Proceeding Paper

Detection and Clustering of Grapevine Varieties via Multispectral Aerial Imagery and Vegetation Indices Analysis †

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Abstract: Viticulture, requires constant and meticulous care throughout the year to ensure a high-quality harvest. Precision agriculture has significantly advanced, enabling the early detection of potential threats or diseases without harming the crops. Understanding the distinct features of various grapevine varieties, such as chlorophyll content, canopy growth, stress, and interactions with specific soil elements, is crucial. To address these challenges, this study employs multispectral images captured by unmanned aerial vehicles (UAVs), providing a method for exploiting the spectral features of vine canopies. The primary objective is to group different grapevine varieties in the same area based on common spectral characteristics.

Keywords: machine learning; multispectral images; remote sensing; vineyards; clustering

1. Introduction

Vineyards are faced with various challenges throughout their lifecycle. Farmers need to monitor several common issues during the growth period of vineyards, including vineyard productivity [1], plant water stress [2] and nutrient concentrations, such as nitrogen (N), phosphorus (P), potassium (K) etc. [3]. Precision agriculture methods enable early detection of dangers or diseases without harming crops [4]. The production of vineyards holds significant economic, social, and environmental importance [5] which means that sustainable vineyard management is crucial. Vegetation monitoring methods fall into laboratory methods are mainly costly, time-consuming, and involve plant damage. On the other hand, non-destructive methods, like proximal and remote sensing, offer plant health information without destruction, at lower cost and time [6]. Remote sensing methods include satellites or unmanned aerial systems (UAS), while proximal sensing uses ground-based cameras. Satellite images cover large areas efficiently but have limits in spatial resolution. Aerial images via UAVs offer high spatial and spectral resolution but cost more and require expertise [7]. Multispectral images provide valuable insights into plant health, as visible spectrum indicates leaf pigments, while the NIR spectrum reveals internal leaf structure and detects elements or diseases. Moreover, spectral values depend on plant variety, growth stage, and tissue content [8]. Besides the right image acquisition method choice, the optimal classification algorithm is crucial for data clustering of vineyard varieties or detecting elements and diseases. Clustering, machine learning, and vegetation indices enhance accuracy in assessing plant conditions by combining various methods and data types.

This work aims to detect and analyze several vineyard varieties through their spectral properties. To this purpose, some vegetation indices, which provide details about the health and the condition of vineyards, will be used.

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2. Material and Methods

2.1. Study Area and Equipment

This research focuses on a vineyard in the northern part of Athens within the Attica region. The study area home 112 different vineyard varieties, offering an ideal setting to apply methods for the evaluation of various characteristics of the plants.

Figure 1. Area of interest.

The vineyard area was captured using the multispectral camera Micasense RedEdge-M in May 2022. With providing bands in five different spectral values, a wealth of information about the vineyard's condition can be extracted from the images.
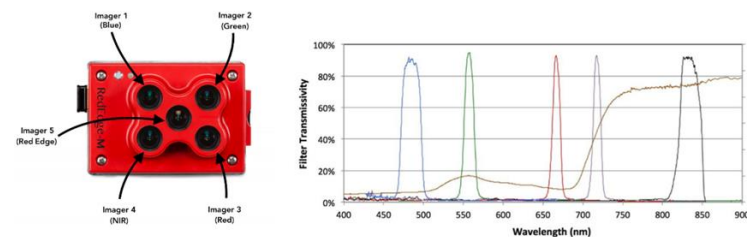
Figure 2. Micasense RedEdge-M multispectral camera.

2.2. Datasets

The aerial images collected, contain information of five different spectral bands. Using these images, the orthophotomap of the vineyard was created via the Metashape software. The procedure includes the stage of sparse and dense point cloud creation, the building of digital elevation model in order to lead on the orthophotomap creation.

Moreover, field measurements for varieties' location identification were con-ducted. For this purpose, the GNSS GINTEC-M20 receiver was used. This receiver is capable of achieving horizontal position accuracy of less than 2 cm. In the vineyard fields, labels for each variety were positioned at the starting point of each variety. The locations of these labels were mapped using the GNSS receiver in the GGRS87 coordinate reference system, which is the National Greek Coordinate system.

2.3. Method

In this study, a methodology was employed to analyze the spectral information of different grapevine varieties through a comparative approach and clustering techniques. Seven spectral indices were computed for each grapevine variety, to identify the most important related to vineyard health. From those, two indices were selected which played a key role in clustering algorithms, and the resultant data underwent analysis to comprehend various factors influencing vineyard health. The study determined the optimal number of classes for dataset classification and assessed their significance in gauging vineyard health.

