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Vegetation Analysis and Land Cover and Crop Types Classification of Granite Quarry Area of Dharmapuri and Krishna Giri Districts of Tamil Nadu

P.Nithya , G. Arulselvi

Abstract: ***Deep Learning (DL) constitutes a recent, modern technique for image processing and data analysis, with promising results and large potential. As deep learning has been successfully applied in various domains, it has recently entered also the domain of agriculture and their allied services. The study mentioned that the aspect and altitude influenced the forest types and vegetation pattern. Deep learning (DL) is a powerful state-of-the-art technique for image processing including Remote Sensing (RS)images. This letter describes a multilevel deep learning (DL) architecture that targets land cover and crop type classification and detection from multitemporal multisource satellite imagery. The ubiquitous and wide applications like scene image understanding, video surveillance, robotics, and self-driving systems triggered vast research in the domain of computer vision in the most recent decade. Being the core of all these applications, visual recognition systems which encompasses image classification, localization and detection have achieved great research now. Due to significant development in neural networks especially deep learning, these visual recognition systems have reached remarkable performance. Object detection is one of these domains witnessing great success in computer vision. This research paper demystifies the role of deep learning techniques based on Convolutional Neural Network(CNN) for object detection. Deep learning frameworks and services available for object detection are also enunciated. Deep learning techniques for state-of-the-art object detection systems are assessed in this research paper. Experiments are carried out for the joint experiment of crop assessment and monitoring test site in Ukraine for classification of crops in a heterogeneous environment using nineteen multitemporal scenes acquired by LANDSAT-8 and SENTINEL-1A RS satellites. The architecture with an ensemble of CNNs outperforms the one with MLPs allowing us to better discriminate certain summer crop types, in particular Teak and Sugarcane, and yielding the target accuracies more than 85% for all major crops in Tamilnadu(Banana Tree, Teak, Paddy, and Sugarcane).***

Index Terms: ***Vegetation, ArcGIS, Land Use Crop Type, Geographic Information System (GIS), Remote Sensing (RS), Images Classification, Deep Learning(DL).***

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I. INTRODUCTION

In recent years, deep learning has been widely used and has become mainstream in artificial intelligence and machine learning[2]. Deep learning is a representation-learning method that can automatically learn internal feature representations with multiple levels from original images instead of empirical feature design, and has proved to be very efficient in image classification and object detection. In contrast, vegetation indices such as NDVI only use several bands and may lead to low performance in complicated situations, e.g., crop classification where the spectrums, periods, geometry, and the interactions of various types of crops might be considered. Whereas, original temporal images used as feature input could contain noises or unfavorable information that decrease the performance of a classifier. Deep learning(DL) requires sufficient manual samples that are difficult to be obtained in our situation when crop types, varieties of a certain types of crop, and planting season vary from time to time. To achieve a satisfactory learning result with limited samples and reduced amount of labor work, here it is introduce a semi-automatic semi-supervised active learning strategy. Active learning is used to pick up the most helpful unlabeled samples (i.e., samples supposed to best improve model performance), according to their scores to each label predicted from the current CNN model, for manual checking, and model retraining, iteratively.

II. OBJECTIVES OF THE STUDY

The present study is mainly aimed to detect the vegetation types on the surrounding environment within 50Kms radius of mines using remote sensing techniques. In view of publications on mining related vegetation impacts, this study will form the baseline work for future comparison and assessment of vegetation impacts in the study area of Krishnagiri and Dharmapuri district.

The objectives of the study are:

The main objective of our study is to represent distinctive spatio-temporal features of crops by deep learning.

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III. STUDY AREA

3.1 Krishna giri District

Krishnagiri district covers an area of 5143km² Krishnagiri district is bound by Vellore and Thiruvannamalai districts to the east, state of Karnataka to the west, the state of Andhra Pradesh to the north and Dharmapuri District to the south. This district is elevated from 300m to 1400m above the mean sea level. The important crops of Krishnagiri District are paddy, maize, ragi, banana, sugarcane, cotton, tamarind, coconut, mango, groundnut, vegetables and flowers. The district has an excellent scope for agri-business. According to the 2011 census, Krishnagiri district had a population of 1,879,809 with a sex-ratio of 963 females for every 1,000 males, much above the national average of 929[5]. It is located between 11°12'N and 12°49'N latitude, 77°27'E to 78°38'E longitude.A total of 217,323 were under the age of six, constituting 112,832 males and 104,491 females. The revenue block of Krishnagiri is Bargur, Hosur, Kaveripattinam, Kelamangalam, Krishnagiri, Mathur, Shoolagiri, Thally, Uthangarai and Veppanapalli. Hosur, one of the most industrialized places in the state, is located in this district.

