Tree Identification and Enumeration on Orchard UAV Imagery

Abstract:

Citrus orchards play a critical role in global fruit production, where precise tree identification, enumeration, and structural analysis are essential for optimized management. This study introduces a nuanced approach that harnesses Unmanned Aerial Vehicle (UAV) imagery to significantly improve citrus tree identification and to accurately extract structural properties, with a particular emphasis on tree height analysis. Our research contrasts two advanced methodologies: the employment of a YOLOv8 object detection model, meticulously trained on well-annotated images for accurate tree enumeration; and the application of orthomosaic imaging coupled with color segmentation and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) for detailed clustering analysis. Further, we explore the extraction of structural properties through the Canopy Height Model (CHM), derived from the integration of Digital Surface Model (DSM) and Digital Terrain Model (DTM), based on comprehensive orthomosaic imagery. This dual-methodological framework not only streamlines tree enumeration but also facilitates the extraction of critical structural insights, enhancing the accuracy of orchard assessments. Preliminary findings indicate a notable improvement in the precision of tree identification and structural property analysis, underscoring the potential of these methodologies to revolutionize precision agriculture practices. By delivering detailed tree counts and structural data, this approach promises to advance disease monitoring, resource allocation, and decision-making processes in orchard management, setting a new benchmark for technological integration in agricultural studies.

1. INTRODUCTION

The integration of Unmanned Aerial Vehicles (UAVs) into agricultural monitoring heralds a new era of precision agriculture, offering unprecedented data quality and spatial coverage. This innovation is particularly pertinent to the management of orchid citrus plantations, where the identification, enumeration, and analysis of structural properties of trees, such as height, are critical for optimizing yield and maintaining plant health. Traditional manual survey methods fall short in efficiency and accuracy, necessitating advanced technological solutions for orchard management.

This paper details a pioneering investigation into the application of cutting-edge image processing methodologies—YOLOv8 and segmentation and clustering techniques—for tree identification, enumeration, and the extraction of structural characteristics from UAV-based imagery of orchid citrus plants. Our research is driven by the hypothesis that automated, algorithm-based approaches can significantly outperform traditional manual methods in accuracy, efficiency, and scalability. To this end, we have meticulously developed and tested two separate methods to ascertain the most effective approach for our specific objectives.

First, we explore the capabilities of YOLOv8, a state-of-the-art object detection algorithm known for its speed and accuracy, to identify and count orchid citrus trees in UAV images. This deep learning model is evaluated for its precision in distinguishing individual trees and their specific features within the complex visual patterns of orchards.

Second, we delve into segmentation and clustering techniques, methods that partition the UAV imagery into meaningful clusters, allowing for the detailed analysis of tree structures and densities. This approach is particularly adept at extracting nuanced spatial properties of orchards, including the height and canopy structure of each tree, which are indispensable metrics for assessing orchard health and productivity.

Through a comparative analysis of these methodologies, our study aims to establish a benchmark for tree monitoring in orchid citrus plantations, evaluating each method's efficacy in terms of accuracy, computational efficiency, and applicability to large-scale agricultural assessments. The implications of our findings extend beyond mere technological advancement; they promise to revolutionize orchard management by offering a scalable, accurate, and cost-effective means of agricultural surveillance, thereby enhancing yield optimization and the sustainability of farming practices in the citrus industry.

2. LITERATURE SURVEY

The study by Csillik et al. (2018) explores the application of convolutional neural networks (CNNs) in identifying citrus trees from aerial imagery captured by unmanned aerial vehicles (UAVs). The primary goal is to demonstrate how advanced machine learning techniques can enhance the accuracy and efficiency of agricultural surveys, specifically in monitoring and managing citrus orchards. The researchers utilized a dataset of UAV-derived images of a citrus orchard, applying CNNs to classify and identify individual citrus trees. The imagery was pre-processed to optimize it for the learning model, including normalization and augmentation techniques to improve the robustness of the neural network against variations in image quality and environmental conditions. The CNN model showed a high level of accuracy in identifying citrus trees, significantly outperforming traditional image processing techniques such as normalized difference vegetation index (NDVI) based methods. The study highlighted the CNN's ability to handle various lighting conditions, tree densities, and occlusions, making it a viable tool for large-scale agricultural applications. This research underscores the potential of integrating UAV technology with deep learning to automate and enhance agricultural monitoring.

The successful application of CNNs for tree identification could lead to more precise agriculture practices, optimized resource allocation, improved crop monitoring, and ultimately, increased yields. Additionally, the methodology can be adapted to other types of crops and environmental monitoring tasks, suggesting a wide range of agricultural applications.[1]

The study by Daliakopoulos et al. (2009) investigates the use of very high resolution (VHR) multispectral satellite imagery for the detection of tree crowns, focusing on improving methods for forest management and land cover mapping. The authors developed a methodology that combines image segmentation and classification techniques to detect tree crowns within multispectral imagery. The process involved multiple steps: preprocessing of images to reduce noise and enhance features, segmentation of the imagery into meaningful clusters, and classification of these clusters into tree crowns using a combination of spectral and spatial information. The results demonstrated that the proposed method could effectively identify tree crowns in diverse forest landscapes, showing promise over traditional pixel-based analysis methods. The use of multispectral data allowed for a better distinction between tree crowns and other land cover types, such as grass or soil, especially in complex environments where tree density and canopy cover vary extensively. This paper highlights the advantages of using VHR satellite imagery combined with sophisticated image processing algorithms for environmental monitoring and forestry management. The ability to accurately detect tree crowns has significant implications for biomass estimation, habitat analysis, and land use planning. [2]

The study by Ammar et al. (2021) aims to automate the process of counting and geolocating palm trees in large agricultural landscapes using deep learning techniques applied to aerial geotagged images. This innovation seeks to improve agricultural efficiency and precision in managing large farms. Utilizing geotagged images captured by drones, the researchers employed convolutional neural networks (CNNs) to not only count the palm trees but also pinpoint their exact geographical locations. This process involved training the CNN with a large dataset of aerial images annotated with the locations of palm trees, which helps the model learn to recognize the trees and their spatial arrangement. The deep learning model demonstrated high accuracy in both counting and geolocating palm trees, significantly reducing the time and labor required for manual counting. The approach proved robust across different tree densities and varying lighting conditions. The technique offers substantial improvements in resource allocation and farm management for large-scale palm growers. By automating tree counting and geolocation, farmers can more accurately assess the health and distribution of their crops, optimize field operations, and enhance yield forecasting,[3] This study focuses on the detection and enumeration of trees using high-resolution imagery from the Cartosat2 satellite, aiming to enhance forest management and ecological monitoring. The approach involves using advanced image processing algorithms and machine learning techniques to analyze satellite images for tree detection. The methodology includes image segmentation, feature extraction, and the application of classification algorithms to distinguish trees from other natural and man-made objects in the imagery. Although specific results are not detailed in your description, typically, such studies show a potential in accurately detecting and enumerating trees, providing vital data for environmental monitoring and land management strategies. The research is crucial for environmental conservation efforts, urban planning, and forestry management, offering a scalable solution to monitor and manage tree populations efficiently over large geographic areas. [4]

This paper presents an automated methodology for detecting and counting olive trees from satellite images, aiming to assist in agricultural management and planning specifically tailored to olive orchards. The authors developed a machine learning model that utilizes satellite imagery to identify olive tree crowns and count them accurately. The methodology includes preprocessing steps to enhance image quality, feature extraction tailored to the unique characteristics of olive trees, and classification algorithms to distinguish trees from the surrounding environment. The model achieved high accuracy in detecting olive trees, showcasing the potential to be applied across different regions and varying densities of olive orchards. This method provides olive growers and agricultural policymakers with valuable tools for better yield estimation, crop management, and spatial analysis, contributing to more sustainable and productive agricultural practices. [5]

Wang et al. (2018) present a comprehensive methodology utilizing unmanned aerial vehicle (UAV) imagery, Histogram of Oriented Gradients (HOG) features, and Support Vector Machine (SVM) classifier for the detection of individual oil palm trees within plantations. The study addresses the imperative need for precise and efficient management strategies in oil palm cultivation, a critical component of the global economy. The first step in their approach involves the acquisition of high-resolution aerial images using UAVs equipped with advanced cameras. These images provide detailed spatial information about the layout of oil palm plantations, including the distribution of individual trees, roads, and other elements. Preprocessing techniques are then applied to enhance the quality of the acquired images, ensuring optimal conditions for subsequent feature extraction and analysis. Feature extraction plays a pivotal role in the detection process, with HOG features selected as the primary descriptor for characterizing the visual appearance of individual oil palm trees. HOG features offer a robust representation of local gradient orientations within image regions, capturing essential information about edges and textures relevant to tree detection. The extracted features serve as input data for training the SVM classifier, a supervised learning algorithm renowned for its effectiveness in classification tasks. Annotated training data, comprising labeled examples of individual palm trees and

background elements, are utilized to train the SVM model. This process involves manually labeling a subset of UAV-acquired images to specify the locations of oil palm trees, ensuring the classifier learns to differentiate between positive and negative samples accurately. Once trained, the SVM classifier is deployed to detect individual oil palm trees in unseen UAV images. The algorithm's performance is evaluated using standard metrics such as accuracy, precision, recall, and F1 score, providing quantitative measures of its effectiveness in tree detection. Comparisons with ground truth data validate the accuracy and reliability of the detection method, demonstrating its practical applicability in agricultural remote sensing. Moreover, the implementation of the proposed methodology entails the use of various software tools and libraries for image processing, feature extraction, machine learning, and evaluation. Parameter tuning and optimization are essential steps to fine-tune the algorithm's performance, ensuring optimal results across different plantation environments and conditions.
In conclusion, the methodology described by Wang et al. (2018) offers a robust framework for enhancing the management and monitoring of oil palm plantations through the integration of UAV imagery, HOG features, and SVM classifier. By providing accurate tree counts and spatial information, this approach facilitates improved disease management, yield prediction, and resource allocation, ultimately contributing to the sustainability and productivity of oil palm cultivation. The detailed implementation insights provided in the paper serve as a valuable resource for researchers and practitioners interested in adopting similar techniques for agricultural remote sensing applications, fostering advancements in precision agriculture and environmental stewardship[6]

