Identification of Land Cover and Crop Type Using Knn Classifier In Sar Image

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Abstract— *Land cover refers to the surface cover on the ground, whether vegetation, urban infrastructure, water, bare soil or other. Identifying, delineating and mapping land cover is important for global monitoring studies, resource management, and planning activities. The information of crop monitoring is most important for food security and it helps to improve our knowledge about the role of agriculture on climate change and crop type identification. This work focuses on an automated KNN classification system for identifying land cover and crop type in Synthetic Aperture Radar (SAR) images. In the first module an unsupervised Kohonen Self-Organizing Mapping (SOM) neural network is used for identifying the land type. In the second module, the local binary pattern (LBP) based features are extracted for identifying the crop type in the crop covered area. The extracted features are given to KNN classifier which classifies the type of crop.*

Keywords—*SAR image, KNN classifier, Self-Organizing Mapping, Prediction.*

I. INTRODUCTION

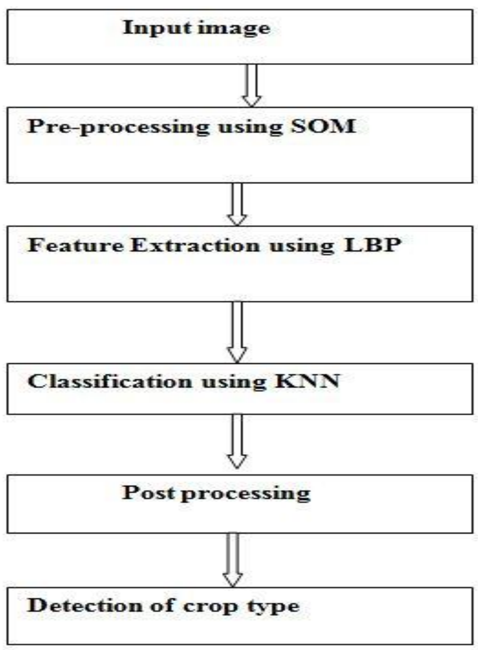
The last several years and onward could be called the years of Big Free Data in remote sensing (RS). Agriculture is the one of primary backbone of Indian economy. Synthetic aperture radar (SAR) satellites were captured with high spatial resolution in particular Sentinel within the European Copernicus program [1], and Landsat-8 within the Landsat Project, In agriculture the parameters like canopy, yield and quality of product were the important measures from the Farmers point of view (Viraj et al,2012).It is identification of land cover and crop type in SAR images is very difficult to understand , since the SAR image is very noise in nature.[3] The aim of the work described in this work is to automate and improve the accuracy in the process of identifying land cover and crop type in SAR images[8].The objectives of this work as follows: To develop a self-organized map based segmentation technique for identifying land cover area in SAR image. To build a KNN classifier based approach for detecting the crop type. The proposed system consists of two stages; in stage1 a SOM based technique is used for identifying the land cover area. Then in stage 2 a KNN classifier based approach is used for identifying the type of the crop. For the classification stage 1 D LBP based features are extracted from the segmented SAR image.

II. METHODOLOGY

A. General Architecture Overview

Four-level method is proposed for classification of crop types from synthetic aperture radar. These levels are preprocessing, feature extraction, classification, post processing, and geospatial analysis. Since optical satellite imagery can be cover with clouds and shadows, one have to deal with missing values in the imagery[11].

Fig 1: General Architecture Overview



In the first stage of the proposed work the input image is segmented using the self-organization map (SOM) based technique. it use used for segment the region with pixel based and After the segmentation, LBP pattern, color, shape, intensity, texture is extracted from segmented images.LBP is composed of 0s and ls which does not have sufficient information of discriminate multiple patterns. Most classifiers accept only valid pixel values as an input, and therefore a preprocessing step should be performed to impute missing values. the next step is KNN method used for classification KNN is the minimum spectral distance between target pixels and reference pixels. In general, KNN classification method applied to estimate and mapping crop type in order to assess accurate estimations in this work. We propose different KNN architectures, for .identifies the land cover all of the types of crop classified with help of the K-NN classifier [13].

B. Level I

The input image is obtained from satellite is the SAR image. For pre-processing. we use self organizing kohonen maps for optical images segmentation and subsequent restoration of missing data in a time series of satellite imagery. SOMs are trained for each spectral band separately using non missing values. gussian method used for filtering the image.

