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Intelligent System for Classification of Residential Areas in Forest

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ABSTRACT: Machine Learning techniques have been widely used to classify spatial objects and it has become one of the well-established research areas of computer science. The identification of residential, non-residential areas, cultivated land, non-cultivated land, forest and others in a real time image is a significant problem. Due to the presence of complex patterns of dense forests and residential areas in forests is one of the difficult classification problems because heterozygous image morphologies are very difficult to preprocess. The proposed approach is very useful during natural disaster such as fire in forest, earthquake, flood etc. This paper has twofold object, one is to classify the forest, residential areas and so on whereas the other is to classify the cultivated and non-cultivated areas within the real time picture. In order to mitigate all above stated problems, this research proposes a methodology where in first stage, we prepare the data; in second stage, the Decision Model is constructed using Bayesian Belief Neural Networks. About 98.36% accuracy of the system is measured by using Confusion Matrix.

Keywords: Machine Learning, Computer Vision, Classification, Forests, Residential Areas, Cultivated Land.

I. INTRODUCTION

Recently forests are the rich source of natural life and majority of population of agricultures-based countries are living in the riverine areas where in case of natural disaster. It is really very hard to recognize the residential areas from the remote sensing image data. Remote sensing is a valuable source of monitoring and mapping forest area data but it needs to be classified that how much area(s) are cultivated and non-cultivated areas whereas identification of residential and non-residential areas(s) is the prime objective this research because in case of fluid alarming situation people are to be alerted to be migrated as safer locations. In order to solve the above stated problems this paper proposes a novel approach so call an intelligent system for classification of residential areas in forest. The approach comprises over three steps. At first step data preparation techniques are used. At second step decision model have been constructed whereas final step is used for the performance of the decision model. The measure estimated accuracy of the system is about 98.36%.

Paper is divided into five sections where section one is dedicated to present the introduction of the paper and section two is used to present the literature review. Section three is used for methodology description. Results are shown is section four whereas conclusion and discussion is made in section five.

II. LITERATURE REVIEW

An approach [1] to visualize trees, forests, land cover and other spatial objects was proposed by using geographic information system. The objective of the research was to measure the loss of trees was proposed. Object detection was done by using region growing techniques of computer vision and classification results have been shown on GIS maps. The reported results show that 90 trees in 140 hectors were lost over a period of 2006 to 2011 in there region of interest with 80% accuracy.

A method was proposed [2] to identify individual tree crown from satellite image by image-to-map rectification. This method is useful for forest management and monitoring. The dataset for this work has been derived from Planets full-frame analytic scene products using its 4-band satellites in sun-synchronous orbit (SSO) and International Space Station using deep learning with the help of the VGG16 model and convolutional neural networks with accuracy of 96.71%.

An approach [3] to visualize the matching of high-resolution satellite image of individual tree crowns using field measured data. The purpose of research was to identify tree crown from Satellite image by image-to-map rectification on octagonal tree crown shape with 16 to 18 meters of height.

A system [4] was designed using three open source python libraries to perform GEOBIA. The data was analyzed over 10's millions rows of raster image. In the results GEOBIA using python packages was flexible to solve complex classification processes due to its modular approach

An approach [5] was purposed, using satellite images and ancillary data to measure the canopy height of mixed forest at 30m resolution. The data was used 2.9 million hectares where canopy height ranges from 0 to 70 m.

An approach [6] was purposed to deal with trees species based on GIS techniques using Quick Bird Satellite Imagery. GIS classification techniques were used to classify five different species. The results were recorded 88.0% accuracy of classified images.

In the study [7] satellite images were used to identify the damages caused by forest fire in Çanakkale Province of Turkey on October 2008. The images were used from LANDSAT and ASTER satellites and various analysis techniques were applied on two classes of Unburned (Agricultural land and others) Where (VI>0) and Forest fire area (VI<0) respectively where the obtained results of satellite images were 5% greater than CFMO estimation.