The study addresses the critical need for precise metrics in forestry management and ecological studies, with a focus on tree heights and crown diameters. These metrics are pivotal for assessing forest health, biomass estimation, and ecological modeling. The methodology centers around the utilization of unmanned aerial vehicles (UAVs) to capture high-resolution images of forested areas. UAVs offer significant advantages over traditional ground-based or manned aerial methods, including the ability to collect data rapidly over large areas with minimal environmental disturbance. The first step involves the acquisition of high-resolution imagery using UAVs equipped with advanced cameras. These cameras are capable of capturing detailed images of the forest canopy, enabling accurate measurement of tree heights and crown diameters. The UAVs are deployed to fly over designated forested areas, capturing images from different angles and perspectives to ensure comprehensive coverage. Following data acquisition, photogrammetric techniques are employed to process the captured imagery and extract relevant information about tree heights and crown diameters. Digital surface models (DSMs) and digital terrain models (DTMs) are generated from the UAV-acquired images using photogrammetric software. These models provide detailed three-dimensional representations of the terrain and vegetation, allowing for precise measurements of tree heights and crown diameters. To determine tree heights, the study utilizes the generated DSMs and DTMs to calculate the difference between the highest point of each tree and the ground level. This approach enables accurate estimation of tree heights, accounting for variations in terrain elevation and canopy structure. The calculated tree heights serve as crucial metrics for assessing forest structure, growth rates, and biomass accumulation. In addition to tree heights, the study also focuses on accurately measuring crown diameters, which provide insights into tree canopy size and spatial distribution. Crown diameters are determined by analyzing the UAV imagery and identifying the outer boundaries of individual tree crowns. Advanced image processing techniques, such as segmentation and edge detection, may be employed to delineate crown boundaries accurately. The accuracy of the measured tree heights and crown diameters is validated by comparing them to ground-based measurements obtained through traditional forestry methods. Field surveys may be conducted to measure tree heights using clinometers or laser rangefinders, while crown diameters can be measured using tape measures or optical instruments. The results of the UAV-based measurements are compared to ground-truth data to assess their reliability and precision. The implementation of the methodology involves the use of specialized UAVs equipped with high-resolution cameras, as well as photogrammetric software for image processing and analysis. The processing of UAV-acquired imagery to generate DSMs and DTMs requires computational resources capable of handling large datasets and performing complex geometric calculations. Furthermore, the integration of ground-based validation surveys into the workflow necessitates coordination and logistical planning to ensure data consistency and accuracy. In conclusion, the study by Panagiotidis et al. demonstrates the effectiveness of UAV-based high-resolution imagery in accurately determining tree heights and crown diameters for forestry management and ecological studies. By leveraging photogrammetric techniques and advanced image processing algorithms, the methodology provides forestry professionals with reliable and precise data for planning, monitoring, and managing forest resources.[7]

The paper by Selim et al. investigates a novel approach to determine the height of objects, specifically trees, using 2-D UAV imagery combined with principles of spherical astronomy. The technique involves analyzing 2-D top-view images from UAVs and applying spherical astronomy methods to estimate the height of trees. The methodology calculates angles and distances based on the position of the sun and the shadows cast by the trees, which are visible in the UAV images. This innovative approach was shown to effectively estimate tree heights without the need for three-dimensional data or complex equipment. The method relies on basic geometric and astronomical calculations, making it accessible and cost-effective. The technique offers a new tool for researchers and professionals in forestry and urban planning who require tree height information but may not have access to more sophisticated 3D imaging technologies. It is particularly useful in regions where resources are limited, allowing for environmental monitoring and urban planning with reduced logistical constraints. [8]

The study by Gonçalves and colleagues focuses on the application of convolutional neural networks (CNNs) to count and geolocate citrus trees using UAV-derived multispectral imagery. This research aims to enhance agricultural efficiency through precision farming techniques. The approach utilizes a CNN to process multispectral images captured by UAVs over citrus orchards. The CNN is trained to recognize citrus trees and differentiate them from other vegetation and objects based on their spectral signatures and spatial features. The CNN model proved effective in accurately counting and pinpointing the location of citrus trees in large orchards. This method allows for detailed orchard mapping and can contribute to better crop management practices by providing precise tree counts and location data. This technology enables more targeted agricultural interventions, such as precise irrigation, fertilization, and pest management, which can lead to increased productivity and sustainability in citrus production. The approach also has potential applications in other types of orchards where tree counting and localization are necessary for effective management. [9]

This study by Marques Ramos focuses on employing convolutional neural networks (CNNs) to count and geolocate citrus trees using multispectral imagery captured by UAVs. The objective is to enhance agricultural management by leveraging the precision of deep learning techniques. The research utilizes CNNs to analyze multispectral images obtained from UAVs flying over citrus orchards. The neural network is trained to identify citrus trees by recognizing specific spectral signatures and spatial features unique to citrus foliage and geometry. The CNN model demonstrated high accuracy in detecting and localizing citrus trees, making it possible to generate detailed orchard maps that facilitate better management and monitoring of citrus production. The application of this method could revolutionize citrus orchard management through improved yield estimation, disease management, and resource allocation. This technique could also be adapted for other crop types, broadening its utility in precision agriculture. [10]

Nazar et al. aim to detect and count poplar trees using deep learning models applied to multispectral UAV imagery. This study is part of broader efforts to improve forest management and inventory processes. The methodology involves the use of deep learning algorithms to process multispectral images, identifying poplar trees based on their distinct spectral signatures compared to other vegetation and background elements. The approach was effectively able to identify and enumerate poplar trees, facilitating more accurate forest inventories and assessments. The success of this method provides valuable insights into sustainable forest management, aiding in the monitoring of forest health and aiding in decisions regarding timber harvesting and reforestation. [11]

The research aims to address the challenge of automating the identification of different tree species from aerial images. Traditional methods for species classification often rely on manual observation or labor-intensive field surveys, which are time-consuming and may lack scalability. By leveraging drone-captured hyperspectral and RGB imagery analyzed with CNNs, the study seeks to develop a scalable and accurate approach for classifying tree species based on their spectral properties and visual appearance. The first step involves the acquisition of drone-captured hyperspectral and RGB imagery of forested areas containing various tree species. Hyperspectral imagery captures a wide range of spectral bands across the electromagnetic spectrum, providing detailed information about the spectral signatures of different materials, including vegetation. RGB imagery, on the other hand, captures color information, which is essential for visual interpretation and analysis. Before feeding the imagery into the CNN model, preprocessing steps are performed to enhance the quality and usability of the data. This may include techniques such as image registration, calibration, and normalization to correct for sensor distortions and ensure consistency across spectral bands. The core of the methodology lies in the utilization of convolutional neural networks (CNNs) for image classification. CNNs are a type of deep learning algorithm specifically designed for image analysis tasks, capable of automatically learning hierarchical features from raw data. The architecture of the CNN model is carefully designed to accommodate both hyperspectral and RGB imagery, leveraging their complementary information for accurate species classification. Annotated training data is essential for training the CNN model to recognize different tree species from the imagery. This involves manually labeling a subset of the drone-captured images, specifying the locations and identities of individual tree species. The annotated data serve as ground truth labels for training the CNN model to associate specific spectral and visual patterns with corresponding tree species. The CNN model is trained using the annotated training data, where it learns to extract relevant features from the hyperspectral and RGB imagery and associate them with the corresponding tree species labels. The training process involves optimization algorithms such as stochastic gradient descent (SGD) to minimize the classification error and fine-tune the model parameters for optimal performance. Once trained, the CNN model is evaluated using a separate validation dataset to assess its accuracy and generalization ability. Performance metrics such as accuracy, precision, recall, and F1 score are calculated to quantify the model's effectiveness in classifying tree species. Additionally, confusion matrices may be generated to analyze the model's performance on individual species and identify any potential misclassifications. The implementation of the methodology involves the use of specialized software libraries and frameworks for deep learning and image analysis. Popular frameworks such as TensorFlow or PyTorch provide robust tools for building and training CNN models, as well as performing image preprocessing and evaluation tasks. High-performance computing resources may be utilized to expedite the training process, particularly when dealing with large datasets and complex model architectures. In conclusion, the research demonstrates the potential of combining drone-captured hyperspectral and RGB imagery with convolutional neural networks for the classification of tree species. By leveraging the rich data content of hyperspectral imagery and the visual information provided by RGB imagery, the CNN model achieves high accuracy in distinguishing among various tree species based on their spectral properties and visual appearance.[12]

