A MODERN WAY TO ANALYSE AND CLASSIFY NATURAL VEGETATION SPECIES USING DEEP LEARNING APPROACHES

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ABSTRACT

As the most visible and functional part of a plant, leaf form, coloration, and size are all susceptible to environmental and biotic influences. Since different plant species have distinctive leaf shapes, these individual components are crucial to the development and implementation of plant recognition systems. Depending on the type of weather and other circumstances (such as the amount of light, humidity, temperature, and wind speed), a plant's leaf production, leaf deformation, leaf colour, leaf location on the branch, and other characteristics may change. Training and testing datasets originated from diverse geographical regions with different image resolutions, and the detection performance of two deep learning approaches, DeepLabV3+ and our customised convolutional neural network (CNN), was compared. In addition, we offer a unique object-based method for detecting vegetation using NDVI, computer vision, and ML. High-resolution airborne colour pictures, including red, green, and blue (RGB) and near-infrared (NIR) bands, were processed using the vegetation detection algorithms. The two deep learning approaches were also tested using RGB colour images only, without the NIR band, to compare their detection efficacies. Sample images from the datasets are used to illustrate the detection performances of the deep learning methods in comparison to the object-based detection approach.

1 Introduction

Applications of land cover classification [1] include change detection monitoring [2], construction surveying [3], agricultural management [4], green vegetation classification [5], locating safe landing zones for unmanned aerial vehicles [6,7], protecting biodiversity [8,9], determining land use [10], and planning cities [11,12]. Identifying vegetation is a significant use for land cover classification. Chlorophyll-rich vegetation recognition was a key step in Skarlatos et al.'s [3] work to enhance the precision of the estimated digital terrain model (DTM). Vegetation was removed from the DSM mechanically upon detection, allowing for more accurate DTM calculations. Autonomous mobile robots that operate in off-road situations benefit from Bradley et al.'s [11] detection of chlorophyll-rich plants to aid in navigation. Some vegetation, such as round bushes, were incorrectly identified as mines by mine detection algorithms, so Zare et al. [12] used vegetation detection for mine detection to minimise false alarms. To track the temporal and spatial changes brought on by forest fires and an increasing population, Miura et al. [13] employed vegetation detection algorithms to keep tabs on Amazonian vegetation patches. Normalised difference vegetation index (NDVI) [14–16] uses the unique spectral absorption phenomena of green plants in the red and near-infrared parts of the sun spectrum to detect vegetation.

Fossils found all around the world show that plants from the Devonian period did not reach very great heights, and that their simple structures was another shared characteristic. Without leaves, these plants instead featured stalks with branching patterns and perhaps spines. Throughout their evolution, they've experienced varying degrees of complexity. In addition, plant species can now be found in every region of the earth, including the oceans. Plants play special roles in their environments and in the lives of other species because of these factors. Understanding their functions is enhanced by thinking about how they affect people's daily lives. Historical records reveal the growth of agricultural technology well before the rise of the Roman Empire, supporting the long-held belief that plants are tremendous energy sources.

Many scientists today are engaged in direct or indirect study of plants, reflecting the expanding role that plants play in contemporary society. Plants have both direct and indirect effects on the climate and ecosystems. Agricultural, energy, environmental, health, medical, and other fields can all benefit from them. Due to rising populations and shifting climatic conditions, global food security has assumed greater significance in the modern era. As a result, researchers have been putting greater effort into creating cutting-edge farming techniques. In addition, there are many facets of farm management that must be taken into account. One such facets is optimisation. One method to making the most of a farm's resources and maximising output is the detection of weeds and pests in agricultural fields. Due to the wide variety of weeds, it is difficult for farmers to be familiar with all of them. There is no financial basis for employing plant specialists to identify plant types, and it is also impractical to host this expertise on farms around the world. When two different plants have the same shape of leaves, human observations are often incorrect due to a lack of knowledge and bias. As a result, there are situations in which it is challenging to disentangle observed human data.

