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Automatic Land Cover Classification Using Learning Techniques with Dynamic Features

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Abstract—Accurate land cover classification is required for government and private research bodies to monitor and to report road maps, forest area, agriculture land and other land classification problems. These reviews suggest that the progress of land use/cover classification method grows along-side the launch of a replacement sequence of Land-set and advancement within the computer or applied science. As land cover changes over the time. Thus monitoring and mapping of land cover and its changes over large areas is made possible by measure of Google earth Pro data collected through Smart GIS, Qgis, ArcGIS, ERDAS, IMAGEINE and Envir. This paper presents study of various land use/cover classification techniques. The method of land use/cover classification is applied to a land-set imagery followed by supervised and unsupervised, object based, pixel based, knowledge based, sub pixel based and contextual based classifiers. This paper covers the various classification approaches, methods, classifiers and techniques. Further analysis is required on the application of hybrid land use/cover classification classifiers as they're precise.

Index Terms: Classification Approach, method, Classifiers, Landset, land cover

I. INTRODUCTION

The terms Land use /Land Cover Classification (LCC) is generally used inter-changeably. Land use/cover refers to the characteristics of surface cover that refers to Earth's Surface, as represented by natural components the same as Highway, Crop, Industrial, River and Residential shown in figure 1. Classification of land cover establish the base line info for behavior like thematic mapping and alter/change recognition analysis [1]. Land covers refer to the activity, cost-effective principle, future exercise, and managing policy placed on the land use/cover sort by humans or land manager. A change in objective or management practice similarly constitutes land use/cover change. When used together the saying land cover normally talk over with the categorization or classification of human actions and natural part on the landscape inside a specific timeframe supported recognized scientific and statistical method of analysis of proper source material[2].

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Land use/cover is that the physical material at the surface of the world. Land cover is the characterization of however communities utilize the land. Socio-economic activities, urban and agricultural or undeveloped land uses are two of the most effective usually perceived high-level categories/classes of use[3]. At any one point, there may be a various and alternative land use or land cover, the specification of which may have a great aspect[4].

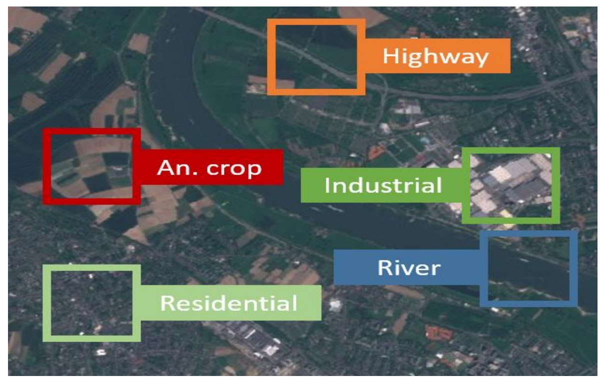

Figure 1 : Land use/cover classification using satellite imagery. Patch is extract from a satellite image with the principle to identify the showed land use/cover class.

A. *Applications of Land Cover Classification*

The land use/cover classifications methods are used to classify the land in the aerial or satellite imagery, and can be used for versatile applications listed as following:

- The military can use the land use classification to classify the terrains across the border to prepare the individual strategies for each of the terrains.[5]
- The agriculture-based planning can be determined by classifying the soil based on the colour or texture of a wide region. This land use classification can be used to plan the target crops in the different type of soils[6].
- The urban planning is the key use of land use classification models. Housing projects can be planned everywhere. The land must be adequately dry, at a specific distance from wetlands and should least cover the cultivated land; hence a detailed land use classification is required when planning the urban areas[7].
- The road projects also require a detailed land use classification surveys to identify the different kinds of obstacles, such as wetlands, rivers, deserts, etc.

B. *Need for Land Use/Cover Classification*

The land use/cover classification is required in all

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of the above applications, because in the bare imagery, we cannot spot the difference between the distinct terrains or lands. The land use classification methods prominently mark the different kinds of land with distinct colours, which makes the different areas quite visible unlike its original imagery[8]. The Figure 2 shows the clear difference between the original and land cover classified image. An apparent difference can be spotted between the different kinds of lands in the classified image in comparison with original image.