Production	Area (hectares)
Paddy	20,687
Ragii	48,944
Other minor crops	11,937
Pulses	48,749
Sugarcane	50,000
Mango	30,017
Coconut	13,192
Tamarind	1,362
Other crops	43,199

Net cultivated, irrigated, double, multiple cropped, cultivable wasteland, water land and forest

1) *Mining based activities*

In Krishnagiri district, quarry leases are being granted for granite in Patta lands. Rough stone and earth quarry leases are being granted in government and patta lands under Tamil Nadu Minor Mineral Concession Rules 1959. The Public Works Department (WRO wing) is operating sand quarry in riverbeds of the study area.

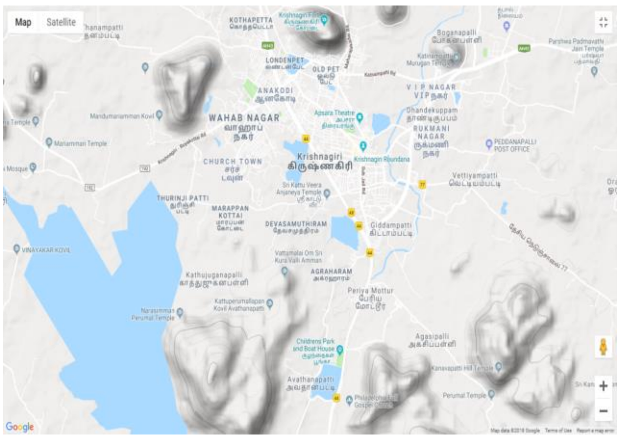

Figure 1: Full map of Krishnagiri

A state owned corporation called Tamil Nadu Metals and Mineral Ltd is also earning quarry and mining grants in government lands. It is ascertained that nearly 27,000 workers are being engaged in quarry activities.

3.2 Dharmapuri District

According to 2011 census, Dharmapuri district had a population of 1,506,843 with a sex-ratio of 946 females for every 1,000 males, much above the national average of 929[3]. A total of 167,940 were under the age of six, constituting 87,777 males and 80,163 females.

Figure:2 Revenue map of Dharmapuri and Krishnagiri Districts

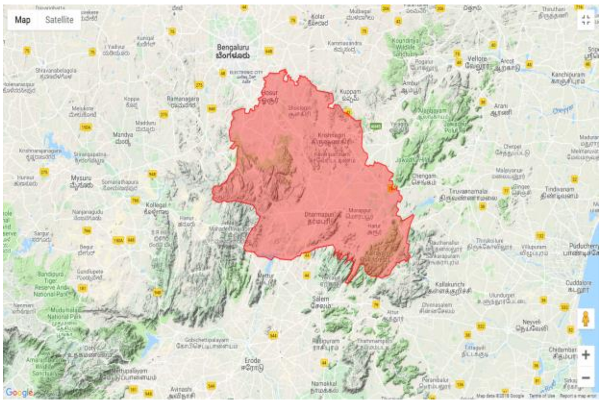

Figure:3 Location map of Dharmapuri and Krishnagiri Districts

Dharmapuri and Krishnagiri districts account for more than 60-70% total mango production in Tamil Nadu.[7] It is a major producer of Ragi and Saamai crops in the state. Exotic crops like dates are also being cultivated by some farmers in the areas around Ariyakulam. Revenue taluks is Dharmapuri, Harur, Karimangalam, Nallampalli, Palacode, Pappireddipatti and Pennagaram.