Identifying plants using traditional methods is sometimes inefficient because of the high cost, lengthy process, and dependence on human input. Therefore, it is necessary to create a system that can automatically recognise and identify plants. Important elements, constraints, and parameters for evaluating the applicability of such a system are its generalisation and characterization. Furthermore, such a system can be implemented and used as the foundation of contemporary agriculture.

The German Federal Ministry of Food and Agriculture is responsible for making broad policy decisions. By holding government competitions like "Our Village has a Future" [6], it hopes to inspire locals to develop and implement their own plans to ensure the continued viability of farms and communities. The significance of adopting cutting-edge farming practises will so reach all corners of the nation.

Even for experts in botany and plant sciences like botanists, identifying plants can be difficult. Because of its relevance to areas as diverse as medicine, the pharmaceutical business, contemporary agriculture, etc., this area of study enjoys a great deal of glitz and glamour. Huge amounts of time and energy have been invested in trying to automate plant detection by finding a solid solution and developing a precise system [7, 8, 9, 10].

Previously [7], FathiKazerouni described and recognised various plant species from the Flavia dataset using up-to-date description methods. The scale-invariant feature transform (SIFT) technique has been utilised for feature detection and extraction, and it has been integrated with two other approaches, the features from accelerated segment test (FAST) and the HARRIS methods. In this case, SVM, a machine learning task, makes use of the outcome. The researchers in [8] used the SURF algorithm and integrated SURF techniques for plant species recognition.

2. LITERATURE SURVEY

Tan, Jing Wei, and Chang, Siow-Wee[1]. In this study, we use convolutional neural networks to analyse photos of leaves from certain tree species. Pre-trained AlexNet CNN, fine-tuned pre-trained AlexNet CNN, and the suggested D-Leaf CNN models were all used. Several classification methods were trained and educated using the extracted features. In this study, five different classifiers were used: a Convolutional Neural Network (CNN), a Support Vector Machine (SVM), an Artificial Neural Network (ANN), a k-NN, and a Naive Bayes (NB). As a baseline, we compared our system to one that segmented leaf veins using the Sobel edge detection methodology and took measurements of vein morphology. The literature review indicates that this is one of the rare studies that apply CNN to the problem of classifying tropical tree species on the basis of their leaves' morphology and venation patterns.

Dr.Thippeswamy G. Pankaja and PankajaK.Countless varieties of plants are easily accessible worldwide. Developing efficient and fast categorization systems to handle massive amounts of data has been an active area of study. Due to their vital role in maintaining a healthy ecosystem, trees and plants require careful categorization. Several auxiliary methods aid the overall order strategy.

Planning a data set with one of the distinct categories allows one to keep an eye on a recognisable proof or Classification problem. The first step of this method is to compile a database of leaf images, complete with test leaf images and their corresponding plant data. Using image editing techniques, we can hide the picture's essentials. The credibility of the established evidence framework depends on the consistency of the highlights. As a result, artificial intelligence techniques are used to interpret the plant or leaf. This document provides a summary of the various methods of proof used to differentiate between leaves.

Using images of leaves and flowers, Thi Thanh-Nhan Nguyen et al. [8] combine deep learning with a carefully crafted human aspect to establish plant identification. This paper makes double-layered promises. We have initially carried out a close evaluation of deep learning and hand-structured element for plant distinguishing evidence, and this has been done for each and every organ image. In our experiments, we use two different methods for deep learning and hand-structured components: convolutional neuron arrange (CNN) and key-value pair descriptors (KDES). Secondly, we offer a method for plant ID by late-combining the distinctive proof after-effects of leaf and flower. This is in light of the fallout from the primary commitment. Experimental results on the ImageClef 2015 dataset demonstrate that, for generally difficult instances (leaf captured on fundamental foundation), hand-planned elements outperform deep learning. Nonetheless, substantial knowledge only proves its worth under typical conditions. Evidence for the identification of a plant based on its leaves is strengthened by include images of its flowers in the mix.