This study aims to map the height and estimate the aboveground biomass of mangrove forests using UAV-LiDAR technology, contributing to conservation efforts and the understanding of these critical ecosystems. UAV-LiDAR sampling was utilized to capture detailed topographical and structural data of mangrove forests. Advanced processing techniques were then applied to this data to estimate tree heights and calculate biomass. The precise data provided by UAV-LiDAR allowed for accurate height measurement and biomass estimation, offering critical insights into the health and carbon storage capacities of mangrove forests. These findings are vital for environmental monitoring, climate change studies, and the management of mangrove ecosystems, which are known for their role in carbon sequestration and as buffers against coastal erosion. [13]

This research focuses on enhancing tree height estimation across the Sierra Nevada by integrating data from spaceborne and airborne LiDAR with optical imagery. The primary aim is to overcome the limitations of traditional methods by combining various sources of remote sensing data to improve the resolution and accuracy of tree height measurements. By integrating data from multiple platforms, including spaceborne and airborne LiDAR along with optical imagery, the study seeks to achieve a more comprehensive analysis of the forest structure. The integration of different data types allows for a holistic approach to tree height estimation, leveraging the strengths of each remote sensing modality. Spaceborne LiDAR provides broad coverage and consistent data acquisition over large areas, while airborne LiDAR offers higher spatial resolution and detailed information about individual tree canopies. Optical imagery complements LiDAR data by providing additional contextual information and enhancing the interpretation of vegetation patterns. The integrated approach yielded highly accurate tree height estimations, surpassing the performance of methods that rely solely on single data sources. This improvement in accuracy is attributed to the synergistic effects of combining data from multiple platforms, which enables a more robust estimation of tree heights across diverse forest landscapes. Accurate tree height data are critical for various applications in environmental science and forest management. They are essential for biomass estimation, habitat analysis, and ecological modeling, providing valuable insights into forest structure and dynamics. By enhancing the accuracy of tree height estimation, the integrated approach proposed in this research offers significant benefits for environmental scientists and forest managers, enabling more informed decision-making and resource management strategies. Overall, the integration of data from spaceborne and airborne LiDAR with optical imagery represents a powerful approach for enhancing tree height estimation and advancing our understanding of forest ecosystems. This methodological advancement has the potential to drive innovation in environmental research and contribute to more sustainable management practices in forested regions such as the Sierra

Nevada.[14]

The research aims to provide a non-destructive method for estimating cotton yield using UAV-based measurements of plant height. Traditional methods of yield estimation often involve destructive sampling, which can be labor-intensive and impractical for large-scale agricultural operations. By leveraging UAV technology to capture plant height data, the study seeks to develop a scalable and efficient approach for predicting cotton yield, with the potential to transform cotton farming practices. The first step involves the deployment of UAVs equipped with high-resolution cameras to capture imagery of cotton fields. The UAVs are programmed to fly over designated areas, capturing images from different angles and perspectives to ensure comprehensive coverage. During the flight, the cameras collect imagery that contains detailed information about the spatial distribution and height of cotton plants within the field. Once the imagery is acquired, image processing techniques are applied to extract plant height data from the UAV-captured images. This involves analyzing the images to identify and measure the height of individual cotton plants. Advanced image processing algorithms, such as feature extraction and segmentation, may be employed to accurately delineate plant boundaries and estimate their heights from the imagery. The extracted plant height data are then correlated with cotton yield measurements obtained from traditional field sampling methods. The hypothesis that taller cotton plants generally produce more cotton is tested by analyzing the relationship between measured plant heights and observed yield values. Statistical methods, such as regression analysis or correlation coefficients, are employed to quantify the strength and direction of the relationship between plant height and yield. Based on the results of the correlation analysis, predictive models are developed to estimate cotton yield based on UAV-derived plant height data. Machine learning algorithms, such as linear regression or random forest, may be employed to train predictive models using the collected data. The models are trained to learn the relationship between plant height and yield, allowing for the prediction of cotton yield from UAV-based height measurements. The accuracy and reliability of the predictive models are assessed through validation using independent datasets. A portion of the collected data is set aside for validation purposes, allowing the performance of the models to be evaluated on unseen data. Performance metrics such as root mean square error (RMSE) or coefficient of determination (R-squared) are used to quantify the predictive accuracy of the models. The implementation of the methodology involves the use of specialized software tools and algorithms for UAV image processing, data analysis, and predictive modeling. Open-source libraries such as OpenCV and scikit-learn may be utilized for image processing and machine learning tasks. Additionally, custom scripts and algorithms may be developed to handle specific data processing requirements and model training procedures. In conclusion, the research demonstrates the potential of using UAV-based measurements of plant height for estimating cotton yield. By leveraging UAV technology and advanced image processing techniques, the study provides a non-destructive and scalable method for predicting cotton yield across large agricultural areas. The positive correlation between measured plant heights and cotton yield suggests that UAV-based height measurements can serve as a reliable predictor of yield, enabling more precise yield forecasts and guiding agricultural practices for sustainable and profitable cotton production.[15]

This study by Borra-Serrano et al. aims to develop and validate a method for measuring canopy height and estimating biomass of Lolium perenne (perennial ryegrass) using UAV-based imagery, facilitating non-destructive agricultural assessments. The research employs high-resolution UAV imagery to capture detailed topographic data of ryegrass fields. Image processing techniques and analytical algorithms are used to measure the canopy height directly from the imagery. These height measurements are then correlated with ground-truthed biomass data to develop predictive models for biomass estimation. The study successfully demonstrates that UAV imagery can be effectively used to measure canopy height accurately. Moreover, the derived height measurements correlate well with biomass, allowing for reliable non-destructive biomass estimation. This methodology offers a significant tool for agronomists and farmers, providing a rapid and cost-effective means of monitoring crop growth and health, optimizing inputs, and predicting yields without the need for physical sampling, thereby enhancing sustainable agricultural practices. [16]

Nevalainen and colleagues investigate the use of UAV-based hyper- and multispectral imaging across multiple time points to detect and monitor bark beetle infestations in Norway spruce forests. The study utilizes a combination of hyperspectral and multispectral imaging technologies mounted on UAVs to capture detailed spectral data indicative of tree health and stress symptoms associated with bark beetle attack. Image processing and analysis techniques, including machine learning models, are applied to detect changes over time that signify infestation. The results indicate that UAV imaging can effectively identify affected areas early in the infestation process by detecting subtle changes in the spectral signatures of the foliage, which are indicative of stress before visible symptoms appear. This approach enhances forest management capabilities by enabling early detection of infestations, which is crucial for mitigating damage and managing forest health. The method provides a scalable and efficient monitoring tool that can be integrated into pest management strategies. [17]

The study by Berni et al. focuses on using UAV-equipped thermal imaging to map canopy conductance and Crop Water Stress Index (CWSI) in olive orchards, aiming to optimize irrigation practices. Thermal sensors on UAVs capture imagery that reflects temperature variations across the orchard. These temperature differences are analyzed to assess canopy conductance and water stress levels. The CWSI is calculated by integrating temperature data with meteorological conditions, providing a detailed map of water stress across different parts of the orchard. The study demonstrates that thermal imagery can effectively reveal variation in water stress and canopy conductance at a high resolution, allowing for precise identification of under-irrigated areas. This technology enables olive growers to apply water more efficiently, targeting areas that specifically need irrigation, thus conserving water resources and improving crop yield and quality. It represents a significant advancement in precision agriculture, particularly in water-scarce environments.[18]

This research by Osco et al. explores the prediction of canopy nitrogen content in citrus trees using UAV-derived spectral vegetation indices and the random forest algorithm, aiming to enhance nutrient management strategies. Multispectral UAV imagery is used to compute several vegetation indices that correlate with plant health and nitrogen status. These indices serve as input features for a random forest model designed to predict the nitrogen content of citrus canopies. The random forest model provided accurate predictions of canopy nitrogen content, outperforming traditional assessment methods and allowing for the detailed mapping of nutrient levels across orchards. The method facilitates precise nitrogen management, potentially reducing fertilizer use and environmental impact while maintaining or enhancing fruit quality and yield. This approach can be adapted for other nutrients and crop types, broadening its applicability in precision agriculture. [19]

Matsubara and colleagues aim to estimate pasture biomass and canopy height in the Brazilian savanna using UAV photogrammetry, contributing to better rangeland management and ecological monitoring. The study employs UAVs to capture high-resolution photogrammetric images of savanna pastures. Image analysis techniques are used to measure canopy height, which is then correlated with biomass estimates obtained through ground-truthing. UAV photogrammetry proved to be an effective method for accurately estimating both canopy height and biomass in a non-destructive manner, providing essential data for managing grazing pressures and assessing ecological health. This approach offers a valuable tool for ecologists and land managers, allowing for the continuous monitoring of pasture conditions, which is vital for sustainable grazing management and conservation efforts in savanna ecosystems. [20]

