A CASE STUDY ON SVM INSPIRED HYBRID CLASSIFIER DESIGN FOR REMOTE SENSED IMAGES

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Abstract: In classification of land use/land cover support vector machines play an important role compared to other pattern recognition algorithms. There is a lot of uncertainty and irregularity in classification of Land use/ Land cover mapping. Many classification techniques like maximum likelihood algorithm fails to give good classification results for land use/ land cover for remotely sensed images. In the proposed paper, many optimization related techniques on the basis of support vector machines like Supervised Support Vector Machines (SSVM) and Unsupervised Support Vector Machines (USVM) and have been discussed. A case study is taken for LIS-III images is taken which suffers from the problem of low resolution images and a hybrid classification algorithm is tested which not only gives good classification results compared to all the other algorithms but also takes into consideration the amounts of irregularities, conflicts and restrictions of inaccurate knowledge. Evaluation of data in land cover and land use has been discussed as well. A hybrid model is suggested which works on the basic framework of support vector machine and neural nets to predict data with the past input with the help of new learning algorithms which pave a way to predict future data under machine learning.

Index Terms: **Support Vector Machines, Image classification, Satellite Image, Machine Learning, Remote Sensing, Landuse/Land cover map**

I. Introduction

Global change is a result of Earth's land cover characteristics and its use which keep on changing with time. In today's world where we are leading towards another big revolution i.e., the information revolution there comes in new advances and challenges which pave paths for new frontiers of revolution [1]. Enormous changes are being made in techniques which are upcoming for earth resource mapping and monitoring. Due to climatic changes and over demand of the growing population in the last few years there has been a significant change in the land use/land cover map across the globe. Satellite based sensors are improving in terms of accuracy for mapping various terrains using geospatial information in remote sensing. Geo-spatial information is captured using satellite sensors and the satellite images that are formed provides information of different objects/features present in that terrain. Multispectral/Hyperspectral imagery is based on number of bands used to represent the data. Capturing remotely sensed data is possible as every object has different spectral signature. Different objects has different features constituting the land cover which reflects electromagnetic radiations at different wavelengths having their own characteristics depending the physical state and chemical composition of the materials [2], [3], [4]. Radiations in discrete spectral bands are measured in case of multispectral images whereas in case of hyperspectral images the spectral signatures form 3 D cube as the band is continuous in nature [5]. A discrete digital number represents spectral response of the material. Classification means separating data into multiple classes having similar features. Statistical structures in the data are determined using clustering algorithms. Homogenous samples of the different land cover are used to identify similar areas in which numerical information of all the spectral bands is used [6]. Classification of images captured through medium spatial resolution sensors is poor due to which classification accuracy becomes major problem. New computing techniques along with advanced tools are better for classifying images have low resolution to improve classification accuracy [7]. When large number of trained samples are available then supervised classification can be used in other cases when training data is not available unsupervised classification can be used. Different classifiers are discussed in the following sections and a hybrid classifier is suggested for improving classification accuracy for medium resolution images.

II. UNSUPERVISED LEARNING

Identification of hidden patterns in unlabeled data is a problem of unsupervised learning. Different algorithms discover interesting properties in a given set and then labelling of this set is done after finding the similar regions. Points are assumed to be drawn independently and are identically distributed. Clustering technique plays an important role under unsupervised classification wherein vectors in multidimensional space are grouped together into clusters in a way where similar patterns are taken together and dissimilar patterns forms different clusters. [10], [11], [12]. K-means clustering, Hierarchical clustering, Anomaly detection and Neural Networks are basic clustering algorithms under unsupervised learning.

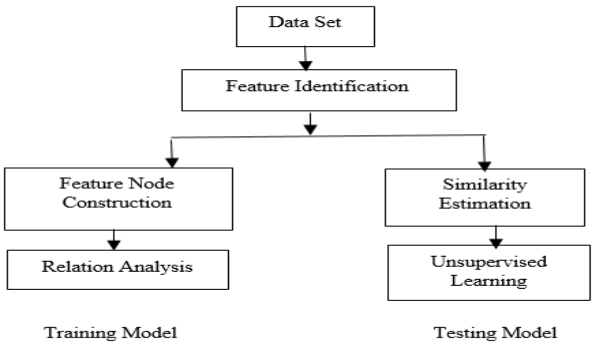


Fig 1: Unsupervised classification

III. SUPERVISED LEARNING

Identification of class boundaries correctly in the training set with the help of learning algorithms with labeled data set is known as Supervised Learning [15], [16], [17]. As this case study targets support vector machines (SVM) hence we will discuss different aspects of SVM in detail. Mapping new data by deriving a function from analyses of training data is the basic operation of supervised learning.