IV. LITERATURE SURVEY

Karl and Axel, (2013) note that using Global Position System (GPS) to obtain vegetation data, may be spatially more accurate than those acquired through satellite imageries, which has their accuracy or precision limited to the resolution of the pixel. Although, there is a possibility of image pixels being compromised when vegetation types are mixed, there would still be problems with the accuracy since DN values for each pixel would remain single.

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Campbell and Wynne(2011) discussed about the accuracy of remotely sensed images are of great concern to prospective users of LULCC maps. Information about the degree of accuracy of the data presented in a LULCC map is needed to ascertain its authenticity. Accuracy of an image can be defined as the measure of agreement between a standard, acknowledged to be correct and an image of unknown quality. On the other hand, precision of an image is defined as the degree of sharpness or certainty of pixels in an image. Accuracy has many practical implications; for example, it affects the legal standing of maps and reports derived from remotely sensed data. Accuracy cannot be assessed solely by the appearance of a map, since the overall accuracy might be unrelated to the map's cosmetic qualities. However, determination of the accuracy of a map of an area understudy, should be done in a manner that allows quantitative measure and comparisons with alternative maps and images of the same area **(Campbell and Wynne, 2011).**

Leaf Recognition. In recent years, many researches have been conducted on leaf recognition. Kumar et.al [11] proposed mobile app for recognize 184 kind of trees by extracting the curvature features.Wang et al. [12] use Pulse-Coupled Neural Network (PCNN) to extract leaf features. They achieve accuracy above 90% in three different datasets. While Hu et al. [13] applies Multiscale Distance Matrix(MDM) to get geometric structure of the leaf shape.

Deep Learning for Leaf Recognition. Recently, several papers start to utilize CNN to do the leaf recognition [9][10]. Data augmentation was added [9] in order to improve the accuracy. Lee et al. [10] used the AlexNet [3] model to identify leaf and visualize its feature to analyze which features are important for the leaf identification.

V. LIMITATION OF EXISTING WORK

- The implementation still lacks in accuracy of result in some cases. More optimization is needed.
- Priori information is needed for segmentation.
- Database extension is needed in order to reach the more accuracy.
- Very few Plant and Trees have been covered. So, work needs to be extended to cover more Plants and Trees.
- The possible reasons that can lead to misclassifications can be as follows: plants and trees varies from one plant to another, features optimization is needed, more training samples are needed in order to cover more cases and to predict the Plants and Trees more accurately.

VI. RESEARCH GAPS

To remove these research gaps a new methodology for automatic detection using Deep Learning(DL) technique as well as classification of plant and Trees using image segmentation has been proposed.

VII. PROBLEM STATEMENT

Dharmapuri and Krishnagiri Districts is endowed with vast rock formations and stone hills, making it an ideal hub for granite quarrying operations. In view of its geology, there has been an emergence of several quarrying companies and activities within the two districts and surrounding communities in recent years. Raw materials from granite quarrying sites are patronized by customers within these region and beyond for various construction activities. Furthermore, the Dharmapuri and Krishnagiri Districts is rapidly urbanizing and its accelerated sprawl is gradually leading towards conversion of forest lands into larger artificial environment. The migration of many settlers from the conventional central business district within the region to our area and its surrounding communities has put enormous pressure on land space coupled with rise in population. The upsurge in demand for land space for constructing residential or commercial facilities has made land acquisition, sole prerogative of the highest bidder. In many cases, land close to granite sites are a seriously encroached upon by desperate land seekers at the expense of environmental protection. Likewise, some of the granite companies also operate in areas close to existing human settlements posing serious environmental and health risk to the exposed communities. In view of these dynamics, this research study attempts to explore and demonstrate the application of remote sensing technique as a useful tool to detect Vegetation Types in the Dharmapuri and Krishnagiri Districts of Tamilnadu is the study.

VIII. ADVANTAGES OF PROPOSED ALGORITHMS

The advantages of proposed algorithm are as follows:
1. Use of estimators for automatic Initialization of cluster centers so there is no need of user input at the time of segmentation.
2.The detection accuracy is enhanced with proposed algorithm.
3.Proposed method is fully automatic while existing methods require user input to select the best segmentation of input image.
4.It also provides environment friendly recovery measures of the identified name of the Trees and Plants.