Figure 2 : Original image   Land use classification image

C. Challenges of Land Cover Classification

This effort faces several technical challenges in land use/cover classification including:

- The shortage of ground truth land use/cover maps makes it complicated to guage the projected way or methods.
- It's tough to manually label a big collected dataset of imagery to training the land use/cover classifiers, especially DL (Deep Learning) based. Therefore, supervised LCC or unsupervised LCC learning is mandatory.
- The dataset imagery at the online sharing websites or resources is extremely noisy in terms of picture/image quality, inaccurate GTF (Geo-Tagged Field) photos, uneven spatial allotment, etc.

The rest of this paper is structured as: Part II introduces the Land Cover Classification, Part III specifies the LCC with Machine Learning, and the Part IV represents LCC with Deep Learning. The conclusions are drawn in the last section.

II. LAND COVER CLASSIFICATION: DATASET, METHOD, CLASSIFIER, ACCURACY

[9] analyses some decade of intensive dry-land farming in the Gadarif area, placed in the Eastern part of Sudan, had led to speedy LULC (Land Use/Land Cover) changes mainly due to agricultural development, government rules and environmental calamities such as scarcity. [10] described the aim of multi-source remote sensed data fusion for developing land cover classification. Land use/cover classification of fine-resolution RS (Remote sensed) data incorporate many sequential, angular, and shadow like options remains partial and therefore the support of various remote sensed features to land use/cover classification correctness remains unsure. [11] describe the Land use/cover classification in arid region was grand significance to the estimation, forecast, and management of land geologic process. Land cover classification show the red-edge group of Rapid-Eye imagery was efficient for plants identification and could develop land cover classification accuracy. The major centered on the representative inland arid desert region placed in Dunhuang Basin of northwestern China. [12] discuss a Large-scale mapping of LCC (Land Use/Cover Classification) was studied a difficulty of automatic processing of large geospatial data, which include the various unpredictability. To exercise three paradigms of computer sciences, namely, the decomposition technique ("divide and conquer") from the theory of algorithmic rule, the technique of active training from intellectual computing, and also the technique of re-enactment of satellite pictures/images from computer process/processing of digital imagery. [13] proposed a very high spatial and sequential resolution remote sensing dataset alter mapping, very complicated and various urban environments. The combined high-resolution aerial digital photos and elevation data, and it ware process exploitation object-based image analysis for mapping urban land use/covers and quantifying buildings. [14] evaluated the supervised classification of land use/cover area and time was a long-standing objective of the Planet Science area. Picture calibration and representative spatiotemporal sampling, these data-sets could be created by supervised classification of time-serial Land sat imagery. The side uncertainty of order extrapolation and also the deficiency of historical reference information or data, strategies should be applied to approximation uncertainty together with predictions over time. [15] discuss DSMs (Digital Surface Models) resulting from LiDAR (Light Detection and Ranging) data have been more and more integrated with high-resolution multispectral satellite or aerial imagery for urban land use/cover classification. An OB (Object-Based) classification approach to study the whether a combination of LiDAR height and moderation of data set can accurately map urban land cover.

TABLE I. LAND COVER CLASSIFICATION

Author/ Year	Classification Approach	Landsat Images	Type of Land cover/ Accuracy
[9]	Post Classification, Change Detection Method	Multi-Temporal Landsat or MSS, ETM+ASTER, Landsat-3,7; Landsat-5 TM	Cultivated, Wood, Fallow and Bare Land, Settlement 86% to 92%
[10]	Pixel Based Supervised using SVM	Landsat-8 OLI, MODIS, CCD, HIS	Forest, Water, Crop, Bare, Grass 87% to 92%
[11]	Random Sampling Method or RF NDVI, NDVI-RE	Rapid-Eye	Bare, Sandy Decertified , Wind Eroded, Saline and Alkaline Land 3.46% to 86.67%
[16]	Object Based and Pixel Based, USGS, LPGS	TM Data	Forest, Grass, Water, Farm Land, Developed Land, Barren Over All Accuracy 96%

[13]	Object- Based DTM, DSM Inheritance Rule, IKONOS	CIR orthophoto, CIR, DTM, DSM	Grass, Water, Shadow, Trees, Roads & Parking, Buildings, Bare land 75% to 96%
[12]	Pixel-by-Pixel, Data Fusion, MLP, NN	Geospatial Data, Satellite Data	Agricultural Land, Forest, Meadow, Water 88% to 97
[14]	Supervised Classification, Sampling and Signature-Modeling, Maximum Likelihood Classifier	Multi-Temporal	Water, Urban, Field, Forest 75% to 88%
[15]	Object-based N-DSM, Multi-Resolution Segmentation Algorithm	LiDAR Dataset	Tree, Pavement, Grass, Building 86.8% to 93.6%