This study focuses on developing a multi-task learning framework that simultaneously performs semantic segmentation and height estimation from multi-modal remote sensing images, aiming to enhance the accuracy and efficiency of geographic information systems. The methodology integrates multi-modal data inputs, such as LiDAR and multispectral imagery, into a single deep learning model. This model leverages shared representations to improve both semantic understanding and height estimation of geographic features. The integration of these tasks within a single framework demonstrated improved performance over traditional single-task models, showing that shared features between segmentation and height estimation can enhance both tasks. This approach offers significant potential for urban planning, forestry management, and environmental monitoring, providing a comprehensive tool for detailed spatial analysis. [21]

This paper investigates the use of unmanned aerial system (UAS) derived multispectral imagery to estimate the threshold levels at which tree crown defoliation can be detected, which is crucial for monitoring forest health and early detection of disease or pest infestation. Multispectral images are analyzed using various vegetation indices to assess their effectiveness in detecting changes in foliage density and health. Statistical models are then used to determine the detection thresholds. Results indicated that specific vegetation indices provide reliable indicators of defoliation thresholds, with significant implications for early intervention in forest management. This methodology enables more precise monitoring and management of forests, helping mitigate the impacts of pests and diseases by allowing for timely and targeted interventions. [22]

The study aims to evaluate the accuracy of orthophotos generated from multi-rotor UAV platforms, which are increasingly utilized for topographic mapping and surveying applications. Orthophotos are essential products in geospatial analysis and mapping, providing accurate representations of terrain and surface features. By assessing the positional quality of UAV-derived orthophotos, the research seeks to validate their suitability for various professional applications, including surveying, urban planning, and environmental monitoring. The first step involves collecting aerial imagery using multi-rotor UAV platforms equipped with high-resolution cameras. The UAVs are flown over the study area, capturing images from different perspectives and altitudes to ensure comprehensive coverage. During the flight, ground control points (GCPs) may be established to facilitate the georeferencing process and enhance the accuracy of the orthophoto generation. Once the aerial imagery is acquired, orthophotos are generated using photogrammetric software or image processing algorithms. The images are processed to correct for distortions caused by terrain relief and camera perspective, resulting in orthorectified images that exhibit uniform scale and minimal geometric distortions. The orthophotos are then georeferenced to a known coordinate system, enabling their integration with existing geospatial data and maps. To assess the accuracy of the UAV-derived orthophotos, ground-truth data are collected through field surveys or traditional surveying methods. This may involve measuring the coordinates of prominent ground features or placing targets at known locations within the study area. The ground-truth data serve as reference points for evaluating the positional accuracy of the orthophotos and assessing their compliance with standard mapping accuracies. The positional accuracy of the UAV-derived orthophotos is evaluated by comparing them against the ground-truth data collected from the field. Various metrics may be used to quantify the discrepancies between the orthophotos and the reference data, including root mean square error (RMSE) or mean positional error (MPE). Statistical analyses are conducted to assess the overall accuracy and precision of the orthophotos and identify any systematic errors or biases. The accuracy of the UAV-derived orthophotos is assessed in relation to established mapping standards and specifications. These standards define the acceptable tolerances for positional accuracy in different mapping applications, such as cadastral mapping, urban

planning, or environmental monitoring. The orthophotos are evaluated against these standards to determine whether they meet the requirements for specific use cases and applications. The results of the accuracy assessment demonstrate that the UAV-derived orthophotos exhibit high positional accuracy, meeting or exceeding the standards required for various geospatial analysis and mapping applications. The validation provides confidence in the use of UAVs for producing high-quality maps and models, supporting their integration into professional surveying workflows, urban planning projects, and environmental monitoring initiatives. The implementation of the methodology involves the use of specialized hardware and software tools for aerial surveying, photogrammetry, and geospatial analysis. Multi-rotor UAV platforms equipped with high-resolution cameras are employed for aerial data collection, while photogrammetric software packages such as Pix4D or Agisoft Metashape are used for orthophoto generation and georeferencing. Ground-truth data collection may involve traditional surveying equipment such as total stations or global navigation satellite systems (GNSS). Statistical software tools such as R or Python may be utilized for data analysis and accuracy assessment.
In conclusion, the study provides a comprehensive assessment of the positional quality of orthophotos produced using multi-rotor UAV platforms. By comparing the UAV-derived orthophotos against ground-truth data and evaluating their compliance with mapping standards, the research demonstrates the high positional accuracy of UAV-based mapping products. These findings support the use of UAVs for generating high-quality maps and models, facilitating their integration into professional surveying, urban planning, and environmental monitoring workflows.[23]

This research explores the potential of UAV-based multispectral imagery to predict the maturity dates of different soybean breeding lines, facilitating better crop management and harvesting strategies. The study employs multispectral imaging to monitor the phenological development of soybean plants. Data analytics and predictive models are then applied to estimate the optimal harvesting time based on observed spectral changes. The models provided accurate predictions of soybean maturity dates, correlating well with actual crop development stages observed in the field. This approach enhances agricultural productivity by optimizing harvesting times, thus improving yield and reducing losses due to untimely harvesting practices. [24]

The objective of this study is to determine leaf water content using spectroscopic methods combined with continuous wavelet analysis, which can provide vital information for assessing plant health and water stress. The technique involves analyzing the spectral reflectance of leaves using wavelet transforms to isolate the spectral features most closely associated with water content. The methodology proved effective in accurately quantifying water content in leaves, demonstrating a high correlation with traditional measurement techniques. This non-destructive method offers a fast and accurate means of monitoring plant hydration, applicable in both agricultural and ecological research settings, aiding in the management of water resources in crops. [25]

This paper compares two models—the optimal band algorithm and the Grey Relational Analysis-Artificial Neural Network (GRA-ANN)—in estimating soil organic matter content from remote sensing data. The study evaluates the performance of these two approaches using multispectral satellite data. Each model's predictive accuracy is assessed through comparison with ground-truth soil samples. The GRA-ANN model outperformed the optimal band algorithm, providing more accurate and reliable estimations of soil organic matter, which is crucial for assessing soil quality and fertility. Accurate remote estimation of soil organic matter can significantly enhance land management strategies and agricultural productivity, supporting sustainable farming practices by allowing for precise nutrient management and monitoring of soil health. [26]

This study addresses the detection and monitoring of wheat yellow rust using multispectral imagery collected by UAVs, aiming to improve disease management in wheat crops. Multispectral images are processed using machine learning techniques to identify the spectral signatures associated with yellow rust. The model is trained and validated on field data where yellow rust incidence is known. The approach successfully identified infected areas, demonstrating high accuracy and potential for early detection of yellow rust in wheat fields. This method allows for timely and targeted disease management practices, reducing crop losses and chemical inputs by applying treatments only where needed. [27]

The research explores the fusion of LiDAR and multispectral data to estimate forest volume and biomass at the plot level, which is crucial for carbon accounting and forest management. By integrating high-resolution LiDAR data with multispectral imagery, the study creates detailed 3D models of forest plots to measure tree volume and biomass more accurately than using either data source alone. The fused data provided a more comprehensive assessment of forest structure and biomass, proving superior to single-source data in terms of accuracy and detail. This approach enhances the precision of forest resource assessments, supporting sustainable management practices and providing reliable data for ecological research and carbon sequestration studies. [28]

Niu and colleagues aim to estimate tree-level evapotranspiration rates for pomegranate trees by integrating lysimeter measurements with UAV-derived multispectral imagery, enhancing water use efficiency in orchards. The study combines direct measurements of water use from lysimeters with spectral data from UAVs to model evapotranspiration at the individual tree level. This model is used to assess water stress and guide irrigation practices. The integrated approach provided detailed insights into the water use patterns of pomegranate trees, allowing for more precise irrigation management tailored to individual tree needs. Optimizing water use in agriculture through such detailed monitoring can significantly improve water conservation efforts and crop yields, particularly in water-scarce regions. [29]

This study develops a vegetation index (VI)-based phenology adaptation technique to monitor rice crop development stages using UAV multispectral imagery, aiming to enhance crop management and yield estimation. Using a series of multispectral images throughout the growing season, the study applies vegetation indices to track phenological changes in rice crops. This data informs a phenology-based model that predicts growth stages and health. The approach accurately tracks rice phenology, correlating well with ground observations and providing essential information for managing fertilization, irrigation, and harvesting times. The method offers rice farmers a powerful tool for precision agriculture, enabling better resource management and potentially increasing yields while reducing environmental impact. [30]