IX. DATA USED AND METHODOLOGY

Dataset Acquisition

Landsat 5/7 satellite images of the southern agricultural growing region of Dharmapuri and Krishnagiri Districtd of Tamilnadu) are used to evaluate and compare the accuracy of the results described here. The longitude is : N: 0.211, E: 1.364, S: 0.211, W: 1.364

9.1. Object detection as foremost step in visual recognition activity

Object detection is the procedure of determining the instance of the class to which the object belongs and estimating the location of the object by outputting the bounding box around the object. Detecting single instance of class from image is called as single class object detection, whereas detecting the classes of all objects present in the image is known as multi class object detection. Different challenges such as partial/full occlusion, varying illumination conditions, poses, scale, etc are needed to be handled while performing the object detection. As shown in the figure 3, object detection is the foremost step in any visual recognition activity.

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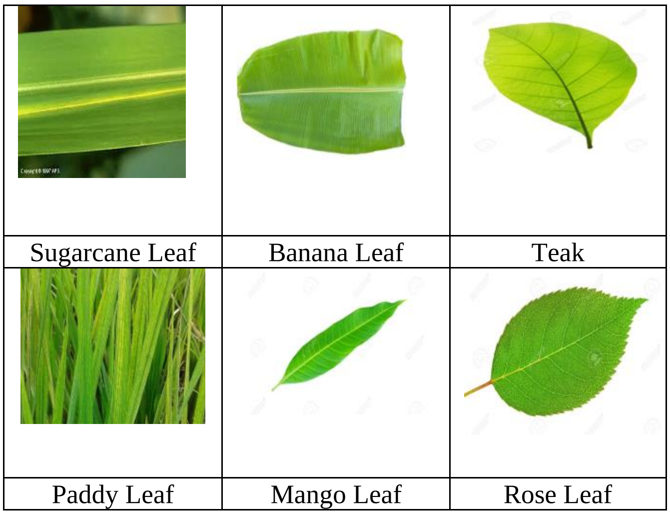
9.2 Object detection using CNN Deep

CNNs have been extensively used for object detection. CNN is a type of feed-forward neural network and works on principle of weight sharing. Convolution is an integration showing how one function overlaps with other function and is a blend of two functions being multiplied. Fig. 4 shows layered architecture of CNN for object detection. Image is convolved with activation function to get feature maps. To reduce spatial complexity of the network, feature maps are treated with pooling layers to get abstracted feature maps. This process is repeated for the desired number of filters and accordingly feature maps are created. Eventually, these feature maps are processed with fully connected layers to get output of image recognition showing confidence score for the predicted class labels. For ameliorating the complexity of the network and reduce the number of parameters, CNN employs different kinds of pooling layers as shown. Pooling layers are translation-invariant. Activation maps are fed as input to the pooling layers. They operate on each patch in the selected map.

9.2.1 Image Pre-Processing

This process is aiming at extracting regions in the image. Because the input image from satellite. So applying some simple image preprocessing techniques on the image is needed, especially in the condition where a leaf is not overlapped with each other.



9.2.2 Image Sharpening

For edge detection is it necessary to sharpen the image, so that edges can be fully retrieved. Image sharpening is achieved by convolving the following kernel K with the input image.

9.2.3 Thresholding

To generate a binary image, a black pixel is used to indicate the foreground and white pixel the background, and the Otsu method [6] is applied to an image that is made grayscale beforehand. Otsu method will automatically select threshold for image segmentation by utilizing the 0-th and the firstorder cumulative moment of the gray-level histogram.