3. Results and Discussion

Utilizing the vast potential of machine learning, supervised algorithms were employed to identify grapevine areas within the orthophotomap. The Maximum Likelihood algorithm displayed an impressive accuracy of 98.79% in correctly pinpointing vine pixels. The resulting grapevine masks were played a crucial role in outlining distinct polygons, each representing a specific grapevine variety. Subsequently, seven different vegetation indices (Chlorophyll Index-Green (CIG), Chlorophyll Index–RedEdge (CIRE), Chlorophyll Vegetation Index (CVI), Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Enhanced Vegetation Index2 (EVI2) and Ratio Vegetation Index (RVI)) were calculated for each polygon, offering valuable insights into the unique characteristics of each variety. To explore relationship between varieties, two pairs of indices (pair1: CVI-RVI, pair2: CLGR-CLRE) were chosen based on lower correlation. Following this, k-Means and Gaussian Mixture Model (GMM) clustering algorithms were applied to categorize varieties into three groups. The k-Means and GMM algorithms successfully categorized 73 and 58 out of 112 varieties, respectively, into three groups, with both pairs of indices yielding the same classification. The remaining varieties were left unclassified. By combining the results of both algorithms, 25 out of 112 varieties were grouped (Group 1-2-3: 13-4-8 varieties) based on specific spectral properties, demonstrating a comprehensive and effective approach.
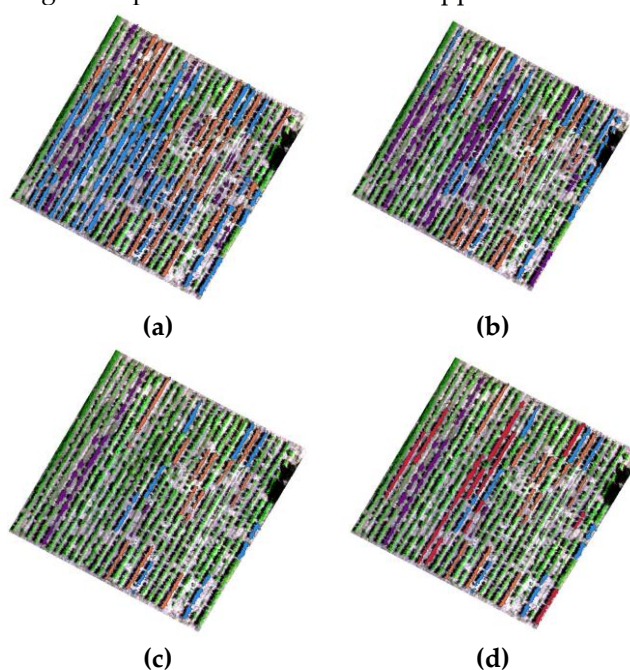

(a)   (b)

(c)   (d)

Figure 3. K-means clustering results (**a**), Gaussian mixture model clustering results (**b**), Combination of algorithms' results (**c**), (**d**).

This study aimed to explore the use of multispectral images for identifying various grapevine varieties. Unlike previous studies that often focused on areas producing either table grapes or wine with a limited number of varieties, this study examined a small area containing a diverse range of grapevine varieties. Initial attempts to classify grape varieties using only the bands of the multispectral camera proved challenging. Consequently, the study employed vegetation indices to create categories, successfully classifying the varieties into three classes. Spatial analysis revealed that varieties classified in the same class were sometimes spatially related, prompting questions about the influence of unique characteristics versus external factors like soil, water, and fertilizer on classification outcomes.

4. Conclusions

In summary, understanding the unique characteristics of different grapevine varieties is paramount for farmers, as it empowers them to optimize yields, make in-formed decisions about planting and harvesting, and implement effective disease management strategies. This knowledge allows farmers to adapt their cultivation practices to specific growing conditions, ultimately maximizing productivity and minimizing crop losses. As this study serves as a foundational exploration into grapevine growth characteristics, there remains vast potential for future applications and scientific investigations in the farming sector. Future attempts may include the integration of hyperspectral images, data fusion with aerial and satellite data, and advanced techniques such as deep learning, time series analysis, and multi-dimensional vector analysis. The ongoing advancement of technology and computational capabilities promises exciting prospects for further enhancing of the understanding of plant growth dynamics and improving agricultural practices.

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