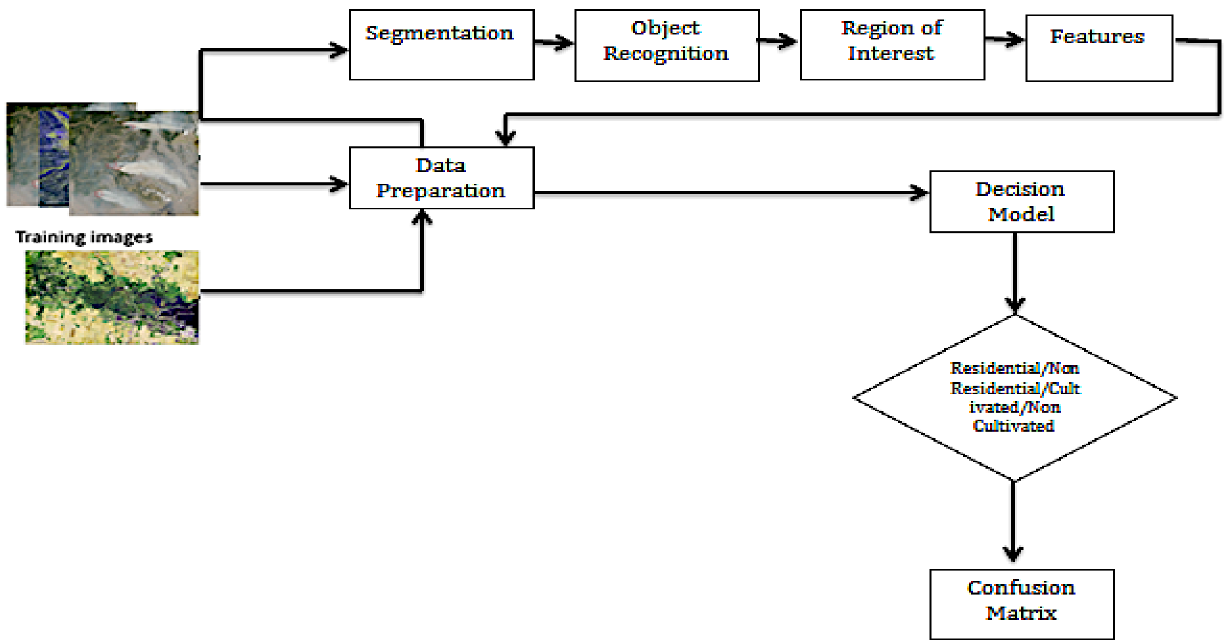

Fig. 1. Intelligent System for Classification of Forest and Residential Areas Workflow

A survey [8] to find out the change in forest data using satellite remote sensing techniques. The study was carried out on 6 different types of forest data on real time basis which were time and cost effective, where the loss of forest was 5.66% recorded from 1973 to 1985 due to growth of population.

A visualization of identifying deforestation hotspots using MODIS satellite images [9]. The study was performed on data of 2005 -2010 to detect the and validate the hot spot Maps for the data of deforestation using different machine learning techniques, digital classification and expert opinion respectively where the accuracy of digital maps was 92.5%. The results were recorded that due to (47.9%) of livestock and agriculture activities deforestation chances.

An approach [10] was purposed to analyze the trees outside forest based on assessment using Satellite images. A technique was used to measure the trees outside the forest by using PCA algorithm for reducing time &cost. The accuracy of algorithm was recorded as 86.6%.

Visualization [11] of forest species and delineation of trees crowns using Quick Bird images based on classification technique. A technique was used for five different groups of forest species where accuracy was recorded as 76%.

A study [12] was conducted for the classification of image using three methods to extract the land usage for Tsukuba city. The overall accuracy using Fuzzy Supervised Method was 87.7% as compared to other machine learning techniques.

In the study [13] five different machine learning algorithms were used for the classification of three different types of forest. The best performer algorithm was MLP with accuracy of 90.43% and KNN was on second with respect to accuracy.

An approach [14] used by combining three methods to answer the planning of forest management on the basis of query based system.

A model [15] was proposed for classification of images using densely deep machine learning technique of random forest, where the model performed best for small dataset. The accuracy was from 97% to 98% based on different trees number.