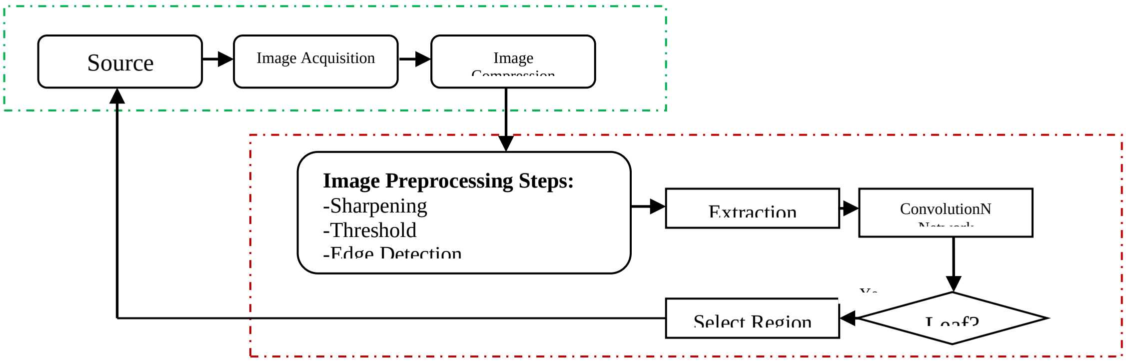


Figure 4. The overall process flows.

9.3 Frameworks and Services of Object Detection

The list of deep learning frameworks available till date is exhaustive. We have mentioned some significant deep learning frameworks. The frameworks are studied from the point of view of features exhibited, interface, support for deep learning model viz. convolutional neural network, recurrent neural network (RNN), Restricted Botltzmann Machine (RBM) and Deep Belief Network (DBN) and support for Multi-node parallel execution, developer of the framework and license. These services can be availed through the APIs mentioned in the table.

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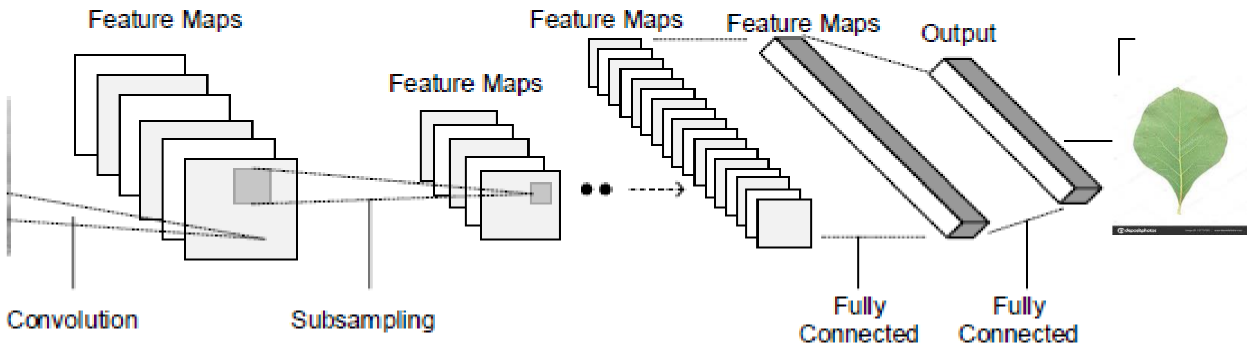

Fig. 5. Use of Convolutional neural network for object detection

In the batch normalization layer, Equation. 2 and 3 are used at each layer to obtain the mean and variance. Using the obtained mean and variance, the input is normalized as shown in Equation 4. The denominator of Equation 4 is the sum of the variance, and the constant and numerator are normalized by dividing the input value minus the mean. The nonlinearity can be obtained by multiplying and adding the scale factor and the shift factor to the normalized value, as shown in Equation 5. Batch normalization solves the overfitting problem by normalizing the inputs to each layer, which allows the learning speed to be fast and achieves regularization.

9.4 Application Domains of Object Detection

Object detection is applicable in many domains ranging from defense (surveillance), human computer interaction, robotics, transportation, retrieval, etc. Sensors used for persistent surveillance generate petabytes of image data in few hours. These data are reduced to geospatial data and integrated with other data to get clear notion of current scenario. This process involves object detection to track entities like people, vehicles and suspicious objects from the raw imagery data [23]. Spotting and detecting the wild animals in the territory of sterile zones like industrial area, detecting the vehicles parked in restricted areas are also some applications of object detection. Detecting the unattended baggage is very crucial application of object detection. For autonomous driving, detecting objects on the road would play important role. Detection of faulty electric wires when the image is captured from drone cameras is also application of object detection. Detecting the drivers' drowsiness on the highway in order to avoid accident may be achieved by object detection. The requirements of aforementioned applications vary according to the use case. Object detection analytics can be performed offline, online or near real time. Other factors like occlusions, rotation invariance, inter-class and intra-class variation, and multi-pose object detection need to be considered for object detection.