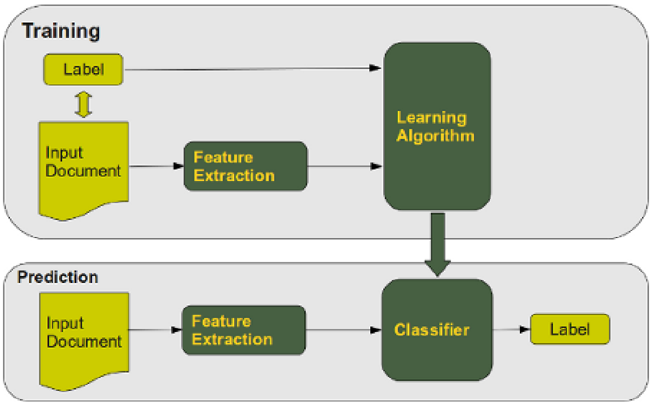


Fig 2: Supervised Learning

IV. SEMI-SUPERVISED LEARNING

Semisupervised learning takes in inherent qualities of Supervised learning and Unsupervised learning. Under Supervised learning a lot of labeled data is required for training purpose which acts as a reference for new data whereas in Unsupervised learning the classification is done on the basis of finding hidden patterns without availability of labeled data as a training set. Both methods have some advantages and disadvantages over each other. Hence, in Semi-supervised learning unlabeled data is used with a small amount of labeled data which improves the overall classification error taking into account the advantages of both the techniques and overcoming the disadvantages. Generative models are an example of semi-supervised learning. Learning accuracy can be increased when unlabeled data used in association with small amount of labeled data increases accuracy to a large extent. Skilled human are required for labeled data which in turn increases the cost and thus fully labeled data becomes infeasible whereas unlabeled data is relatively inexpensive [18], [19], [20]. Thus Semi-supervised learning comes into picture to keep the cost low but still increase the accuracy of classification.

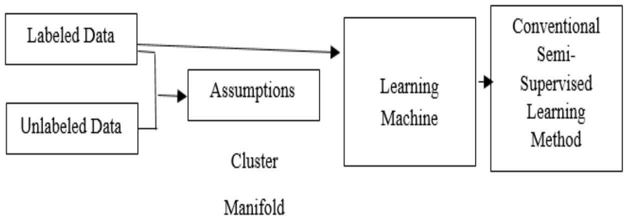


Fig 3: Semi-Supervised classification

V. SUPPORT VECTOR MACHINES

Supervised classification and regression are addressed using support vector machines commonly known as SVM. In the original formulation of SVMs, the method is presented with a set of data samples, and the SVM training algorithm determines a hyperplane that separates the data set into discrete predefined number of classes in a way that resembles training set. Decision plane defines the boundaries for classification under Support Vector Machines [17]. Objects belonging to different classes are separated using decision plane. An example is shown wherein there are predetermined classes where an object will either belong to class green or red. The objects on left side are separated from the objects on right side by a separating line which defines a boundary. Objects on left side belongs to class red whereas objects on right side belongs to class green. New objects that are supposed to be classified if falls on the left side then are labeled as red otherwise are labeled as class green.

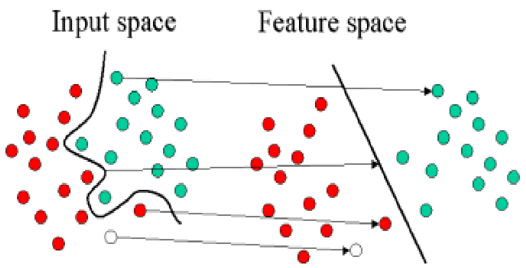


Fig 4: Support Vector Machine (SVM)