SalarRazavi, Hulya Yalcin [9] With mounting pressures over growing global populations and finite food supplies, it's imperative that we take advantage of the advantages of modern recruiting technology to boost the productivity of plant fields. Preparation progress is vital not just to food production endeavours but also to robust people and other relevant authorities. It's not out of the question that this will increase farmers' productivity, give them a deeper understanding of the link between widespread plantings and bountiful harvests, cut down on labour expenses, and make transportation faster and more precise. Realising AI techniques, such as large neural frameworks on data cultivation, has recently widened the scope of monster thought. Adapting management strategies for different plant species is a major challenge.

The group led by SURBHI GUPTA [10] The changed identification of plants is shown in the evidence of species recognition in plants. However, many factors, such as leaf, owers, natural items, and seeds, could contribute to the decision; however, leaf characteristics are the most significant. It is simple to read a plant leaf as identification evidence because it is always available when the plant is separated from other parts. This research presented a new plant creature bunches classifier that uses a Multilayer Perceptron with Ad boosting to extract morphological information. Preparation, feature extraction, incorporation decision, and characterization are all parts of the proposed framework.

3. Materials and Methods

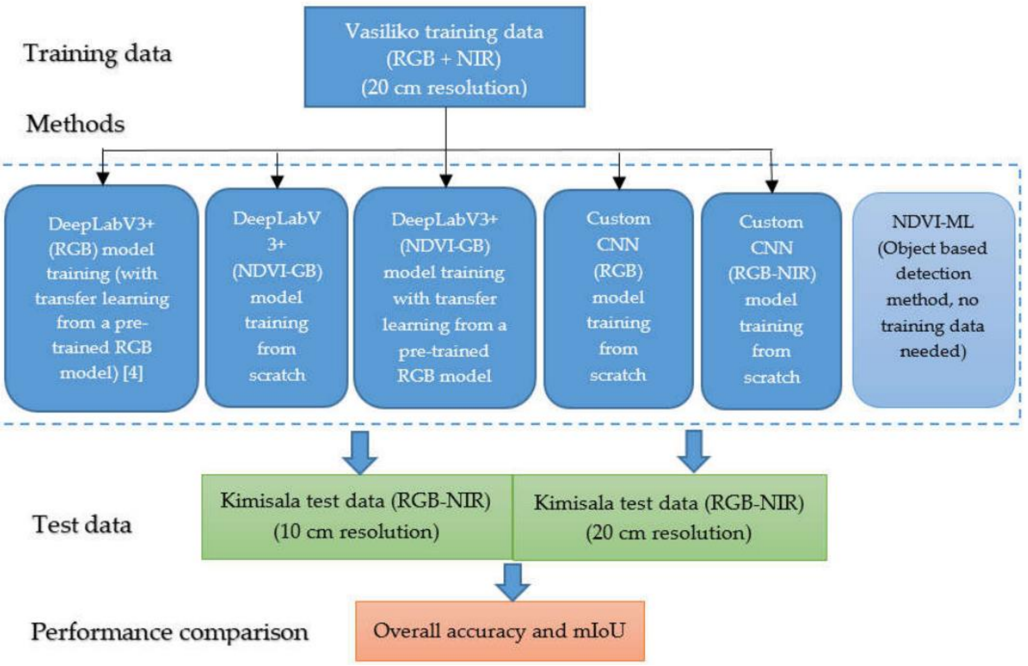

Figure 1. Block diagram showing the used dataset and applied methods. mIoU is the meanintersection-of-union metric.

Figure 1 is a block schematic of the dataset and methodologies utilised in this work.

