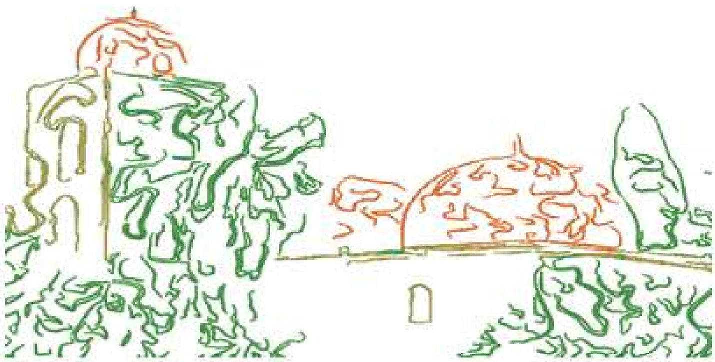
PROCEEDINGS

Edited By: Giada Adelfio and Antonino Abbruzzo

GRASPA 2023



GRASPA-SIS BIENNAL CONFERENCE

The Researcher Group for Environmental Statistics of The Italian Statistical Society

TIES EUROPEAN REGIONAL MEETING

The International Environmetrics Society

Palermo, 10-11 July, 2023

Dipartimento di Scienze Economiche Aziendali e Statistiche, Università degli Studi di Palermo

Proceedings of the GRASPA 2023 Conference
Palermo, 10-11 July 2023
Edited by: Giada Adelfio and Antonino Abbruzzo
-
Palermo: Università degli Studi di Palermo.

ISBN: 979-12-210-3389-2

Sponsored by:

Contents

Preface

The international conference GRASPA2023, held in Palermo, Italy, 10-11 July 2023, is organised by the Department of Economics Business and Statistics of the University of Palermo. GRASPA has become a permanent working group of the Italian Statistical Society (SIS) since May 2013. GRASPA2023 is the biennial conference of the Italian research group for Environmental Statistics GRASPA-SIS and the major event on Environmental Statistics in Italy. This conference endorses co-operation among statisticians, academics as well as practitioners from government and independent environmental agencies, and it allows sharing of research interests related to the development and the use of statistical methods in environmental sciences. Moreover, GRASPA2023 is the 2023 European regional conference of The International Environmetrics Society (TIES).
Brian Reich (North Carolina State University) and Frederic Schoenberg (University of California Los Angeles) are the keynote speakers, and six invited tracks on various statistical and environmental topics are the conference's core. More than thirty contributed papers, presented in an extensive poster session, and informal moments of discussion and interaction between the participants will enrich the conference. Moreover, a Best Poster Award Committee will evaluate all posters on their design, clarity of the presentation and scientific content.
The book of short papers of GRASPA2023 includes abstracts of the keynote, and papers of invited and contributing authors, listed alphabetically according to the conference sessions and the first author's family name. Notably, extended versions of a selection of invited and contributed papers will be considered for publication in a Springer book series' Springer Proceedings in Mathematics & Statistics', with the associated Electronic ISSN 2194-1017 and Print ISSN 2194-1009.
We want to thank all the reviewers for their constructive comments on the papers and the members of the organising team and the scientific committee. Special acknowledgement goes to the generous partners for their overall sponsorship.
Please enjoy the technical program, enjoy Palermo, and continue studying new statistical methods and approaches, hopefully contributing to fostering Environment protection.

Palermo, July 10th, 2023

Giada Adelfio and Antonino Abbruzzo
Editors

UAV plant image Classification Using Combined Machine Learning And Deep Learning Models

Anna Simonetto [1,*], Girma Tariku [2], and Gianni Gilioli [1]

[1] *Department of Civil Engineering, Architecture, Land and Environment, and Mathematics (DICATAM), anna.simonetto@unibs.it, gianni.gilioli@unibs.it*
[2] *Girma Tariku Department of Information Engineering (DII), University of Brescia, via Branze 38, Brescia email: g.tariku@unibs.it*
Corresponding author: Anna Simonetto, anna.simonetto@unibs.it