9.5 State-of-the-art deep learning-based approaches of Object Detection

Table 8 compares deep learning methods for object detection which is useful for the research community to work further in the domain of deep learning-based object detection. Szegedy et al. pioneered the use of deep CNN for object detection [33] by modeling object detection as a regression problem. They have replaced last layer in the AlexNet [2] with regression layer for object detection. Both the tasks of detection and localization have been performed using object mask regression. DeepMultiBox [34] extended the approach of [33] to detect multiple objects in an image. How the CNN learns the feature is a major issue. The task of visualizing the CNN features is done by Zeiler et al. [35]. They applied both CNN and deconvolution process for visualization of features. This approach outperforms [2]. They have also justified that performance of deep model is affected by the depth of the network. Overfeat model [36] applies Sliding window approach based on multi-scaling for jointly performing classification, detection and localization. Girshick et al. [37] proposed deep model based on Region proposals. In this approach, image is divided into small regions and then deep CNN is used for getting feature vectors. Features vectors are used for classification by linear SVM. Object localization is done using bounding-box regression.

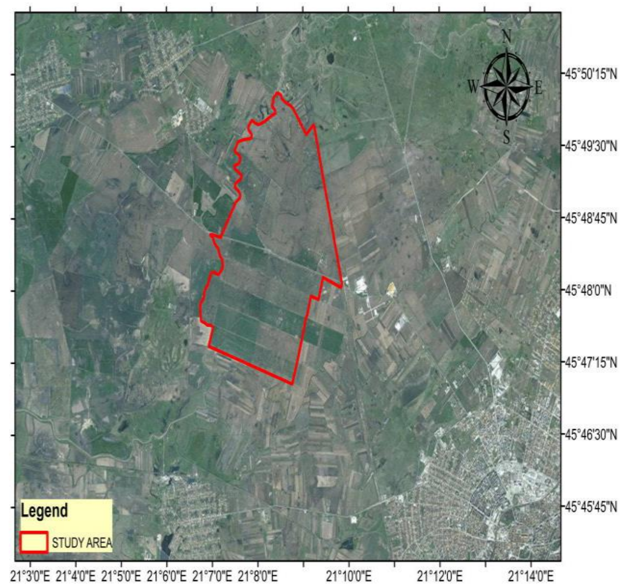

Figure 6: Study areas of Krishnagiri District

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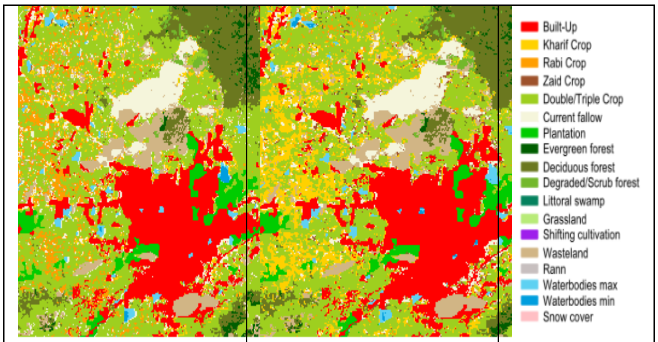

(7a)Image retrived in the year 2014 from Krishnagiri District	2(7b) Image retrived in the year 2018 from Krishnagiri District	

Figure 7: Images retrived from LANSAT satellite

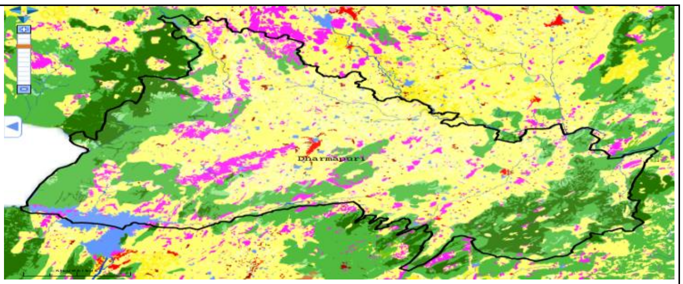

Figure 8a: Image retrived from LANDSAT sattilite (Dharmapuri District)in the year 2014