Dataset Used for Training and Testing

The dataset used in this work comes from two previously examined sites, Vasiliko in Cyprus and Kimisala on Rhode Island, and was first used in Skarlatos and Vlachos [3]. Two independent UAV flights were used to take the photos and the data was gathered with a customised, non-calibrated near-infrared camera. SwingletCam UAV was used for both flights, which were carried out on separate occasions. A Canon IXUS 220HS camera was carried aloft in the maiden trip, which averaged 78 metres in altitude. The second flight was carried out at a height of 100 m and utilised a Canon PowerShot ELPH 300HS camera customised for near infrared photography. SensFly, a producer of UAVs, supplied both cameras. Two orthophotos were generated by processing the raw UAV images with Agisoft'sPhotoscan. Colour RGB and NIR orthophotos were created from the extracted Digital Surface Model of the two sites. All of the RGB and NIR images were adjusted using a standard bundle technique to ensure proper overlap and co-registration of the orthophotos.

Vasiliko Site Data Used for Training

In the studies, the Vasiliko image (RGB and NIR) was used as training data, and its height and width were 3450 and 3645, respectively. Vasiliko's image has a 20 cm per pixel resolution. This means that the investigational imaging region is roughly half a square kilometre in size. This image has been divided into 1764 overlapping image tiles of size 512 512 for use in DeepLabV3+ analyses. Two consecutive photographs in the column direction will have 440 rows of overlap, while two consecutive images in the row direction will have 435 rows of overlap. By introducing rotated versions of the picture patches, this partitioning can be seen as data augmentation that increases the number of image patches in the Vasiliko training dataset. To maximise the size of the training data set, we use a large number of overlapping pixels in both the row and column directions. There are four types of land use marked in this image. In Figure 2, we see two colour images from the Vasiliko dataset annotated with land cover information.