Tian and colleagues aim to enhance UAV stability and control by investigating the performance of sensor fusion algorithms in estimating critical flight angles. The angle of attack and sideslip angle are crucial parameters for UAV flight control, influencing stability, maneuverability, and overall performance. By testing various fusion algorithms and integrating data from onboard sensors during flight tests, the study seeks to improve angle estimation accuracy under different flight conditions, ultimately contributing to the development of more advanced UAV control systems. The study is motivated by the increasing demand for UAVs in various applications, including surveillance, mapping, and aerial photography. In complex flight environments or adverse weather conditions, accurate estimation of flight angles becomes essential for safe and reliable UAV operation. Traditional methods of angle estimation may be limited by sensor noise, measurement errors, or environmental disturbances. Sensor fusion techniques offer a promising solution by integrating data from multiple sensors to improve accuracy and reliability. The experimental setup involves conducting UAV flight tests with onboard sensors configured to measure relevant flight parameters, including airspeed, altitude, angular rates, and accelerations. In addition to standard inertial measurement units (IMUs), specialized sensors such as pitot tubes or wind vanes may be used to provide additional data for angle estimation. The UAV is equipped with a data logging system to record sensor measurements during flight.
Several sensor fusion algorithms are selected for evaluation, including complementary filters, Kalman filters, and particle filters. Each algorithm has its advantages and limitations in terms of computational complexity, robustness, and accuracy. Complementary filters are computationally efficient but may suffer from drift over time. Kalman filters offer optimal estimation under Gaussian noise assumptions but may require tuning for non-linear systems. Particle filters provide robustness against non-linearities and sensor outliers but may be computationally intensive. The UAV is flown through a series of flight maneuvers designed to induce variations

in the angle of attack and sideslip angle. These maneuvers may include straight and level flight, climbs, descents, turns, and banked turns at different airspeeds and altitudes. The flight tests are conducted in varying weather conditions to assess the algorithms' performance under different environmental factors, such as wind gusts or turbulence. During flight tests, sensor measurements and estimated angles are recorded for subsequent analysis. The recorded data are processed offline to evaluate the performance of each fusion algorithm in estimating the angle of attack and sideslip angle. Performance metrics such as root mean square error (RMSE), mean absolute error (MAE), and correlation coefficients are calculated to quantify the accuracy and reliability of angle estimations across different flight conditions. The results of the evaluation demonstrate varying levels of accuracy and reliability among the tested fusion algorithms. Some algorithms may exhibit better performance under specific flight conditions or sensor configurations. For example, Kalman filters may perform well in stable flight conditions with minimal sensor noise, while particle filters may offer better robustness in turbulent or dynamic environments. The discussion highlights the strengths and weaknesses of each algorithm and provides insights into potential improvements or refinements for future research. In conclusion, the study by Tian and colleagues contributes to advancing UAV control systems by investigating the performance of sensor fusion algorithms in estimating critical flight angles. By integrating data from onboard sensors and testing various fusion algorithms during flight tests, the research enhances our understanding of angle estimation techniques and their applicability to real-world UAV operations. The findings provide valuable insights for the development of more advanced UAV control systems capable of operating reliably in complex environments. [31]

3. Methodology

Our study introduces a dual-method approach for enhancing tree detection and structural analysis in citrus orchards using UAV imagery, leveraging the strengths of YOLOv8 object detection and segmentation with clustering techniques. Each methodology is developed and tested independently to evaluate its effectiveness in tree identification, enumeration, and structural property extraction.

3.1 YOLOv8 Object Detection Approach

We utilized the YOLOv8 object detection model, chosen for its precision and speed, tailored to the unique requirements of citrus orchard monitoring. The process began with extensive data annotation using OpenCV and YOLO box tools to capture the varied tree dimensions within orchards accurately. After normalization and data cleansing, the model underwent fine-tuning with orchard-specific parameters, enhancing its accuracy in detecting canopy variations and tree heights. A separate testing set confirmed the model's generalization abilities, showcasing its reliability for orchard surveillance.

For object detection tasks such as tree detection in UAV images, YOLO is a popular deep learning model. While the model's details are complex, its objective function during training can be simplified as: [29]

Equation: $\lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} l_{ij}^{obj} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] + \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} l_{ij}^{noobj} (C_i - \hat{C}_i)^2 + \sum_{i=0}^{S^2} l_i^{obj} \sum_{c \in classes} (p_i(c) - \hat{p}_i(c))^2$

Explanation: This equation represents a part of the loss function used in YOLO, where it tries to minimize the difference between predicted values ($\hat{x}_i, \hat{y}_i, \hat{C}_i, \hat{p}_i(c)$) and true values ($x_i, y_i, C_i, p_i(c)$). The weights λ_{coord} and λ_{noobj} balance the importance of detecting objects vs. penalizing false detections.

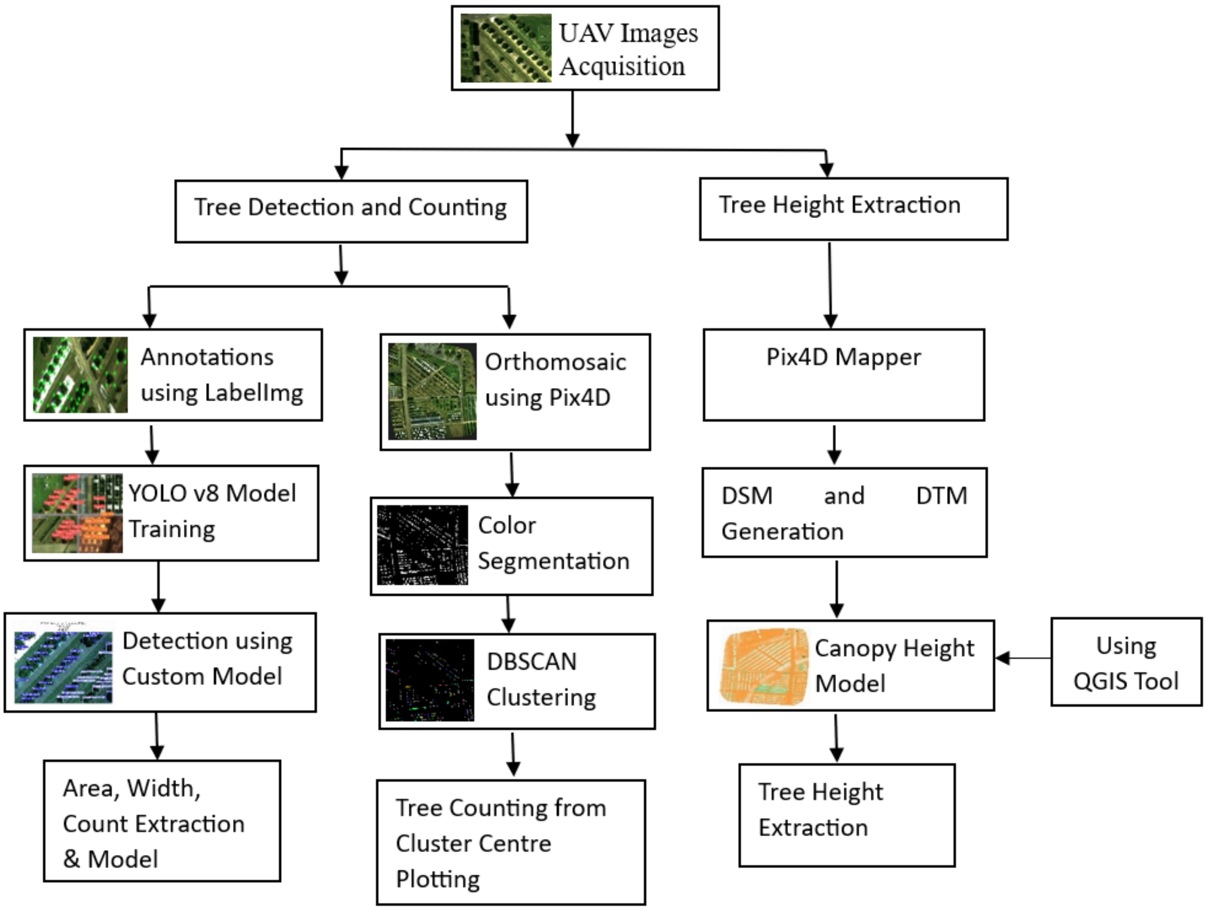


Fig. 1 Flow Diagram of Proposed Methodology

3.2 Segmentation and Clustering Technique

Alternatively, our segmentation and clustering approach analyzed UAV imagery through generated orthomosaic images and color space conversion to isolate citrus tree foliage's green spectrum. Applying the DBSCAN algorithm facilitated tree pixel grouping by density, offering a visual representation of tree distribution. This method supported accurate tree enumeration and provided insights into orchard structure.

Furthermore, we focused on extracting crucial structural properties like tree height using the Canopy Height Model (CHM), derived from Digital Surface Model (DSM) and Digital Terrain Model (DTM). QGIS played a vital role in visualizing and extracting this data, supplemented by a Python script for efficient processing and binary image techniques to evaluate tree coverage, thus offering a comprehensive landscape analysis.
For calculating tree height from UAV images, a common approach is to use DSM and DTM.

Equation: Tree Height = DSM - DTM
DSM represents the earth's surface and includes all objects on it. DTM represents the bare ground surface without any objects. The difference gives the height of objects, including trees.

While each methodology operates independently, their combined application underscores a strategic comparative analysis, highlighting the advantages and potential limitations within the context of precision agriculture. This approach not only enriches our understanding of effective UAV-based monitoring strategies in citrus orchards but also opens avenues for technological advancements and methodological enhancements in agricultural research.

4. IMPLEMENTATION

4.1 YOLO v8 Object Detection Algorithm

4.1.1 UAV Image Acquisition

Our data collection process commenced with the deployment of Unmanned Aerial Vehicles (UAVs) over three distinct citrus orchards. Each UAV was equipped with high-resolution cameras capable of capturing both RGB and Near-Infrared (NIR) imagery. This dual-band approach ensured comprehensive coverage across various lighting conditions, tree densities, and orchard layouts. The vast dataset collected was systematically organized, forming a robust foundation for subsequent analysis phases.