III. LAND COVER CLASSIFICATION WITH MACHINE LEARNING: DATASET, METHOD, CLASSIFIER, ACCURACY

[17] investigated that the High resolution formation/raster information or data set for land use/cover map or modification analysis are normally non heritable through satellite or aerial imagery. Given a brand new technique was accomplished of map garrigue or phrygana vegetation furthermore as karst or ground-armour parcel in photos capture by a photographic camera. Include a reference pattern in each or every frame, the automated technique/method estimate the entire area covered by each or every land cover type. [18] studied the monitor land use/cover amendment was critical to economical environmental management and urban planning. To define two objectives: initial was to check/compare pixel-based (PB) random forest (RF) and decision tree (DT) classifier ways and a support vector machine (SVM) algorithmic program each in pixel and object primarily based approach for classification of land use/cover during a heterogeneous landscape for 2010. The second was to look at examine spatiotemporal land use/cover change or amendment over the previous twenty years (1990–2010) victimization Land sat data. [19] examined Optech Titan sensing element, multi-spectral data/information was for the primary or first time given for 3D ALS information/data set point clouds from a single sensing element. Totally different static aerial read/view, the technology was self-determining of external illumination standing, and there aren't any shadows on strength of images factor-made or manufactured from the info or data. [20] discuss the suitable methodologies for exact Land use/cover classification in the location Joshi-math district, (India). To proposed K-mean cluster algorithm approach for accurate mapping of land cover. [21] attempted to data fusion was a powerful tool for the merging of multiple sources of information to produce a better output as compared to the individual source. The data fusion also provide land cover varieties: uncovered land, cultivated land, uninhabited rangeland, green meadow, and Sutlej basin river land coped from remote sensing. [22] conducted a picture classification from RS (Remote Sensing) was attractive more and more urgent for monitor environmental change. Analyze the efficient algorithms to enhance classification correctness was critical. The use of multispectral HJ1B and ALOS (Advanced Land Observant Satellite) PALSAR L-band (Phased Array kind of L-band Artificial/Synthetic Aperture Radar) for the land use/cover classification exploitation learning-based algorithms. [23] attempted to GLCC (Global Land Use/Cover) info was essential for environmental amendment studies, land resource management, property development, and lots of alternative social advantages/benefits. The automated land use/cover classifiers, interactive method were use just in case of classification in troublesome areas and for internal control, leading to the POK-based (Pixel, Object and Knowledge Based) operational approach [24] studied the Random Forest (RF) classifiers for land use/cover classification of a difficult area was explore. Estimation was based on a number of criteria: mapping correctness, sensitivity to data set range and noise. The performance of the random forest with a number of trees and random split variables, decrease in training data set and noise adding up in terms of oob (oob error) and testing accuracy.

TABLE II. LAND COVER CLASSIFICATION WITH MACHINE LEARNING

Author/Year	Classification Approach	Landsat Images	Type of Land cover/ Accuracy
[17]	Pixel Based, Supervised Decision Tree Method, NN, SVM, and FL	Synthetic Aperture Radar (SAR)	Vegetation and Non-vegetation Areas
[18]	Pixel Based, Object-Based, Discriminative Method, Post-Classification Change Detection Method, DT, RF, SVM, OSVM	TM and ETM+	Forest, Water, Grassland, Farmland, Built-up area 86% to 93%
[19]	Object-Based, Land Cover 1. Classification method i. DSM, ii. DTM, 2. Change Detection Method, Histogram	ALS Dataset, Titan Dataset	Building, Trees, Asphalt, Gravel, Rocky Areas 90% to 96%
[20]	Pixel Based, Supervised, Unsupervised, Artificial Neural Network and Maximum Likelihood Field Classifier, K-mean Clustering and Iso-Cluster	Geo-Referenced (ArcMAP 10.2.1 Software), Landsat Imagery	Snow and Hills, Cloud, Vegetation Grassland, Water Body 77.8% to 93.5%