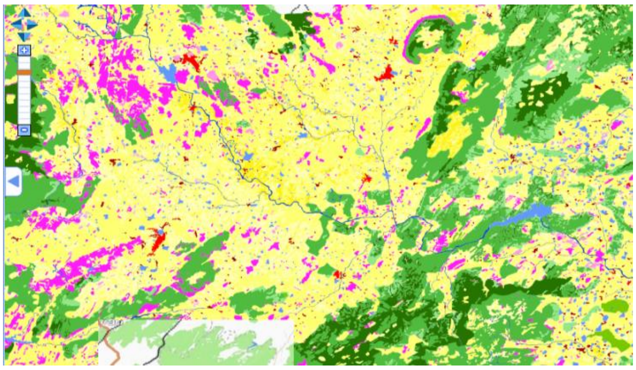

Figure 8b: Image retrived from LANDSAT sattilite (Dharmapuri District)in the year 2018

On the similar lines, [38] used regionlets for generic object detection irrespective of context information. They designed Support Pixel Integral Image metric to extract features based histogram of gradients, covariance features and sparse CNN. Earlier before the dawn of deep learning, object detection was preferably performed using deformable part model technique [39]. Deformable part model technique performs multi-scale based object detection and localization. Based on the principles of this model, Ouyang et al. [40] put forth pooling layer for handling the deformation properties of objects for the sake of detection.

Table 1. Comparison of deep learning-based Object Detection methods

Method	Working	Features	Reference
Deep saliency network	CNNs are used for extracting the high-level and multi-scale features.	It is challenging to detect the boundaries of salient regions due to the fact that pixel residing in the boundary region have similar receptive fields. Due to this, network may come with inaccurate map and shape of the object to be detected.	[13]
Generating image (or pixels)	This method is used when the occurrence of occlusions and deformations is rare in the dataset.	This method generates new images with occlusions and deformations only when training data contains occurrences of occlusions and deformations.	[14]
Generating all possible occlusions and deformations	In this method, all sets of possible occlusions and deformations are generated to train the object detectors.	This method is not scalable since deformations and occlusions incur large space.	[15-16]
Adversarial learning	Instead of generating all deformations and occlusions, this method use adversarial network which selectively generates features mimicking the occlusions and deformations which are hard to be recognized by the object detector.	As this method generates the examples on-the fly, it is good candidate to be applied in real time object detection. As it selectively generates the features, it is also scalable.	[19]

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Part-based method	This method represents object as collection of local parts and spatial structure. This method exhaustively searches for multiple parts for object detection.	This method addresses the issue of intra-class variations in object categories Such variations occur due to variation in poses, cluttered background, partial occlusions	[20]
CNN with part-based method	In this method, deformable part model is used for modelling the spatial structure of the local parts whereas CNN is used for learning the discriminative features.	This method handles the issue of partial occlusions. But requires multiple CNN models for part based object detection. Finding out the optimal number of parts per object is also challenging.	[21-23]
Fine-grained object detection method	This methods works on annotated object parts during training phase. Part-localization is the fundamental component used in testing phase.	This method has capability to figure out the differences in inter-class objects at finer level. And they work more on discriminative parts compared to generic object detection methods.	[32-35]

X. COMPARATIVE RESULTS

ResNet require more time to train because of its deep architecture and uses much bigger memory to save that model. However, it recognizes digits much faster than CNN even though it had deeper network structure, it spends 12-13 seconds to make prediction. Since it shares the same parameters during training process and uses shortcut connections to avoid vanishing and degradation problems as mentioned earlier. This behavior allows the network to act much faster during prediction, as showed in [14] our results also reflected similar outcomes concerning this condition. Unlikely,our proposed also uses big memory to save the model 68.5Mb, but it recognizes digits very fast and very accurately. Other essential factor is number of inputs:

Table 2. Evaluation time, Accuracy, training time, number of inputs and memory usage

