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OPTIMAL FEATURE SELECTION FROM REMOTE SENSING IMAGES FOR AGRICULTURAL ACREAGE ESTIMATION

Pooja G. Mate*, Kavita R. Singh, Anand Khobragade
Dept. of Computer Technology, YCCE, Nagpur, Maharashtra, India
Dept. of Computer Technology, YCCE, Nagpur, Maharashtra, India
Dept. of Planning Gov. of Maharashtra, MRSAC, Nagpur Maharashtra, India

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ABSTRACT

Feature extraction directly affect the classification process poor features leads to inaccurate classification results. Feature extraction is complex task when we classify any sort of data may be it textual data, simple image and complex image like remote sensing multispectral images. On the place of basic features used across the world, very specific features are used for crop classification in the agricultural field. Finding those relevant features out of available one is the first job on priority. Researcher used those features as an input for estimating agricultural acreage from remote sensing images. This can introduced the concept of feature dimension reductionality.

KEYWORDS: Remote Sensing, Feature Extraction, Image Classification

INTRODUCTION

Feature selection and feature extraction has a vital role in image classification. It is used to classify any sort of data may be textual database, simple image or complex images like Remote Sensing Images collected through satellites. In addition to features that available for usual data types used across the world, more specific features may be needed for classifying agricultural areas or crops within agricultural fields. As classification accuracy is depending on number of features we have selected, the more specific feature selection gives more accurate result. A feature selection problem plays a key role when set of features are belonging to different domain like remote sensing. Whenever we classify the object it represents in terms of set of features, feature selection problem consist of selecting very specific features from whole set of available features and it is helpful that selection of very specific features provides the most discriminative power.

a) Image Classification using SVM

During last decades, SVMs is more referable for various classification problems due to its flexibility, computational efficiency and ability to handle high dimensional data [1,2]. Therefore, classification of image should be done using SVM (Support Vector Machine) because it is proven through studies to be one of the best classifier as compare to other (like neural network algorithm, fuzzy logic etc.). Researchers examined hyperspectral images by applying machine learning algorithms like Maximum Likelihood, Decision Tree, Artificial Neural Network and Support Vector and also tested sub-pixel classification algorithms like LMM, ANN, & SVM for its behavior on effect of dimensionality of feature space, effect of training sample size, and number of bands used to achieve better classification accuracy. The finding of their research illustrate that upcoming statistical learning classifier SVM produces the best accuracies as compared to other algorithms, even if number of bands increases to more than 100. [8].

PROPOSED WORK

a) Basic Steps for Image Classification

The following Fig 2 shows the basic steps for image classification process.