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[21]	Inter-Pixel, Fusion Method, ML, RF, J48, Naïve Bayes	Satellite Landsat, TM, Fused and Multispec traldataset , MSR5	Bare, Desert Rangel, Fertile Cultivated, Green Pastur, Sutlej Basin River Land 96.67% to 99.60
[22]	Pixel-Based and Object-Based, HJ1B and ALOS/PALSAR, SVM, RF, Maximum, Likelihood Classifier, (MLC), Decision Trees (DTs)	Enhanced Thematic Mapper Plus (ETM+), Thematic Mapper (TM)	Building/Urban, Cropland, Broadleaf Forest, Coniferous Forest, Mixed Forest, Sand, Grassland, Water, Improve The Overall Accuracy 5.7%
[23]	Pixel-Based, C-correction Support Vector Machine (SVM), RF	OLI, MODIS, HJ-1A, and ASTER	Water, Forest, Arable, Bare, Impervious, Shrub-Land 92.31% to 87.78%
[24]	Pixel-Based, Ensemble Learning Algorithms, Random Forest (RF), Classification Trees (CT), Bagging and Boosting	Thematic Mapper Landsat, Multi-Temporal Landsat	Water, Tropical Crops, Bare Soils, Herb. Dry, Lig. Irrig, Herb. Irrig, Oak Grove, Grasslands, Olive Grove, Shrub-Lands, Green- Lands, Conifers, Poplar Grove, Urban, 92%

IV. LAND COVER CLASSIFICATION WITH DEEP LEARNING: DATASET, METHOD, CLASSIFIER, ACCURACY

[25] discuss the deep learning techniques and strategies well-tried appropriate to group action with RS (Remote Sensing) data set primarily for scene of classification i.e. CNN (Convolution Neural Networks) on single image/picture, very little studies exist referring to the seral/sequential deep learning approaches i.e., RNNs (Recurrent Neural Networks) to compact with RS (Remote Sensing) series. [26] studied the DCNNs (Deep Convolution Neural Networks) had an instant ago emerged as a main paradigm for machine learning technique in a variety of domains. Used by deep convolution neural network for land use/cover classification in high-resolution RS (Remote Sensing) imagery. [27] researched in classify and acceptance of these photos was time-consuming. The land use/cover type's acceptance model for field photos was instructed supported on the deep learning technique. The model combines a pre-trained convolution neural network (CNN) because the image/picture feature extractor and therefore the multinomial provision regression model as the feature classifier. The label field photos from the Global Geo-Referenced Field Photo/picture Library (http://eomf.ou.edu/photos) were choosing for model training and validation.

TABLE III. LAND COVER CLASSIFICATION WITH DEEP LEARNING

Author/Year	Classification Approach	Landsat Images	Type of Land cover/ Accuracy
[25]	Pixel-Based and Object-Based, RNs, LSTM, RF, Naive Bayes, KNN, and SVMs	Thau Data Set, Reunion Island Data Set	Water, Forest and Woods, Summer Crops, Winter Crops, Grassland, Sclerophyll Vegetation, Truck Farming, Bare Soils, Salt Marshes, Vineyards, Urban Areas, Sparse Vegetation, Rocky and Bare Soil, Sugarcane Crops
[26]	Regions and Objects, FE, DCNN	UC Merced (UCM), SVM, RSD	98.5%
[27]	Feature Extraction and Fine-Tunin, Transfer Learning, Convolutional Neural Network (CNN)	Geo-Referenced Dataset, YFCC (Yahoo Flickr Creative Commons) Dataset, ImageNet Dataset,	Forest, Shrublands, Savannas, Cropland, Plantations, Grassland, Wetlands, Urban Barren, Open Water Snow and Ice, 48.40% to 76.24%

V. CONCLUSION

This paper presents the survey of the work done in last year's pre processing algorithms in the area of land cover classification. Also issues related to the insufficient training samples, accuracy and greater types of objects for classification has been observed. Study ashore set land use/cover classification have report the higher performance of object based mostly and pixel based in numerous landscapes like forest, water, bare land, tillage, inexperienced and wetlands. The major advantage of object based mostly and pixel based is that it represents the categorization units as real word objects on the bottom or earth position and hence reduces among the category variability. These approaches additionally involves several steps in its work-flow like choosing coaching /training dataset samples, developing rule the sets and selecting classifiers, all of that have the potential to have an effect on the classification accuracy or correctness if not properly done.

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