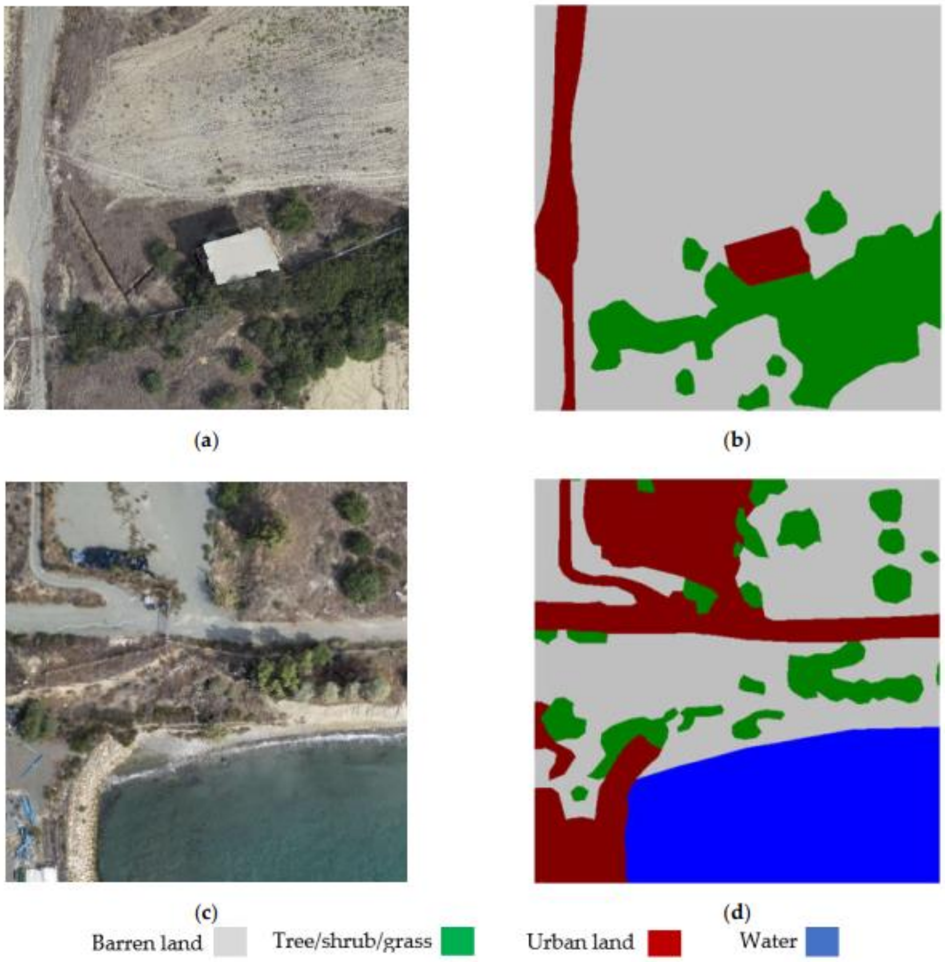

Figure 2. Here are some examples of images from the Vasiliko dataset along with their corresponding land cover map annotations (where silver indicates bare land, green indicates tree/shrub/grass, red indicates urban land, and blue indicates water). a colour picture of mari_20_3_8; b a map of mari_20_3_8's actual land cover; c a picture of mari_20_42_4's colour terrain; and d a map of mari_20_42_4's actual land cover.

To train and test models in DeepLabv3+, we use a PC running Windows 10 equipped with a graphics processing unit (RTX2070) and 16GB of RAM for the TensorFlow framework. Weights from a pre-trained model (without the logits) are used as a basis for training a land cover model with the training datasets, with the resulting model then undergoing fine-tuning through additional training. These seed values are from a trained model ("deeplabv3_pascal_train_aug_2018_01_04.tar.gz") that was applied to the PASCAL VOC 2012 dataset. The Xception-65 architecture served as the basis for this design. The logit weights in the baseline model are omitted due to the discrepancy between the number of land covers in the Vasiliko and Kimisala dataset and the number of classes in the PASCAL VOC-2012 dataset.

4. RESULTS

Table 1. Accuracy and mIoU measures for Kimisala-10 vegetation detection

Vol 12 Issue 03 2023

ISSN NO: 2230-5807

Method	Accuracy	mIoU (Vegetation& Non-Vegetation)
DeepLabV3+ (model trained with Slovenia) [5]	0.6171	0.4454
DeepLabV3+ (model trained with DeepGlobe [5]	Very poor	Very poor
DeepLabV3+ (model trained with Vasiliko)	0.8578	0.7435

Table 2. Accuracy and mIoU measures for Kimisala-20 vegetation detection.

Method	Accuracy	mIoU (Vegetation & Non-Vegetation)
DeepLabV3+ (model trained with Slovenia) [5]	0.6304	0.4355
DeepLabV3+ (model trained with DeepGlobe) [5]	Very poor	Very poor
DeepLabV3+ (model trained with Vasiliko)	0.8015	0.6541