An approach [16] was used to visualize the satellite images for optimize the object-based images in forest for land cover mapping. The multiresolution segmentation algorithm was used for the comparison of Multitemporal Rapid Eye and SPOT images. The experimental result was generated by SPc and MRS algorithms for the accuracy

Two approaches [17] were introduced for classification of object, one was object based classification and other was pixel based, where pixel based classification approached perform best for watery and forest areas .

A study [18] has been done for forest, tree species and land, where six different machine learning classification algorithms were applied. Each algorithm was different accuracy and results depend on type and pattern of tree species.

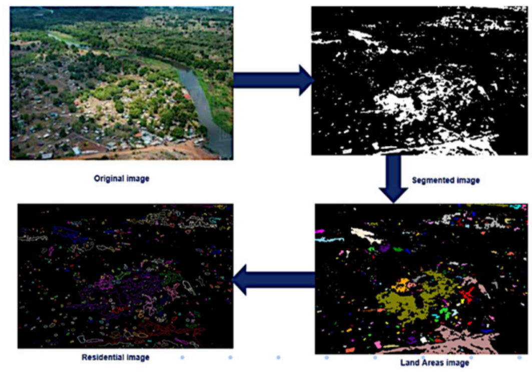

Fig. 2. Identification of Residential and non-Residential Areas.

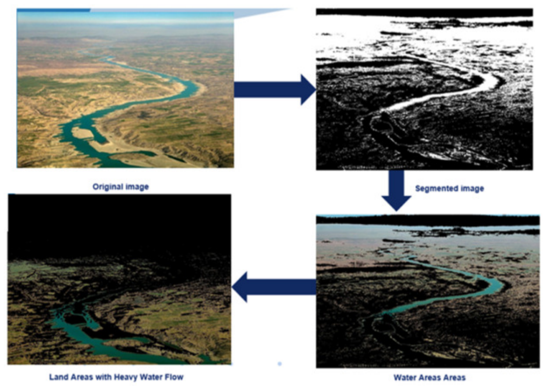

Fig. 3. Identification of Cultivated and non- Cultivated areas.

III. METHODOLOGY

The methodology of this paper deals with the classification problem of remote sensing imagery datasets to predict the forest, Residential, Non-Residential areas, Cultivated Land, Non-Cultivated Land areas. Our proposed methodology consists over three main stages. At first stage we use data preparation which comprises over some series of sub steps. The second stage is used to construct the decision model to train as well as test data and finally measuring accuracy using confusion matrix.

Data pre-preparation: Data preparation from the remote sensing images is of the complex problems, because heterogynous morphologies of Buildings, land areas, forests, parks, Cultivated Land and others are very difficult to recognize. The data preparation consists upon sub-step such as segmentation, object recognition, region of interest and feature extraction from the inputted image dataset. Since foreground of the objects are further processed and the object recognition is manually cropped and label attribute is include as shown in [Figure 1]. The features of every object have been recorded with careful observations to create the training and testing dataset.

Representation of NIS (Natural Image segmentation) was done by considering the sets of pixels based upon the same intensity levels. The cultivated land areas and non-cultivated areas could be detected as a set of objects where two-dimension array of pixels are need to considered on similarity index of the pixels. The segmentation approach of the paper converts objects into the fore ground and back ground partitions. Locating the cultivating areas and non-cultivated areas may become very challenging when the residential are a detection task is incorporated where all other objects are to be detected as non-residential areas because these areas could comprised over several number of objects which are to be removed by considering the noise. On a later stage these objects are carefully investigated by considering the morphological behaviors either the fall into the categories of cultivated and non-cultivated areas. The counters are used to detect the morphological boundaries of the objects where each object is to be filled with same set of color by applying the watershed segmentation. The watershed segmentation could be distinguished the objects by computing the same set of objects on the basis of edges so called morphological behaviors of the objects. Often these curves, lines and boundaries become cause of confusion because unsupervised techniques could not be classified with traditional findings.