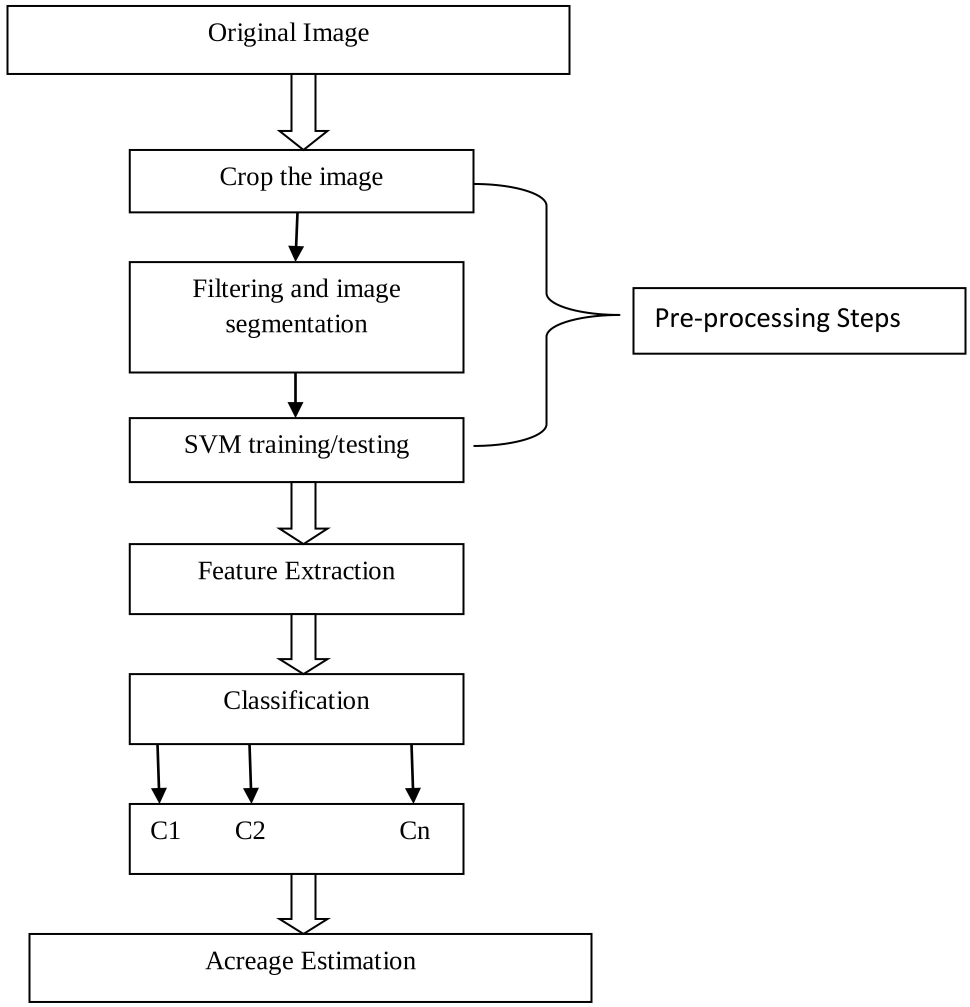

Fig 2: Proposed System

In the Fig. 2 above, C1, C2, .., Cn refers to the classes or categories that images are classified into. In our case we classified image into grain and non grain. Therefore the output shows in grain and non grain. Step 1, pre-processing, is required before applying any image analysis methods. First of all we crop the selected portion of image the we are applying the noise filter and segmenting the image into different segments. In the step 2, feature extraction is done. Here we extract number of features like length, width, height, area, roundness, brightness, shape, mean, GLCM, border index, border length, entropy, height, standard deviation, shadow, roughness, rectangularity, entropy, NDVI, connectivity etc. we will give these features as a input to our classification system. Finally, images are classified into the responsive classes as grain and non grain by using SVM. Based on the classification results we can perform acreage estimation.

RESULTS AND DISCUSSION

The following Fig 3 shows the feature vector for training samples. According to that features SVM classify result into grain and non grain. The row shows the number of features that can be extracted. And column shows number of training samples.

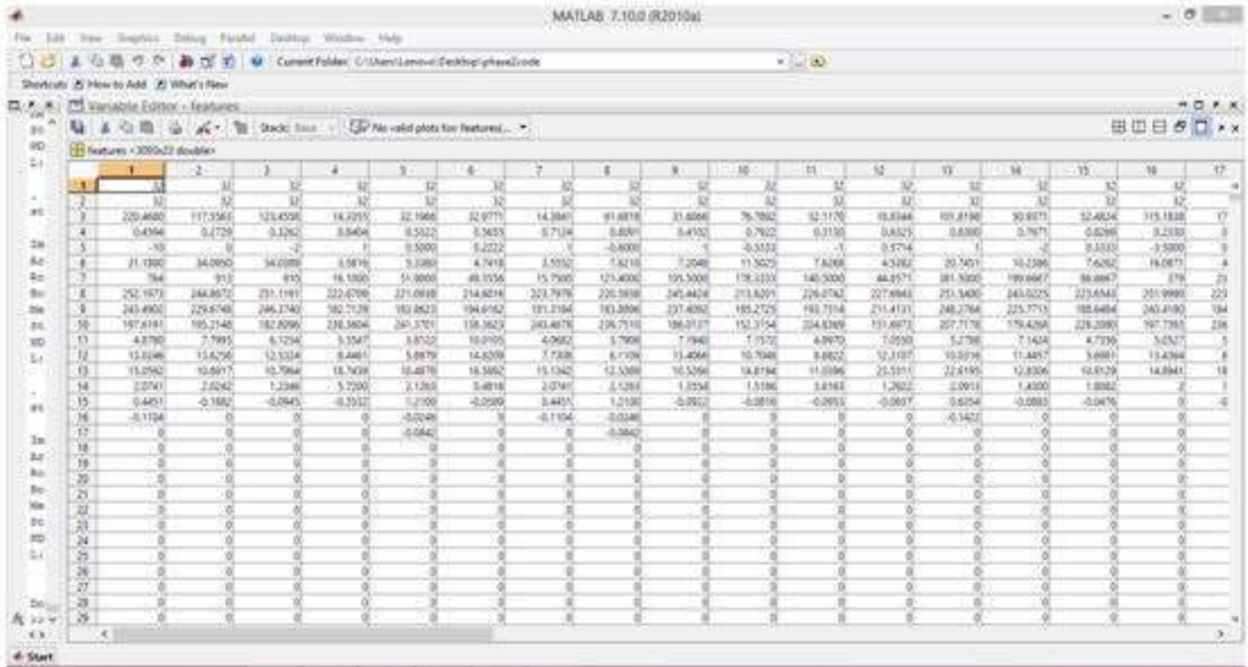

Fig 3: Feature Vector

Here we have to find accuracy of the classified image for this we have two images for comparison. One is the original image and second is the reference image and applies the accuracy formulae on it. Here the reference image is nothing but the pre-classified image that can be processed in software or we can apply filter on the original image to use it as a reference image or it can be image on which we can manually do labelling in paint. The following Fig 4 shows the original image and reference image.

a) Original Image ***b) Reference Image***

Fig 4: Images used for experimentation

Finally, by using training data set it can calculate the results. The following Fig 5 shows the acreage of total grain area. We find the acreage out of total area which us the area of the field to total grain area. Here the total acreage is 3.1641 acres.