---

Abstract. *Plant identification using Unmanned aerial vehicles is a powerful tool that can provide farmers and researchers with valuable information about crops and vegetation. In precision agriculture, identifying and classifying plants is a complex process. Due to various factors, such as the quality and resolution of the image, recognizing the exact type can be challenging. For plant identification purposes, more deep learning (DL) and machine learning (ML) methods are used. In this work, an integrated approach combining deep learning (DL) and machine learning (ML) methods is developed to improve the plant-type classification by improving the quality of the image dataset using image preprocessed techniques Enhanced super-resolution generative adversarial network (ESRGAN) and Contrast Limited Adaptive Histogram Equalization (CLAHE). A convolutional neural network 16 layers deep (VGG-16 mode) is used for feature extraction and classification using Machine Learning models including Random Forest classification and Support Vector Machines. To identify the best predictive model, a comparative study was carried and the hybrid method VGG-16 with Support Vector Machine using image preprocessed ESRGAN and CLAHE gives the optimum results of 98.06% accuracy.*

Keywords. *Classification; VGG-16; Support Vector Machine; Random forest*

---

1 Introduction

The digital revolution in agricultural and environmental sciences is supporting the transition of food systems towards more efficient, productive, and sustainable paradigms [9]. Plant image classification has the potential to provide fast, accurate, and cost-effective methods for plant identification[4], disease detection [1, 11], crop management, and ecosystem services assessment. Unmanned aerial vehicles (UAVs), also known as drones, have become increasingly popular as a tool for remote sensing and data acquisition [9]. However, UAVs have limitations on their flight time [6]. To monitor a large geographic area in a short amount of time, UAV should fly at high altitudes resulting in a loss of spatial resolution [13]. Furthermore, camera's optics and pixel size have limitations that can affect the clarity and quality of the images captured. This makes plant image classification a challenging task due to the high variability and complexity of plant images captured from UAVs.

Artificial intelligence (AI) models, machine learning (ML), and deep learning (DL) techniques [2, 3, 14] advanced rapidly in their use to improve plant-type predictions. DL classifiers, such as deep neural networks [20], use multiple layers of artificial neurons to learn representations of the input data hierarchically and are well-suited for tasks involving large and complex datasets, such as image[16] and speech recognition[8]. As a drawback, DL classifiers require a large amount of labeled data and extensive computing resources to train effectively [12]. ML classifiers, such as support vector machines (SVM) and random forest (RF) classifiers, work well when the input data has a relatively small number of features and the relationships between features and class labels are not too complex [17]. The combination of DL and ML techniques, performing an ensemble learning approach, can often allow for achieving higher accuracy and robustness than any individual model [10], building more powerful and accurate models. In this work, we used RGB UAV plant image datasets that were acquired 30 m from the ground and improved the resolution and quality of images using different image preprocessing techniques, such as ESRGAN (an enhanced super-resolution generative additive network) [18], Contrast Limited Adaptive Histogram Equalization (CLAHE) [5]. Then a hybrid of DL and ML models was applied to handle the RGB UAV plants image classification problem. The pre-trained DL model VGG-16 was used to extract features from the data samples, SVM and RF were applied to obtain plant classification.

To identify the best predictive model, a comparative study was carried out using the hybrid method VGG-16 with SVM and random forest for different datasets: the dataset collected from UAV, the dataset after pre-processing image analysis with ESRGAN, and the dataset after pre-processing image analysis with ESRGAN and CLAHE.

2 Proposed Methodology

In this work, we aim to classify plant species based on RGB images of plant canopies acquired by UAVs. The input dataset is prepared based on the procedure of the paper [7] consisting of three steps: Pre-processing of images, feature extraction, and classification (Fig. 1).

2.1 Pre-processing of images

Image augmentation is a technique used in computer vision and DL to increase the size of a dataset by creating modified versions of existing images. We modified rotation, shearing, flip vertical, and brightness to increase the total number of images from 433 to 793.