4.1.2 Image Annotation

A pivotal step in our methodology was the precise annotation of the UAV-acquired images. Utilizing the LabelImg Annotation Tool, each image was meticulously annotated to identify and classify different tree types within the orchards.
We defined four specific classes for annotation:
Tree (RGB): Mature trees in RGB images.
Small Tree (RGB): Younger, smaller trees in RGB images.
Tree (NIR): Mature trees in NIR images.
Small Tree (NIR): Smaller trees in NIR images.
This classification allowed for a nuanced analysis of the orchard, ensuring the YOLOv8 model could accurately distinguish between tree types and sizes. The annotation process not only provided essential ground truth data for model training but also enriched the dataset with detailed insights into orchard composition.

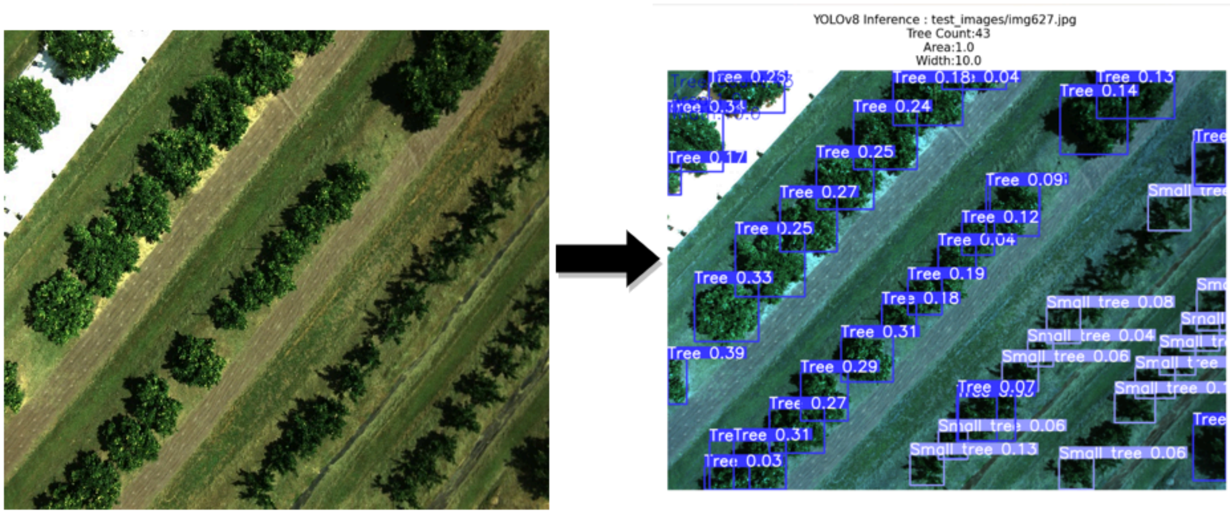
4.1.3 Model Selection & Training

Selecting the YOLOv8 algorithm for object detection was a strategic choice, driven by its proven efficacy in real-time image processing and its adaptability to diverse datasets. The model was extensively trained using the annotated dataset, undergoing a rigorous fine-tuning process to align its detection capabilities with the specific characteristics of citrus orchards. We employed batch processing with 16 images per batch, optimizing the training process for efficiency without compromising on learning depth. This careful calibration of the model ensured its sensitivity to the subtleties of tree structure variations within the dataset.
Figure 2 Illustrates the training process of the YOLOv8 object detection model using annotated UAV images from citrus orchards.

Fig. 2 YOLO v8 Model Training

4.1.4 Model Testing & Evaluation

Post-training, the YOLOv8 model underwent a comprehensive testing phase, where its precision in tree detection and its capability to discern structural properties were evaluated. This phase was critical in assessing the model's real-world applicability and its effectiveness in generating actionable insights for orchard management. Through innovative image processing techniques, we extrapolated tree height, canopy width, and area coverage from the model's detections, providing a multifaceted view of orchard health and density.



a **b**

Fig. 3 a. Input Image for YOLO v8 Model b. Output from YOLO v8

Visualization of YOLOv8 predictions with annotations highlighting tree count, area coverage, and canopy width.

Figure 3a shows an input image to the YOLOv8 model and Figure 3b shows an output image showing detected trees, area coverage, and canopy width.

4.2 Color Segmentation & Clustering

4.2.1 UAV Image Acquisition and Orthomosaic Generation

Parallel to the YOLOv8 implementation, we initiated a color segmentation and clustering analysis. High-resolution orthomosaic images were generated using Pix4D Mapper, stitching together hundreds of UAV-captured images to form a comprehensive visual map of each orchard. This map served as the basis for our segmentation analysis.

Figure 4 displays an orthomosaic image generated using Pix4D Mapper. It stitches together hundreds of UAV-captured images to form a comprehensive visual map of the orchard. The rectified image ensures accurate alignment and correction of any distortions, serving as the basis for subsequent segmentation analysis.

Fig. 4 Orthomosaic and Rectified Image

4.2.2 Image Processing and Color Space Conversion

To facilitate effective tree detection, the orthomosaic images were converted into the HSV color space. This conversion was pivotal in enhancing the contrast between the green foliage of citrus trees and the surrounding soil, making tree detection more accurate and efficient.

4.2.3 Color Thresholding and Tree Pixel Clustering

Applying color thresholding techniques, we isolated the green spectrum indicative of tree foliage. The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm was then employed to cluster these green pixels, effectively distinguishing individual trees within the imagery. This method provided a clear visual representation of tree distribution, supporting accurate tree enumeration and spatial analysis.

4.2.4 Tree Counting Using Cluster Center Calculation

The culmination of our segmentation and clustering approach was the precise calculation of tree counts within the orchards. By determining the center of each tree cluster, we could accurately enumerate the trees, offering valuable data for yield prediction and orchard management.

4.3 Structural Properties Extraction: Tree Height Analysis

Building on the data gathered, our study further ventured into the extraction of critical structural properties, particularly focusing on tree height. Utilizing the Digital Surface Model (DSM) and Digital Terrain Model (DTM) derived from the orthomosaic images, we computed the Canopy Height Model (CHM). This computation revealed the vertical extent of citrus trees, providing insights into the orchard's three-dimensional structure.

Advanced image processing techniques and the deployment of QGIS tools facilitated a granular examination of individual tree heights. This analysis was instrumental in assessing the overall health and productivity of the orchard, guiding strategic decisions in orchard management and cultivation practices.

5. RESULTS

Our results illustrate the efficacy of integrating advanced image processing techniques with UAV technology for precision agriculture in citrus orchards. This section delves into the performance metrics of the YOLOv8 model, the outcomes of color segmentation and clustering, and the insights gained from structural properties analysis, particularly tree height.

5.1 YOLOv8 Model Results

Performance Metrics

The YOLOv8 model underwent rigorous quantitative analysis, focusing on its precision across different tree classifications. Utilizing precision-recall and precision-confidence curves, we observed:

The RGB-based classes, "Tree (RGB)" and "Small Tree (RGB)," exhibited lower precision scores of 0.429 and 0.366, respectively. This variance underscores the challenges in distinguishing tree features within the visible spectrum.

In contrast, NIR-based classes, "Tree_ (NIR)" and "Small Tree_ (NIR)," demonstrated significantly higher precision, with scores of 0.649 and 0.643. These results highlight the model's enhanced capability in the NIR spectrum to detect and classify trees with greater accuracy.

The mean Average Precision (mAP) across all classes at an Intersection over Union (IoU) threshold of 0.5 was 0.522. This metric indicates a solid performance of the model in identifying and classifying trees within the orchard environment.

Confidence in Predictive Accuracy

Remarkably, at a confidence threshold of 0.857, the model achieved peak precision of 1.00 across all classes. This peak performance emphasizes the model's high confidence in accurately detecting tree-related features from UAV imagery, showcasing its potential as a reliable tool for orchard monitoring.
Figure 5 shows the trade-off between precision and recall for the YOLOv8 model in detecting citrus trees and Figure 6 depicts the model's precision at various confidence levels, highlighting peak precision.