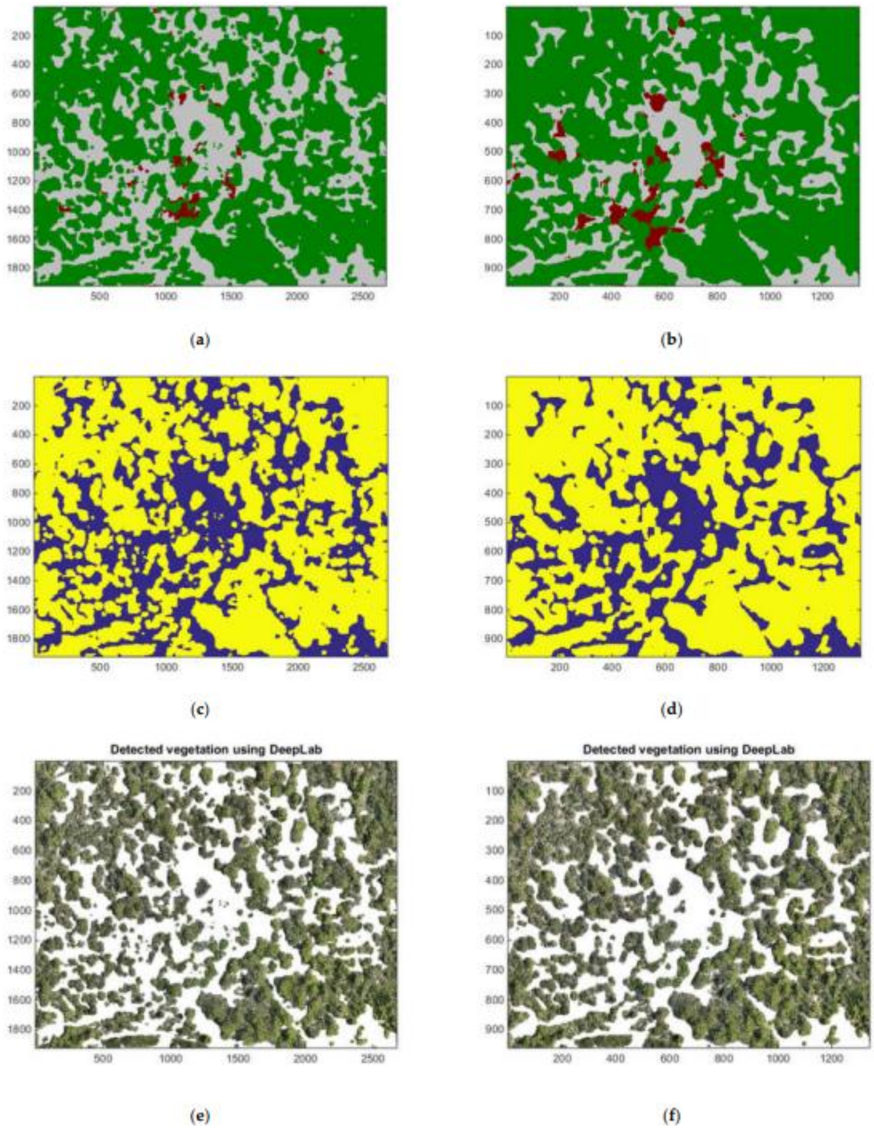

Figure 3. For the two Kimisala test photos, DeepLabV3+'s model trained on the Vasiliko dataset successfully detected vegetation. Results for Kimisala-10 (a) and Kimisala-20 (b) using DeepLabV3+ (green: Tree/shrub/grass, silver: Barren land, red: urban land); (c) a map of estimated vegetation for Kimisala-10 using DeepLabV3+ (yellow: Vegetation, blue: Non-vegetation); (d) a map of estimated vegetation for Kimisala-20 using DeepLabV3+; (e) vegetation detected using

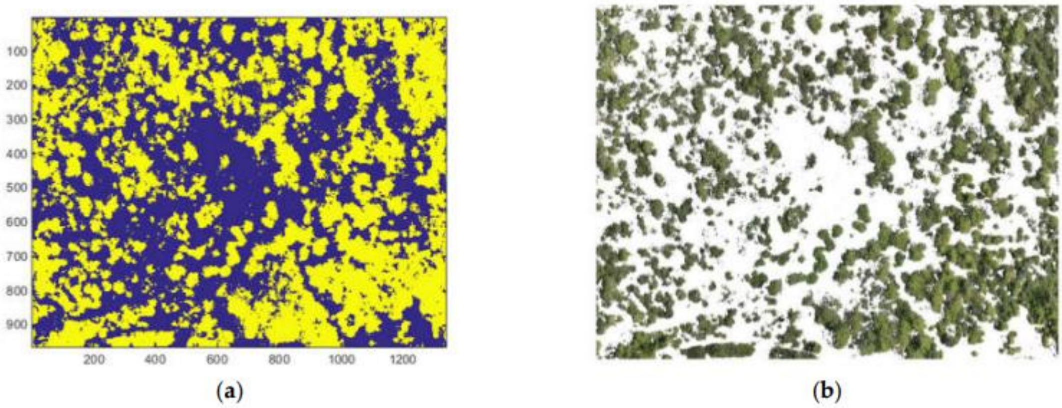

Figure 4. The CNN model trained on the Vasiliko dataset successfully detects vegetation in the Kimisala-20 test image. (a) a CNN-estimated Kimisala-20 vegetation binary map (yellow: vegetation, blue: non-vegetation); (b) a CNN-detected Kimisala-20 vegetation.