We improved the quality of each image in the augmented image datase by Enhanced super-resolution generative adversarial network (ESRGAN), a DL algorithm used for image super-resolution [18]. Image super-resolution is the process of generating a high-resolution image from a low-resolution input image. The ESRGAN model is trained using a combination of loss functions, including mean squared error (MSE) and perceptual loss [19]. MSE measures the pixel-wise difference between the predicted high-resolution image and the ground truth image. Perceptual loss measures the difference between the high-resolution image generated by the model and the ground truth image in terms of perceptual similarity.

We applied an image processing technique (the Contrast Limited Adaptive Histogram Equalization - CLAHE) to enhance the contrast of an image by redistributing the pixel values based on the local histogram of the image.

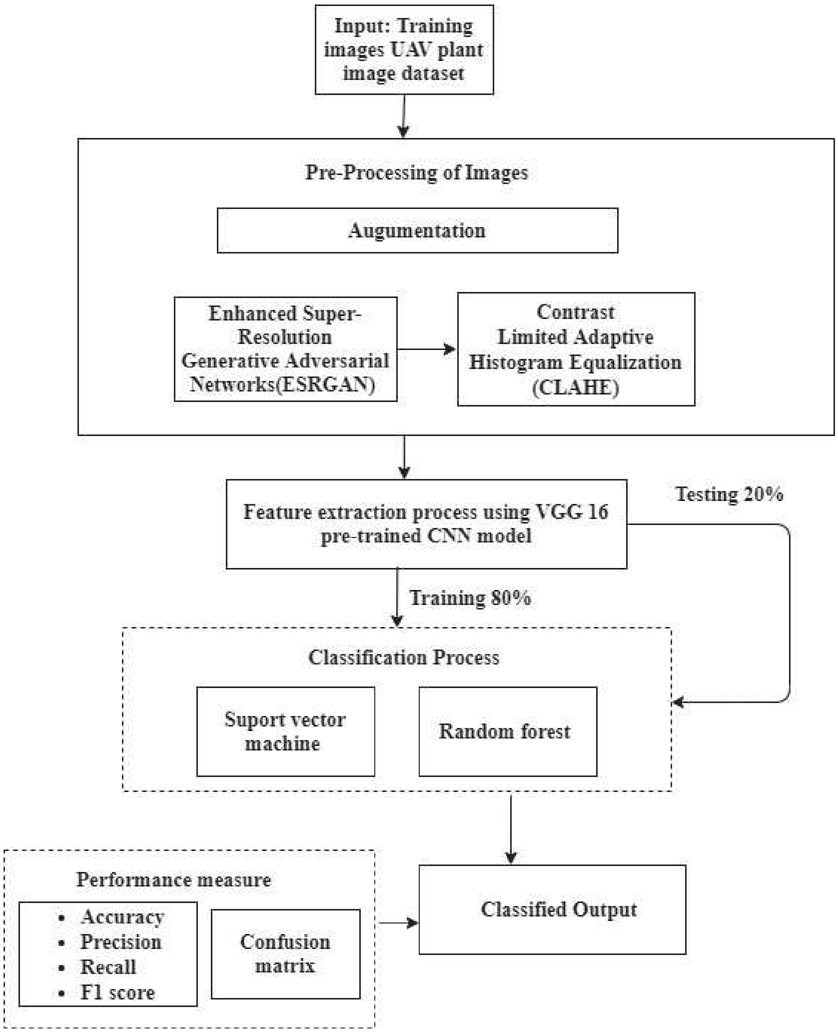


Figure 1: Overall working process of Proposed Method.

2.2 Feature extraction using VGG-16

We applied a standard deep Convolutional Neural Network (CNN) architecture with 16 deep layer developed by the Visual Geometry Groups (VGG-16 architecture) as a feature extractor for our classification task [15]. Feature extraction refers to the process of using a pre-trained CNN to extract useful features from an image, which can then be used for a wide range of computer vision tasks, such as object detection, image segmentation, and image retrieval. To use VGG-16 as a feature extractor, the last fully connected layer of the network is removed, and the output of the final convolutional layer is used as the feature representation of the image. This output is a tensor with dimensions

$$(N,H,W,C)$$

, where N is the number of images, H and W are the height and width of the feature maps, and C is the number of channels (or filters) in the layer.