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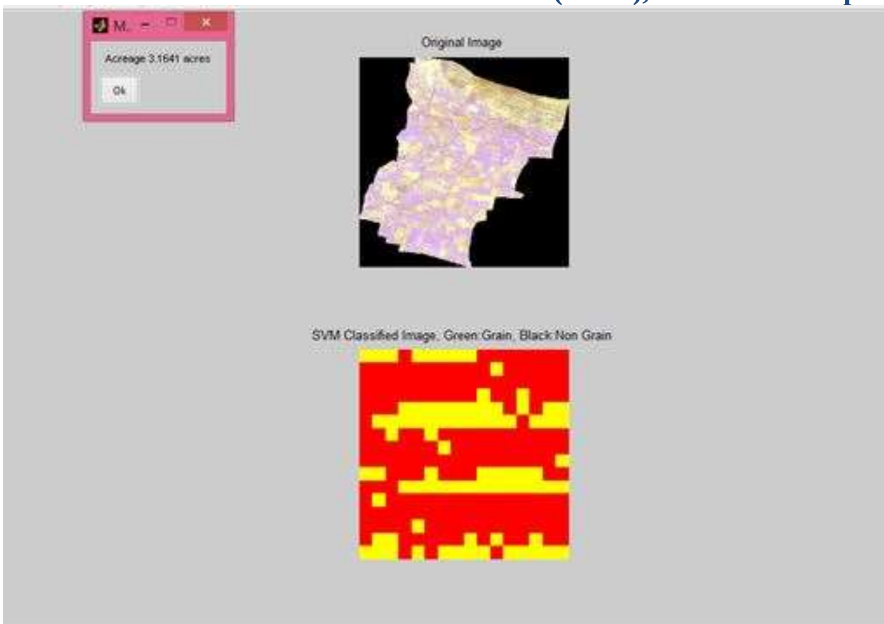

Fig 5: Total Acreage of Grain Area

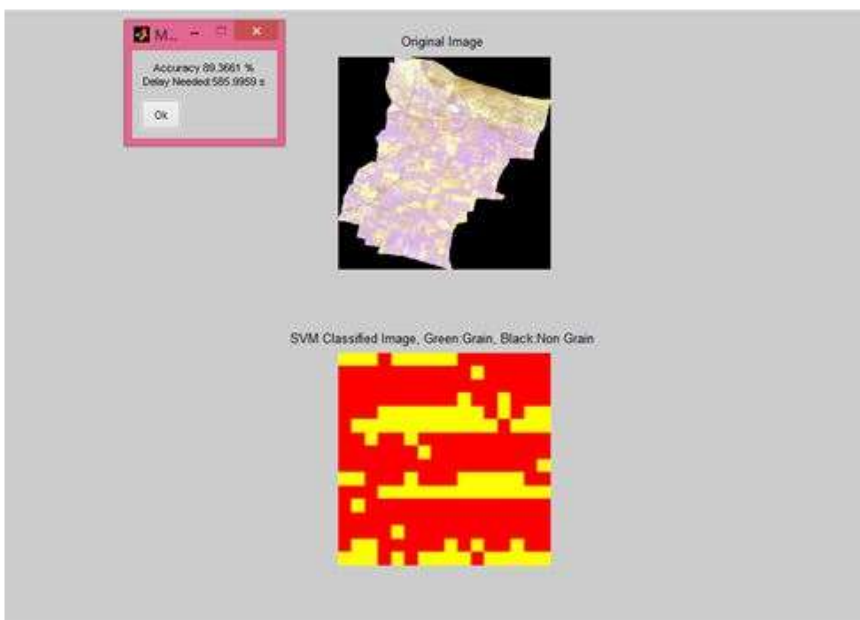

Fig 6: Accuracy of Classified Image

The above Fig 6 shows the accuracy of classification. We find accuracy on the basis of features to be selected. There are total 3093 features from these we need to find combination of features which gives more accurate result. There is need to find combination of features those are more accurate. This task we have to do manually. The following Fig 9 indicate the accuracy of all 3093 features in 89.36%, with respect to this it gives classification result into grain and non grain. Also it gives time delay in seconds it takes 585.99 s.

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CONCLUSION

We proposed the crop classification system. In this we can extract multiple features like glcm, standard deviation, shadow, NDVI etc. and on the basis of these features we classify the result into grain and non grain. We evaluated the performance of features by using linear SVM. On the basis of this classification we found the acreage of the total area containing grain crop. Also we found the accuracy of classification. Here, the result shows the total acreage as 3.1641 acres and accuracy of classification is 89.36%, it required time delay as 585.99 s.

The future work we have to do is that finding the most relevant combination of features for agricultural field. Even, this project can be extends to find best parameters for crop identification using remote sensing image sets. The use of Evolutionary algorithms is envisaged for optimization of best features for said application.

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