrics defined below[25-26]. The formulae for sensitivity, specificity, prevalence, and detection rate and detection prevalence are given in (10), (11), (11), (13) and (14)

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

$$\text{Specificity} = \frac{\text{TP}}{(\text{TP+FP})} \times 100 \quad (11)$$

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

$$\text{Detection rate} = \frac{\text{TN}}{(\text{TP+FN+FP+TN})} \text{x}100 \quad (13)$$

$$\text{Detection Prevalence} = \frac{\text{TN+FP}}{(\text{TP+FN+FP+TN})} \text{ X } 100 \quad (14)$$

Result Scrutiny

The performance of the proposed classifier SVM with linear kernel is examined and likened with SVM, Decision Tree, MLP and Naïve Bayes and the results are mentioned below.

Table III: 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.

CONCLUSION

The research is related to the classification of rainfall data as belonging to various districts of Andhra Pradesh using SVM. The same is compared withdecision tree, MLP and Naïve Bayesmethods. The research has concluded that the SVM approach of classification is more effective and efficient.

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