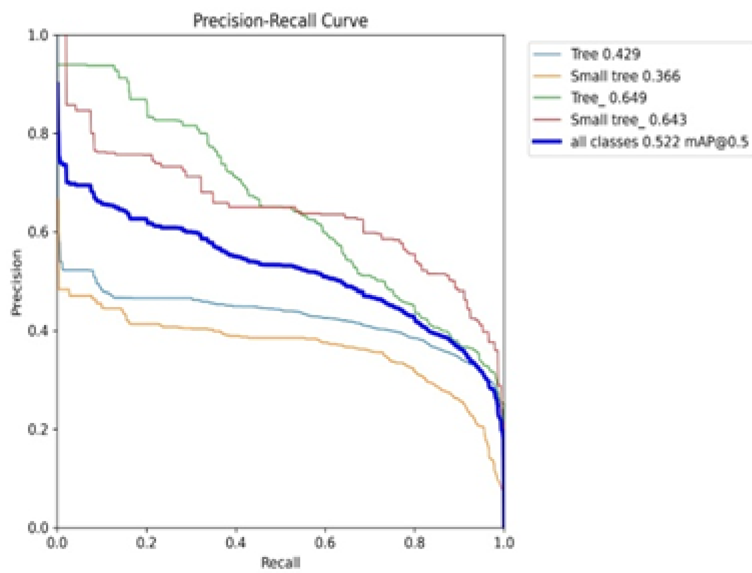


Fig. 5 Precision-Recall Curve

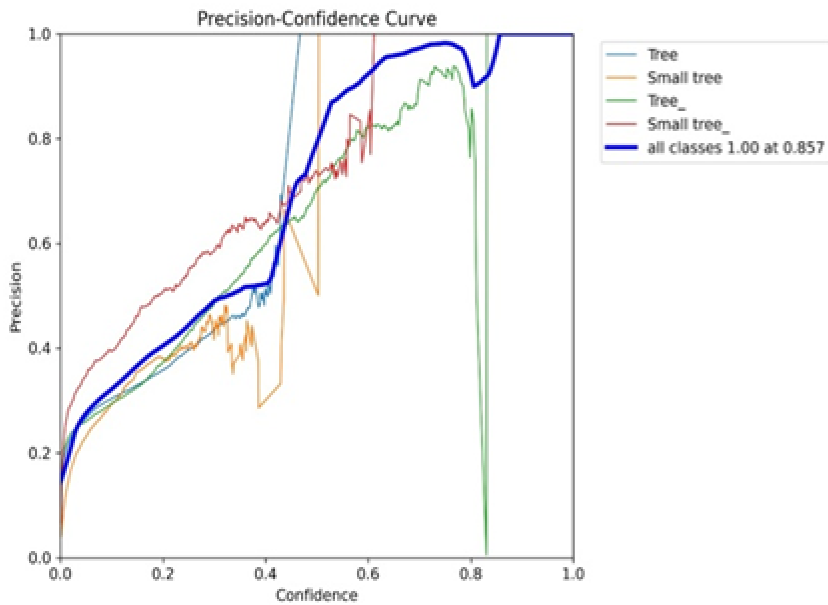


Fig. 6 Precision-Confidence Curve

5.2 Color Segmentation & Clustering Results

Tree Cluster Delineation

The application of color segmentation and clustering to RGB orthomosaic images facilitated the successful identification and enumeration of tree clusters. This technique effectively distinguished individual trees within the citrus fields, illustrating the method's utility in enhancing orchard surveys and management strategies.

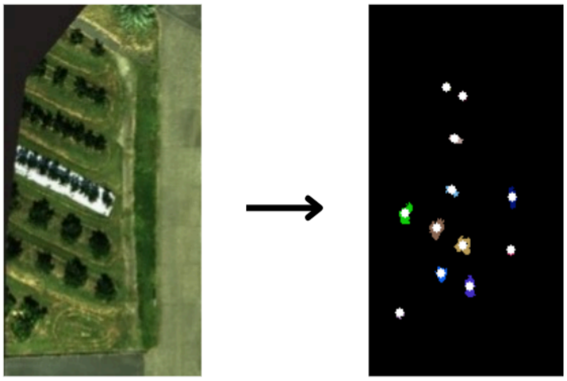
Figure 7a shows the Orthomosaic image of the orchard.and Figure 7b shows Color-segmented and clustered image showing tree clusters identified using the DBSCAN algorithm.

a b

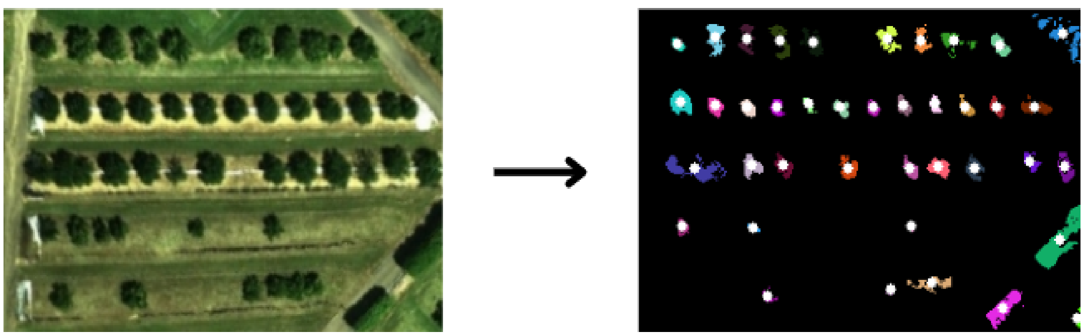
Fig. 7 a. Orthomosaiced and Rectified Image 7 b. Color Segmented & Clustered Image

Also in this study orthomosaic image was divided into 10 individual plots for analysis, then color segmentation and DBSCAN clustering techniques on orthomosaic imagery of an orchard to identify and enumerate trees. The results obtained from our approach were compared with manual tree counts for each plot, revealing both accuracy in tree count and variation in estimated tree heights. The manual tree counts for each plot ranged from 10 to 46, with our method retrieving counts close to manual counts in most cases. The accuracy for tree count ranged from 73.33% to 100%, indicating the effectiveness of our approach in accurately identifying trees within the orchard UAV imagery.