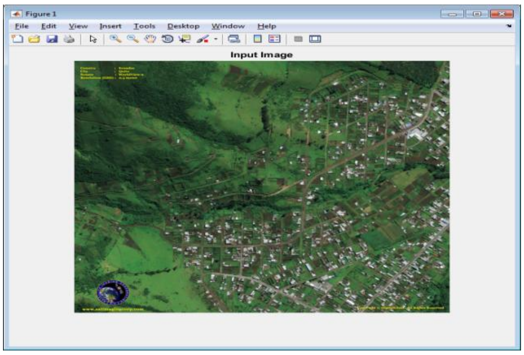


Fig 2: Input image

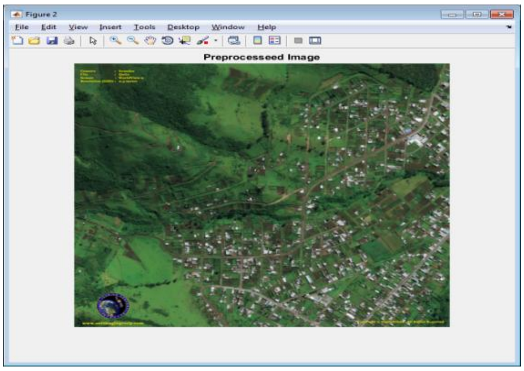


Fig 3: Pre-processed Image

It is one of the neural network method For pre-processing, SOMs are trained for region separately using nonmissing values. Missing values are restored through a special procedure that substitutes input sample's missing components[18].

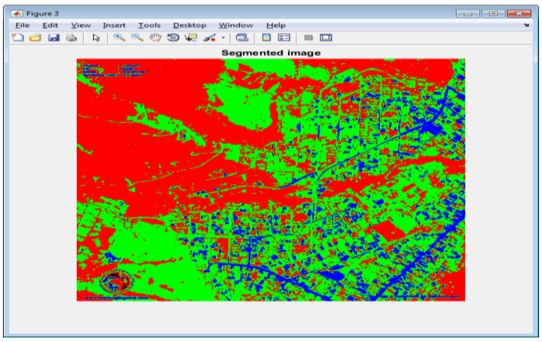


Fig 4: Segmentation Image

C. Level II

General Overview: The core element of the model is the supervised feature extraction, it is performed at the second stage (level II). We explain the two different paradigms: state-of the-art methods (RF an ENN) and compare those classifiers After the segmentation, LBP pattern, colour, shape, intensity, texture is extracted from segmented images.LBP is composed of 0s and 1s which does not have sufficient information of discriminate multiple patterns[10].

$$D(X,Y) = \sqrt{\sum_{i=1}^{n}(xi - yi)^2}$$

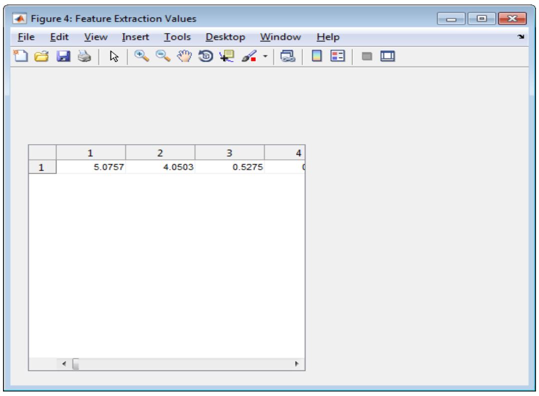


Fig 5: Feature Extraction Values

D. Level III & IV

Post processing and performance Analysis To improve the quality of the resulting map, It is developed several filtering algorithms, based on the KNN classifier [14], available information on quality of input data. The classification result improve the accuracy and performance In the result, we obtained a clear parcel-based classification map.

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Accuracy =

      9.523809523809523e-01

ERR =

      4.761904761904762e-02

Sensitivity =

      1

Specificity =

      9.433962264150944e-01
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The final level of data processing provides data fusion with multisource heterogeneous information, in particular, statistical data.

III. Result

Overall classification accuracies for RF, ENN, ensemble of 1-D and 2-D CNNs were 88.7%, 92.7%, 93.5%, and 94.6%, respectively .we proposed the KNN classifier algorithm for improve the accuracy and efficiency. The RF and ENN Method provide the lowest accuracy compare with KNN classifier. At the same time, major of using KNN comparing to RF were achieved for maize, sugar beet, soybeans . Using the ensemble of KNN, we were able to discriminate these classes more reliably.

IV. Conclusion

In this work, we have presented a classification for time series satellite image. The information of crop monitoring is most important for food security and it helps to improve our knowledge about the role of agriculture on climate change, crop type identification, land cover etc. This work presents an automated KNN classification system for identifying land cover and crop type in Synthetic Aperture Radar images. The land cover area of the input SAR image is identified by segmenting the image using self-organizing map. After the land identification, the 1 dimension segmentation results gives to the feature extraction .Local binary pattern based features are extracted from segmentation image for identify the crop type in crop covered area. The extracted features are given to KNN classifier for identify the type of crop. The proposed system able to detects types of crop such as Rice, Wheat, Maize, Millets etc.

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