VI. TRADITIONAL MACHINE LEARNING ALGORITHMS FOR REMOTELY SENSED IMAGES

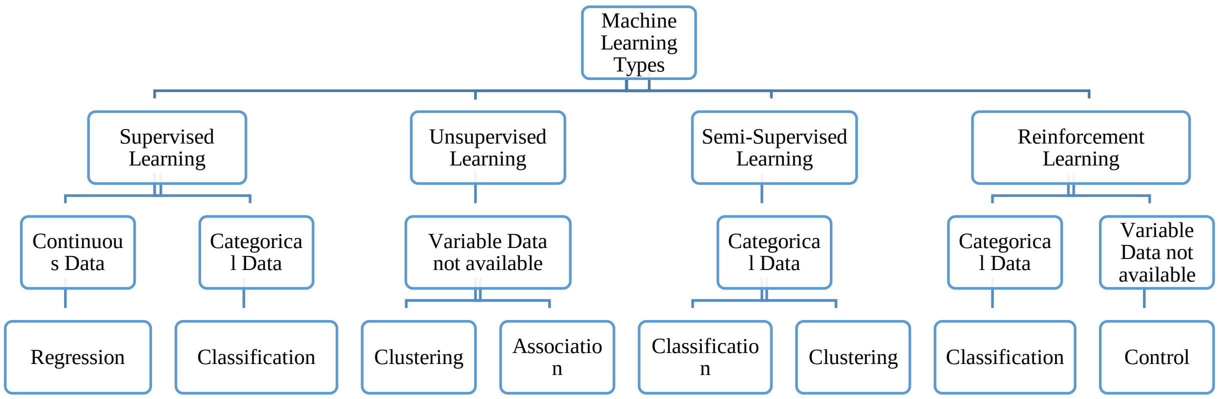


Fig 5: Machine Learning Categorization

Formation of Land cover map depends entirely on remote sensing technology because of its ability to capture land surfaces at various spectral and spatial levels. Separation of land cover images into various classes is done using classification algorithms. Neural networks, Decision tress, K-NN classifiers are very well known for classification of remote sensed images for various use. There are certain parametric classifiers and certain non-parametric classifiers based on statistical fundamentals amongst which Maximum likelihood classifier is a parametric classifier whereas neural network is a non-parametric classifier. In neural network multilayer perceptrons are used commonly for Landuse/landcover map whereas decision trees are used for normal classification as it is the simplest of all the classifiers.

The process of machine learning involves gathering of data from various sources at the primary level [17]. Homogeneity among the dataset helps in reducing classification error. Thus data is cleared to belong either to one class or to another. Further model is built by selecting the right classification algorithm for the dataset. Insights are gained from the model for future data prediction and finally data visualization is done for forming data graphs which gives us a model which can be used as a training set for new data. Figure 5 shows the complete machine learning process and Figure 6 shows how machine learning algorithms are categorized. In machine learning we have four types of processes which are separated from each other on the basis of data available. Data can be continuous, categorical or variable. If data is continuous then we can use supervised learning but if the data is categorical then we can us either supervised learning or semi-supervised learning or reinforcement learning. If data is not fixed then we can use unsupervised learning or reinforcement learning.

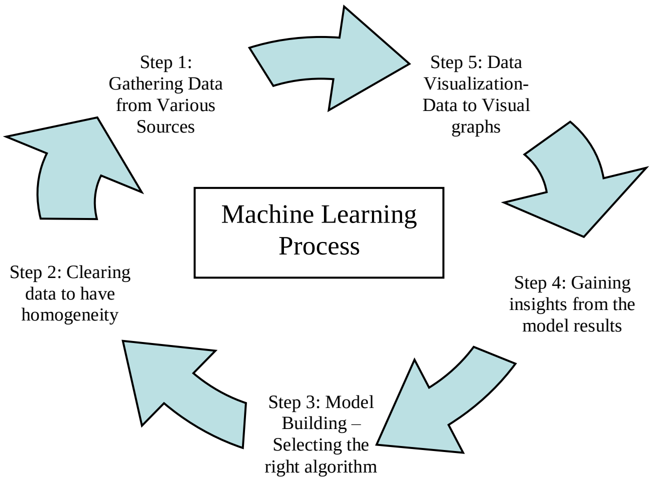


Fig 6: Machine learning process

VII. SVM BASED MACHINE LEARNING ALGORITHMS FOR REMOTELY SENSED IMAGES

In remote sensing, SVM based techniques were used efficiently for hyperspectral images. Acquiring labeled data is very expensive and time consuming also it requires trained humans for proper classification many SVM based techniques were designed which were developed on properties of RS images. Semi-supervised classifiers were used extensively as the address the basic problem of labeled data. According to Hughes phenomenon there exists a very small ratio between the number of training samples available and the number of features. Although SVM provides strong models for classification but they fail when the number of labeled samples are less. Exploration of unlabeled samples for increasing the training samples results in new model. In this case study, we have focused on SVM-based approaches, and have developed a hybrid model for addressing RS image classification problems. We will discuss a few SVM based classifiers in the following section.