S.No	Performance	Regression Model	CNN	ResNet	CapsNet	Proposed
1.	Evaluation time (s)	5-8	12-13	9-11	3-4	1-2
2.	Memory (MB)	6.5	45.25	55.10	67.25	68.5
			Dataset			
3.	Accuracy (%)	93.5	92.1	98.1	97.3	99.4
4.	Training time (min)	12	25	44	45	55
5.	Number of inputs	50000	50000	50000	50000	40000

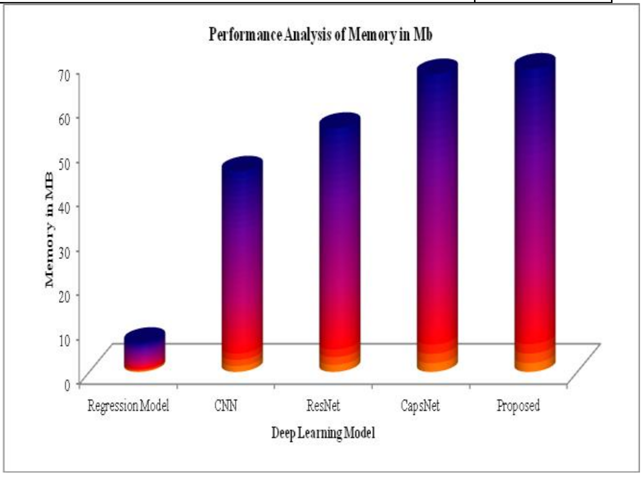

Figure 9: Performance Analysis of Memory in Mb

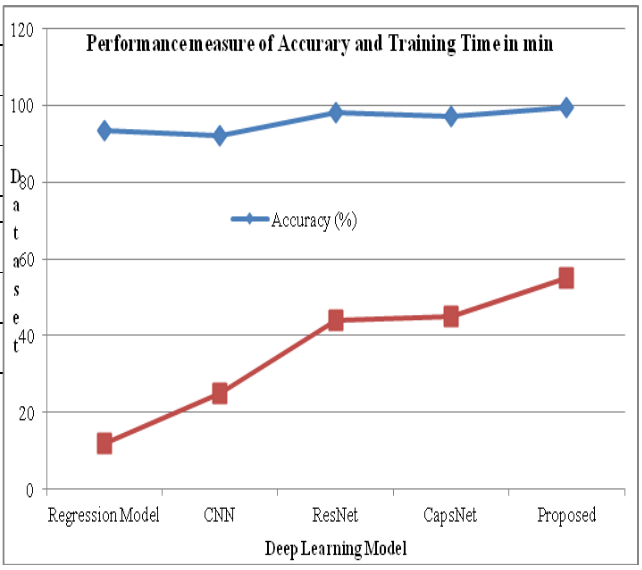

Figure 10: Performance measure of Accurary and Training Time

Here it is use 50,000 inputs to train our models accept CapsNet. Here it is reduce the number of inputs for our proposed and use 40,000 inputs to feed the network. Surprisingly, our proposed model reaches the highest accuracy

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among remainders with smaller number of inputs Table 2.

XI. DISADVANTAGES

The main disadvantages in this system was need to take all the images/photoes in broad daylight failing which accuracy could be adversely affected.

XII. CONCLUSION

The study indicated that there are 11 land use land cover classes in Krishnagiri and Dharmapuri District of Tamilnadu. The forest vegetation pattern is influenced by many factors among them altitude and aspect are important once to decide the vegetation. This paper presents the different trees and plants classification techniques used for trees and plants detection and an algorithm for image segmentation technique that can be used for automatic detection as well as classification of plant and trees using leaf later. Banana, beans, jackfruit, lemon, mango, potato, tomato, and sapota are some of those ten species on which proposed algorithm is tested. Therefore, related leaf for these plants and trees were taken for identification. With very less computational efforts the optimum results were obtained, which also shows the efficiency of proposed algorithm in recognition and classification of the Trees and Leaf types. To improve recognition rate in classification process Artificial Neural Network, Bayes classifier, Fuzzy Logic and hybrid algorithms can also be used.

XIII. FUTURE ENHANCEMENT

In our future wok, here intend to create a system which is more robust to light variation and to include vein patterns as a feature. We will also create more elaborate dataset.

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