In-order to convert the detected objects into the meaningful labeled objects, this approach follows the rules of supervised learning where manually objects are cropped as region of interest such as cultivated and non-cultivated, residential and non-residential areas. After cropping each object, the color movements such as RGB combination of feature constructed into the dataset and each observation is tagged with class label attribute as per task defined in above paragraph.

Table 1: Confusion Matrix.

	Residential areas	Non-Residential areas	Cultivated Land Areas	Non-Cultivated Land areas
Residential areas	217	15	6	9
Non-Residential areas	3	110	13	12
Cultivated Land areas	3	7	210	7
Non- Cultivated Land areas	6	8	5	253
Over all accuracy		**98.36%**		

Table 2: Comparison with Literature.

Approach	Technology (satellite images /others)	Perspectives (Buildings / land areas / forests / parks / others)	Machine Learning techniques	Accuracy (Percentage)
1	Satellite	Trees	Multi resolution techniques, region growing technique	80%
2	Satellite	Trees	Deep Learning and convolutional neural networks	96.71%
3	Satellite	Tree crown	clustering	—
4	Satellite	Others(Images)	Classification	—
5	Satellite	Forest	Regression	—
6	Satellite	Trees	Supervised Classification	88%
7	Satellite	Forest	Image classification	5% more accurate than previous results
8	Satellite	Forest		85.5%
9	Satellite	Forest	Classification and Regression	92.5%
10	Satellite	Trees	Thresholding	86.6%
11	Satellite	Trees	Object Oriented classification	76%
12	Satellite	Forest	Classification and Fuzzy Supervised Method	87.7%
13	Satellite	Forest	Classification	90.43% with MLP, and 89.1013% with k-NN classifier
14	Satellite	Forest	Regression and Query based approach	—
15	Satellite	Forest	Densely Connected Deep Random Forest	97.44%
16	Satellite	Forest, Land areas	Random Forest and Superpixel Contour algorithm	—
17	Satellite	Forest, Land areas	Classification	—
18	Satellite	Forest, Trees, Land areas	Classification	different for each algorithm
Estimated accuracy of the proposed approach				**98.36%**

Decision Model: The Bayesian belief network constructs a statistical model based upon the probabilistic observations. The conditional dependencies are estimated using directed acyclic graph which represents the set of variables on the basis of conditional probability such as likelihood for every class label attribute could be predicted. The inference of the class label attribute could be approximated by constructing the decision model to differentiate the cultivated and non-cultivated as well as residential and non-residential regions. An alternative approach have been applied for structural learning where scoring function is used by following the divided and conquer strategy constructed through function as posterior probability, Classification results are to be visualized by using confusion matrix.

IV. RESULTS

Through decision model we have classified the portion of Residential and Non-Residential areas in [Fig. 2] whereas cultivated and non-cultivated land areas in a forest in [Fig. 3] meanwhile confusion matrix is visualized to show the estimated accuracy of the system in [Table 1] and the compression of our technique have been shown in [Table 2].

The confusion matrix shows that 217 number of observations have been classified as residential areas in forest whereas 110 records were identified as nonresidential areas. Cultivated land area and non-cultivated land areas were recognized as 210 and 253 objects respectively, additionally results show that it is possible to classify forest and residential areas using segmentation technique combine with object detection with widely available satellite images to identify different objects in an image, that classify different labels using decision model. The overall accuracy of the proposed system is 98.36% that would-be cost-effective visualization system to check effectiveness and accuracy and to perform in depth analysis of residential areas and forest areas.

V. CONCLUSION AND DISCUSSION

The objective of the proposed research is to classify residential areas, nonresidential areas, non-cultivated land areas, cultivated land in forest, green environment and others. The research is significantly important for public, policy makers, academicians and industrial stockholders to investigate the dense forest areas, residential areas and to find out residential areas in the forest. This research concludes that in case of occurrences of natural disasters stakeholders may identify the population of humans in dense forests. The proposed approach provides assistance to combat the emergency scenarios in rural areas. The measure accuracy of proposed system was measured as 98.36%.

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