A. Naive Baye’s Classifier

Naive Bayes is the simplest of all the classifier which assigns class labels to target instances represented as feature vectors. This classifiers solely depends on the assumption that the digital number of a particular feature is independent of the digital number of any other feature. Naïve Baye’s classifier works best when the feature vectors are independent in nature and when there is no correlation between two classes i.e, one object will belong to only one class.

B. K-NN Classifier

Feature vectors belonging to feature space having unique class labels are stored to form training set. K is a constant which can be set by the user as per the requirement. An unlabeled vector is classified by assigning the label which is most frequent among the k training samples nearest to that query point.

C. RF Classifier

Decision trees are very famous under machine learning. As decision tress are invariant under scaling and various other transformations it forms a robust model. Random forests are one of the best decision tree techniques for RS images. RF decreases the variance with the help of deep decision trees trained on same training set at different parts. The disadvantage of RF classifier is some loss of interpretability and a small increase in the bias. Regardless of this disadvantage the final model is robust and performs well under various conditions.

D. SVM Classifier

A training set consists of training data which belongs to one or the other two categories. New data is assigned to either one category or the other based on binary classification which is developed further for making an SVM model. Examples are represented as points in space which are divided from each other by a clear wide gap. New data is then mapped and predicted to fall on one side of the category. Supervised learning is not possible when labeled data is not present in such a condition unsupervised technique is used, which serves to find natural clustering of the data to groups and then map new data to these groups.

E. ANN Classifier

Artificial neural networks (ANNs) are developed on the fundamental of biological neural networks. In ANN, system learns task by considering examples which are not task specific. No priori information is involved in this task.

The algorithm evolves itself by understanding its own set of relevant characteristics from the learning material. Collection of connected units or nodes forms artificial neurons in ANN. Artificial neurons transmit signal from one another by end-to-end connection. Each neuron processes the information received by it and then transmits further to the other neurons. The network formed by connecting the output of neurons with the input of other neurons to form a weighted graph.

VIII. METHODOLOGY & CASE STUDY

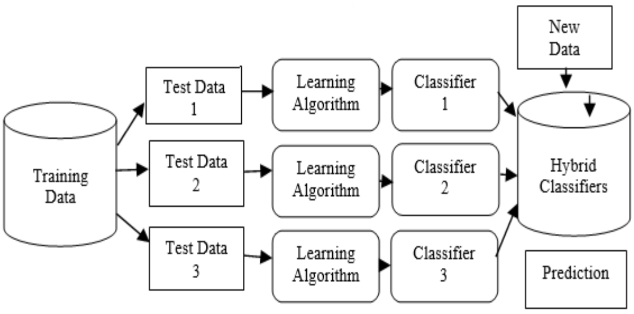
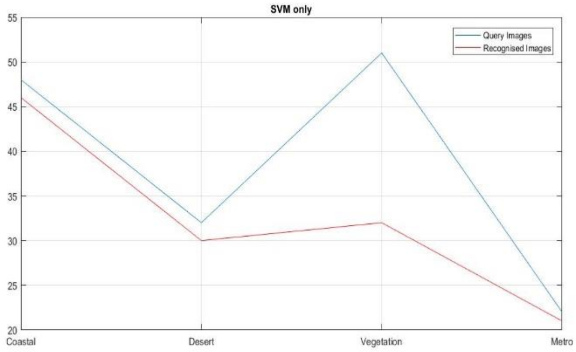


Fig 7: Hybrid Classifiers

Taking the case of LISS-III data wherein the images are having low spatial resolution, when we apply any one type of classifier to classify the image for landuse/landcover map, then the output we get is of low quality having low classification accuracy. Hence, we come up with a solution of using mixing two to three classification techniques to overcome the problem which forms our hybrid classifier. In hybrid classifier we use a mix of SVM based classifier and an ANN classifier. The reason to select these two classifiers is firstly SVM works with labeled data whereas ANN works with unlabeled data. When the amount of labeled data is less thus, we go for semi-supervised SVM which allows us to work with small amount of labeled data. In ANN a weighted graph is formed by using artificial neurons which discover a self-generating pattern. In the above architecture a set of training data is available which is used for new data which is further used with different learning algorithms associated with different classifiers whose results are finally mixed for creating a hybrid classifier.
The experiments are implemented using MATLAB 2017a, and the platform has CORE i5 processor, 3.2GHz CPU, and 4GB memory with Windows operating system. LIS-III low resolution images are selected. The database is labeled into four land cover semantic categories namely Ocean, Metro, Desert and Vegetation. Results show classification using SVM+ANN gives better recognition rate as compared to classification using ANN and SVM.