2.3 Machine Learning for Classification

To perform ML classification, we need to replace the last few layers of pre-trained CNN model, which are typically the fully connected layers, with a new classifier. We used SVM and Random Forest. In classification, random forest is used to classify data into different categories based on input features. It works by building a collection of decision trees, where each tree is trained on a subset of the data and a subset of the input features. During training, the algorithm randomly selects data points and input features to create each decision tree, which helps to reduce overfitting and improve the accuracy of the model. SVM is a supervised learning algorithm commonly used for classification and regression analysis. SVMs are particularly well-suited for problems where the data is not linearly separable, meaning that the classes cannot be separated by a straight line or hyperplane in the feature space. One of the advantages of SVMs is that they can handle high-dimensional data very well, and they are relatively robust to overfitting.

3 Experimental Results and Discussions

The total dataset consists of 769 plant images of size 224 x 224 pixels of four plant species (*Ailanthus altissima*, *Arrhenatherum elatius, Artemisia verlotiorum*, and *Ulmus minor*) extracted from orthophotos collected in an agroecosystem. We randomly selected 80% of them for training purposes (i.e., 614 images), and the remaining 20% (i.e., 155 images) are kept as a test dataset. The plant prediction networks output layer identifies four classes corresponding to the plant species.

Based on the confusion matrix and the True positive (TP), True negative (TN), False positive (FP), and False negative (FN), we used accuracy [(TP) / (Total number of classifications)], recall [TP /(TP+FN)], precision [TP / (TP+FP)], and F1 score [2TP / (2TP + FP + FN)] to evaluate the fitting of models. The results of the two hybrid classification models (VGG-16 and Random forest, VGG-16 and SVM) applied to the image augmented dataset, the augmented dataset pre-processed by ERSGAN, and the augmented dataset pre-processed by ERSGAN and CLAHE are reported in Table 1. It appears from the performance indices that pre-processing techniques result in improved prediction performance, and within the same dataset, the hybridized approach with the SVM results in better estimates than the hybrid approach with Random forest. The best strategy is VGG-16 DL feature extractor in conjunction with a SVM classifier on the dataset after using the ESRGAN and CLAHE image pre-processing methods: the model classifies with 98% accuracy, an F1 value of 0.981, a recall of 0.98, and a precision of 0.983 (Fig. 2).

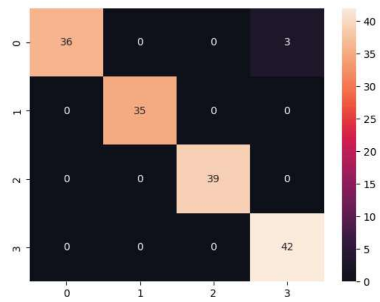


Figure 2: confusion matrix when combining VGG-16 with SVM on the image dataset pre-processed with ESRGAN and CLAHE.

Input Image dataset type	Hybrid classification model	Accuracy (%)	F1 score	Recall	Precision
Image augmented dataset	VGG-16 + Random Forest	89	0.901	0.897	0.9
(base)	VGG-16 + SVM	95	0.956	0.955	0.957
Base pre-processed	VGG-16 + Random Forest	90	0.913	0.912	0.917
by ESRGAN	VGG-16 + SVM	96	0.962	0.962	0.963
Base pre-processed	VGG-16 + Random Forest	92	0.931	0.930	0.934
by ESRGAN and CLAHE	VGG-16 + SVM	98	0.981	0.980	0.983

Table 1: Accuracy, F1 score, recall, and precision value for image dataset without pre-processing, the dataset pre-processed by ESRGAN, and dataset pre-processed by ESRGAN and CLAHE.

4 Conclusion

In this study, a modelling approach based on a combination of ML and DL techniques is suggested to improve classification accuracy in plant identification problems. After a detailed comparison, it was found that the VGG-16 pre-trained neural network with Support Vector Machine Classifier provides the most accurate predictions, with an accuracy rate of 98.06%.