CONCLUSIONS

In this paper, we compared three different approaches to detecting vegetation. The first two are deep learning-based approaches; the third is an object-based approach that makes use of NDVI, computer vision, and machine learning. The DeepLabV3+ model that included the RGB channels fared adequately in the experiments. However, expanding that model to incorporate the NIR band in addition to the three RGB bands is difficult. Slight improvements in detection were observed when the NDVI band was swapped out for the red band to allow for the use of all four input channels to some extent while still satisfying DeepLabV3+'s three input channels only restriction. Our modified CNN model, in contrast to DeepLabV3+, is simply applied to RBG+NIR spectrums. For the Kimisala-20 dataset, our modified CNN model performed slightly better than DeepLabV3+ when using the RGB and NIR bands.

REFERENCES

[1] Jing Wei Tan, Siow-Wee Chang, Sameem Abdul-Kareem, Hwa Jen Yap, Kien-Thai Yong(2018)" Deep Learning for Plant Species Classification using Leaf Vein Morphometric "

[2]Willis, K.J. (ed.)2017 State of the World's Plants 2017. Report. Royal Botanic Gardens, Kew

[3].Metre, V., &Ghorpade, J. (2013). An overview of the research on texture based plant leaf classification. arXiv preprint arXiv:1306.4345.

[4]Cope, J. S., Remagnino, P., Barman, S., & Wilkin, P. (2010, December). The extraction of venation from leaf images by evolved vein classifiers and ant colony algorithms. In International Conference on Advanced Concepts for Intelligent Vision Systems (pp. 135-144). Springer Berlin Heidelberg.

[5]Anami, B. S., Suvarna, S. N., & Govardhan, A. (2010). A combined color, texture and edge features based approach for identification and classification of indian medicinal plants. International Journal of Computer Applications,6(12), 45-51.

[6] Larese, M., Craviotto, R., Arango, M., Gallo, C., &Granitto, P. (2012). Legume identification by leaf vein images classification. Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications, 447-454.

[7]Kadir, A., Nugroho, L. E., Susanto, A., &Santosa, P. I. (2013). Neural network application on foliage plant identification. arXiv preprint arXiv:1311.5829.

[8] Pankaja K and Dr.Thippeswamy, "Survey on Leaf Recognization and Classification", International Conference on Innovative Mechanisms for Industry Applications (ICIMIA 2017)

[9]SalarRazavi, Hulya Yalcin, "Thi Thanh-Nhan Nguyen, Thi-Lan Le, Hai Vu, Huy-Hoang Nguyen and Van-Sam Hoang". Springer International Publishing AG 2017 D. Król et al. (eds.), Advanced Topics in Intelligent Information and Database Systems, Studies in Computational Intelligence 710, DOI 10.1007/978-3-319-56660-3_20.

[10]MUNISH KUMAR 1, SURBHI GUPTA 2, XIAO-ZHI GAO 3, AND AMITOJ SINGH, "Plant Species Recognition Using Morphological Features and Adaptive Boosting Methodology", Digital Object Identifier 10.1109/ACCESS.2019.2952176.
[11]SigitAdinugroho, Yuita Arum Sari, "Leaves Classification Using Neural Network Based on Ensemble Features", 2018 5th International Conference on Electrical and Electronics Engineering, 978-1-5386-6392-9/18/$31.00 ©2018 IEEE.
[12]EsraaElhariri, Nashwa El-Bendary, Aboul Ella Hassanien, "Plant Classification System based on Leaf Features", 978-1-4799-6594- 6/14/$31.00 ©2014 IEEE.
[13]Mohamed Abbas Hedjazi, IkramKourbane, YakupGenc, "On Identifying Leaves: A Comparison of CNN with Classical ML Methods", 978-1-5090-6494-6/17/$31.00 c 2017 IEEE