The graph shows classification accuracy for query images in the four databases coastal, desert, vegetation and metro using SVM classifier

Classification Accuracy

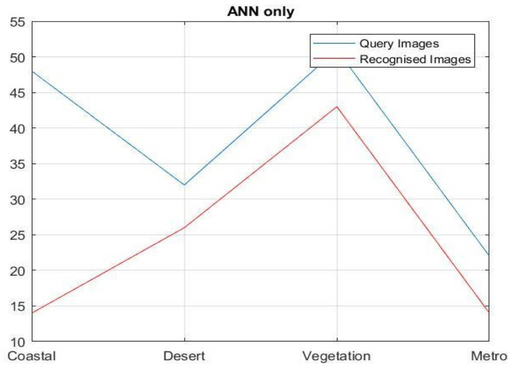


Class

Fig 8: Classification using SVM

The graph shows classification accuracy for query images in the four databases for coastal, desert, vegetation and metro using ANN classifier.

Classification Accuracy

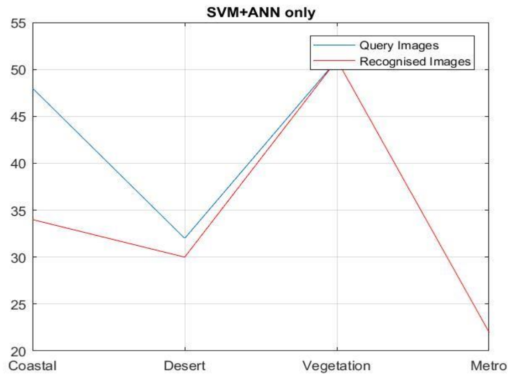


Class

Fig 9: Classification using ANN

The graph shows classification accuracy for query images in the four databases for coastal, desert, vegetation and metro using SVM+ANN classifier.

Classification Accuracy

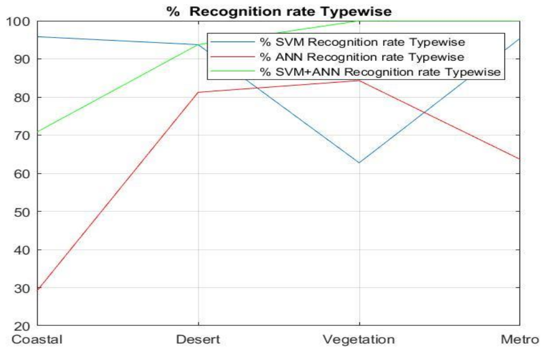


Class

Fig 10: Classification using SVM+ANN

The graph shows classification accuracy for all the four datasets typewise using SVM, ANN and hybrid classifier.

Classification Accuracy



Class

Fig 11: Type wise classification using SVM, ANN & SVM+ANN

Recognition Rate

Class

Fig 12: Overall Recognition rate using SVM, ANN & SVM+ANN

The classification accuracy increases with the use of hybrid classifiers. Recognition rate is 83% with SVM classifier whereas it is 62% with ANN classifier. Recognition rate increases to 89% with hybrid classifiers. Thus, it can be very well justified that with the use of hybrid classifiers classification accuracy increases and in turn the recognition rate is increased. Low resolution LIS-III images can be classified easily for land use/ land cover map using hybrid classifiers with overall increase in the classification accuracy.

IX. CONCLUSION & RECOMMENDATIONS

A quick reference of the compendium of recently developed classification techniques in RS applications is provided. We also pointed out traditional methods used for image classification. Most of the findings indicate that there is sufficient empirical evidence to support the adoption of these processing algorithms. SVM-based strategies are discussed extensively as they provide good classification results for land use/ land cover for remotely sensed images. A hybrid classification technique is discussed which takes into account characteristics of SVM based classifier and Neural network based classifier and gives good results compared to them applied separately. The hybrid classification technique takes into account certain constraints, such as linearity, balanced data set. A case of LIS-III images are discussed which faces low resolution problem. Classification of land use/ land cover with LIS-III images becomes difficult with SVM or ANN alone.

Hybrid technique increases overall classification accuracy which helps in proper classification of land use land cover maps. Future research will focus on using these algorithms together such that the strengths of this technique can be exploited. The classifiers that perform better for a particular land cover class will be considered more reliable during conflict resolution. Future research will also focus on using multi-spectral multi resolution and multi sensor image fused image for great success.

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