References

[1] G Geetharamani and Arun Pandian. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. *Computers & Electrical Engineering*, 76:323–338, 2019.

[2] ASM Mahmudul Hasan, Ferdous Sohel, Dean Diepeveen, Hamid Laga, and Michael GK Jones. A survey of deep learning techniques for weed detection from images. *Computers and Electronics in Agriculture*, 184:106067, 2021.

[3] Andreas Kamilaris and Francesc X Prenafeta-Boldú. Deep learning in agriculture: A survey. *Computers and electronics in agriculture*, 147:70–90, 2018.

[4] Sue Han Lee, Chee Seng Chan, Simon Joseph Mayo, and Paolo Remagnino. How deep learning extracts and learns leaf features for plant classification. *Pattern Recognition*, 71:1–13, 2017.

[5] A. Mishra. Contrast limited adaptive histogram equalization (clahe) approach for enhancement of the microstructures of friction stir welded joints. In *arXiv preprint arXiv:*, page 2109.00886.

[6] Syed Agha Hassnain Mohsan, Nawaf Qasem Hamood Othman, Yanlong Li, Mohammed H Alsharif, and Muhammad Asghar Khan. Unmanned aerial vehicles (uavs): practical aspects, applications, open challenges, security issues, and future trends. *Intelligent Service Robotics*, pages 1–29, 2023.

[7] S Natesan, C Armenakis, and U Vepakomma. Resnet-based tree species classification using uav images. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*, 2019.

[8] Dimitri Palaz, Mathew Magimai-Doss, and Ronan Collobert. End-to-end acoustic modeling using convolutional neural networks for hmm-based automatic speech recognition. *Speech Communication*, 108:15–32, 2019.

[9] Panagiotis Radoglou-Grammatikis, Panagiotis Sarigiannidis, Thomas Lagkas, and Ioannis Moscholios. A compilation of uav applications for precision agriculture. *Computer Networks*, 172:107148, 2020.

[10] Omer Sagi and Lior Rokach. Ensemble learning: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 8(4):e1249, 2018.

[11] Muhammad Hammad Saleem, Johan Potgieter, and Khalid Mahmood Arif. Plant disease detection and classification by deep learning. *Plants*, 8(11):468, 2019.

[12] Iqbal H Sarker. Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. *SN Computer Science*, 2(6):420, 2021.

[13] Erich Seifert, Stefan Seifert, Holger Vogt, David Drew, Jan Van Aardt, Anton Kunneke, and Thomas Seifert. Influence of drone altitude, image overlap, and optical sensor resolution on multi-view reconstruction of forest images. *Remote sensing*, 11(10):1252, 2019.

[14] Abhinav Sharma, Arpit Jain, Prateek Gupta, and Vinay Chowdary. Machine learning applications for precision agriculture: A comprehensive review. *IEEE Access*, 9:4843–4873, 2020.

[15] Zisserman A. Simonyan, K. Very deep convolutional networks for large-scale image recognition. In *arXiv preprint arXiv:*, page 1409.1556.

[16] Yanan Sun, Bing Xue, Mengjie Zhang, and Gary G Yen. Evolving deep convolutional neural networks for image classification. *IEEE Transactions on Evolutionary Computation*, 24(2):394–407, 2019.

[17] Pin Wang, En Fan, and Peng Wang. Comparative analysis of image classification algorithms based on traditional machine learning and deep learning. *Pattern Recognition Letters*, 141:61–67, 2021.

[18] Zhangxi Ye, Jiahao Wei, Yuwei Lin, Qian Guo, Jian Zhang, Houxi Zhang, Hui Deng, and Kaijie Yang. Extraction of olive crown based on uav visible images and the u2-net deep learning model. *Remote Sensing*, 14(6):1523, 2022.

[19] Isola P. Efros A. A. Shechtman E. Wang O Zhang, R. The unreasonable effectiveness of deep features as a perceptual metric. *In Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 586–595, 2018.

[20] Ding-Xuan Zhou. Deep distributed convolutional neural networks: Universality. *Analysis and Applications*, 16(06):895–919, 2018.