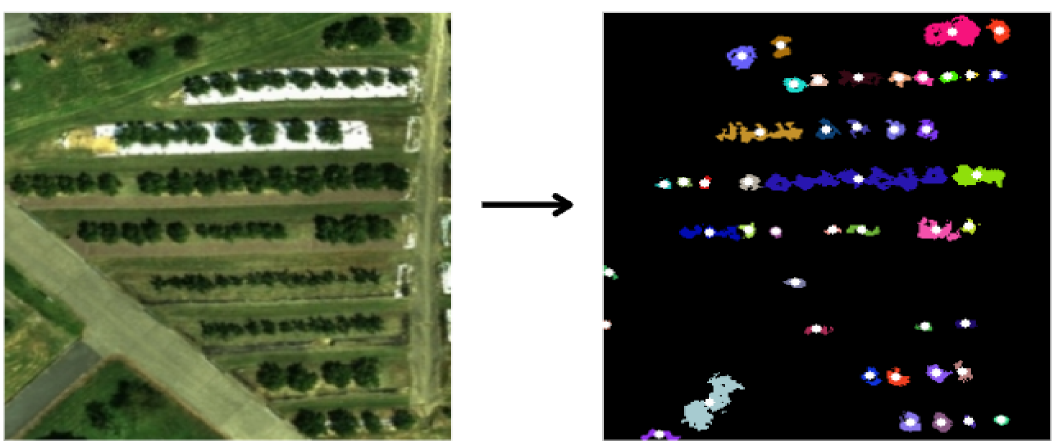
PLOT - 1



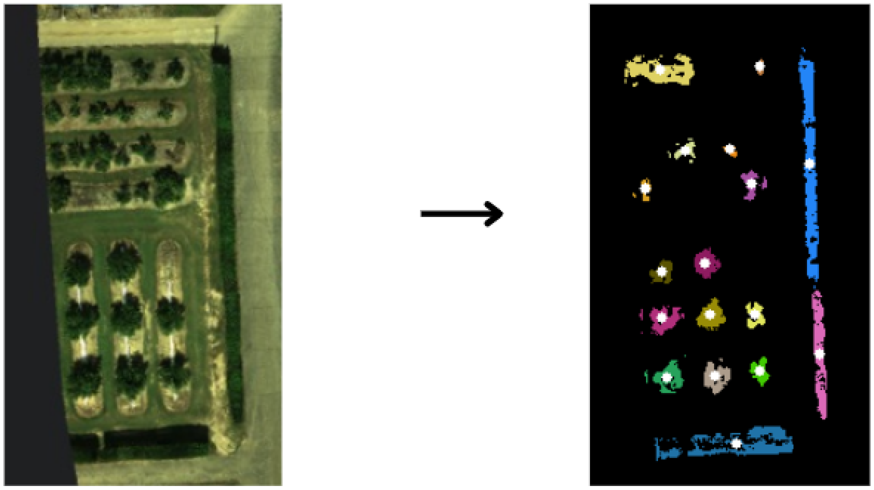
PLOT - 2



PLOT -3

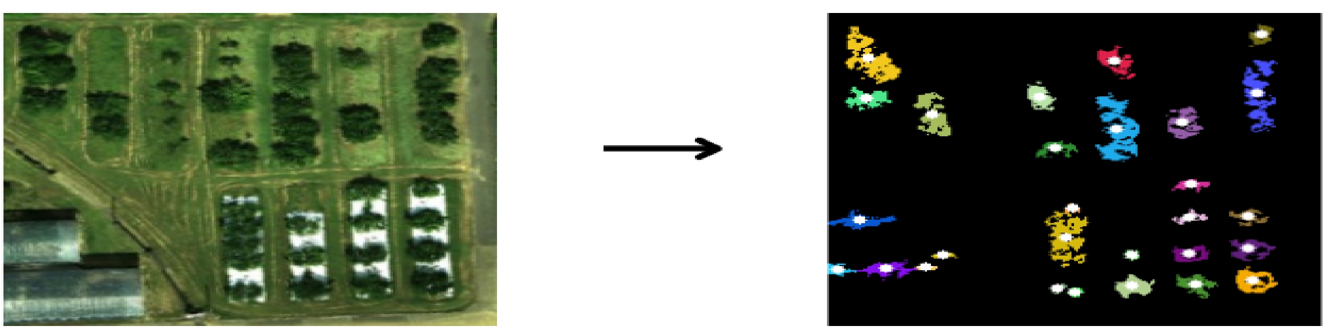


PLOT - 4



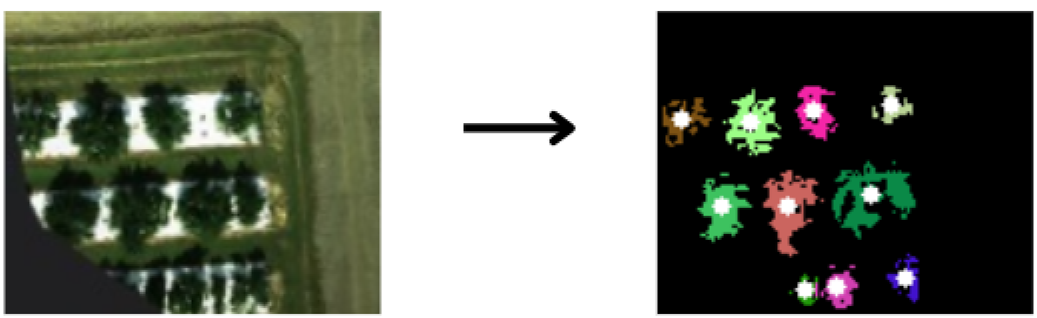
PLOT - 5

PLOT - 6



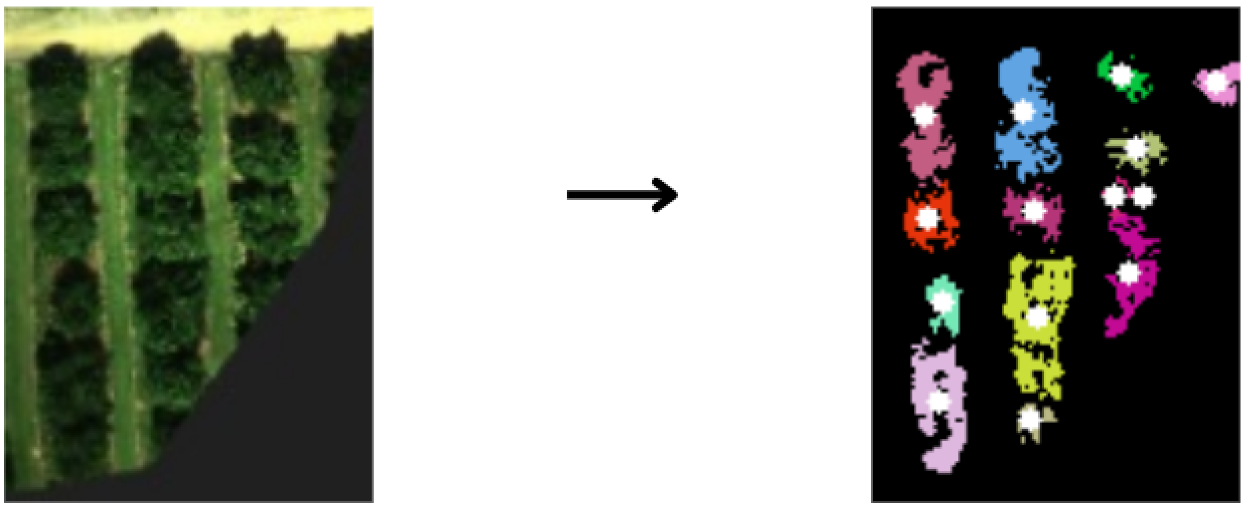
PLOT - 7

PLOT - 8



PLOT - 9

PLOT - 10



Plot Number	Manual Tree Count	Results Retrieved	Minimum Tree Height	Maximum Tree Height	Mean Tree Height	Accuracy for Tree Count
Plot 1	14	12	1.84	3.27	2.31	85.71
Plot 2	43	40	2.25	3.71	2.83	93.02
Plot 3	46	37	1.74	3.55	2.76	80.43
Plot 4	13	11	1.39	3.49	2.25	84.61
Plot 5	33	31	1.37	3.39	2.72	93.93
Plot 6	30	22	1.51	3.25	2.51	73.33
Plot 7	26	24	1.57	2.98	2.3	92.3
Plot 8	10	10	1.25	3.25	2.16	100

Plot 9	28	23	1.27	3.15	2.41	82.14
Plot 10	16	14	1.9	3.7	2.92	87.5

Table 1 Plot Wise Results for Orthomosaic Image

Table 1 presents the manual tree count, results retrieved, minimum tree height, maximum tree height, mean tree height, and accuracy for tree count across 10 different plots in the orchard.

5.3 Structural Properties Extraction: Tree Height Analysis

Further analysis using the Canopy Height Model (CHM), derived from DSM and DTM models, enriched our understanding of the orchard's vertical structure. We determined the mean tree height, the height of the tallest tree, and the shortest tree, providing a comprehensive view of the orchard's vertical growth patterns. These measurements are instrumental in assessing the health and productivity of the citrus orchard.

Furthermore, we analyzed the minimum, maximum, and mean tree heights within each plot using a Canopy Height Model (CHM) generated from Digital Surface Model (DSM) and Digital Terrain Model (DTM) data processed in QGIS. The heights varied across plots, with minimum heights ranging from 1.25 to 2.25 meters, maximum heights ranging from 2.98 to 3.71 meters, and mean heights ranging from 2.16 to 2.92 meters. Overall, our approach demonstrated promising results in both tree identification and enumeration, providing valuable insights into the tree distribution and characteristics within the orchard. However, further refinement of the methodology may be required to improve accuracy, particularly in cases where discrepancies between manual and retrieved counts were observed.
Figure 8 visualizes tree height variations within the orchard, derived from DSM and DTM data.

Fig. 8 Final CHM image generated using QGIS

S. No.	Tree Height in Meters
1.	2.08
2.	1.91
3.	1.95
4.	1.94
5.	1.84
6.	2.18
7.	2.26
8.	3.27
9.	2.11
10.	1.86
11.	3.1
12.	2.63
13.	2.39
14.	2.84

Table 2 Height in Meters for Trees in Plot 1

Table 2 lists the heights of 14 individual trees in Plot 1, with values ranging from a minimum of 1.84 meters to a maximum of 3.27 meters. The mean height is calculated to be 2.28 meters.

The heights of individual trees within Plot 1 of the citrus farm were measured using QGIS tool from an orthomosaic image. A total of 14 trees were observed and their respective heights, in meters, are presented in Table 2.

- **Minimum Height: 1.84 meters**
- **Maximum Height: 3.27 meters**
- **Mean Height: 2.28 meters**

The height distribution across the observed trees indicates considerable variability, with the tallest tree reaching 3.27 meters and the shortest standing at 1.84 meters. The average height of the trees in Plot 1 is 2.28 meters, providing an insight into the overall stature of the citrus trees within this specific area of the farm.

6. CONCLUSION

This study successfully integrates YOLOv8 Object Detection with Color Segmentation and Clustering methodologies, alongside an innovative approach to extracting structural properties like tree height, to advance tree detection in UAV imagery of citrus orchards. Our findings reveal that the YOLOv8 model excels in NIR spectrums, offering high precision in tree identification and classification. Concurrently, the color segmentation and clustering method efficiently enumerates tree clusters, with the Canopy Height Model (CHM) providing invaluable insights into tree height variations.

These methodologies collectively enhance precision agriculture by offering:

- Improved Accuracy: Achieving precise tree detection and classification, crucial for monitoring orchard health and development.
- Adaptability: Demonstrating robustness across varying orchard conditions, enabling a comprehensive understanding of orchard dynamics.
- Informed Management: Facilitating data-driven decision-making through accurate tree counts and structural analyses, optimizing resource allocation in orchard management.

This holistic approach not only marks a significant advancement in agricultural technology application but also sets a new standard for operational efficiency and accuracy in orchard management, heralding a new era of data-driven agriculture.

7. FUTURE SCOPE

While our study makes notable strides in precision agriculture, the journey towards fully realizing technology's potential in this domain is ongoing. Future research directions include:

- Enhanced Feature Discrimination: Addressing the challenge of distinguishing non-citrus trees in the color thresholding and clustering system by incorporating machine learning algorithms that can learn and identify additional citrus tree features, improving detection accuracy.
- Optimization of YOLOv8 Model: Further refining the YOLOv8 model to enhance its performance, especially by increasing the utilization of NIR band images which have shown promise in improving tree classification accuracy.
- Beyond Detection and Counting: Expanding the scope of our methodologies to include detailed analyses of tree structural properties such as canopy width and plant area coverage. Employing advanced imaging and machine learning techniques can offer deeper insights into orchard dynamics, potentially revolutionizing orchard management practices.
- Integration with IoT Devices: Exploring the integration of our methodologies with IoT devices for real-time monitoring and management, opening new avenues for precision agriculture to thrive on automation and advanced analytics.

These future endeavors aim to not only refine the existing methodologies but also explore new dimensions in precision agriculture, driving innovation and efficiency in orchard management and beyond.

CHALLENGES:

In this study, we explored advanced methodologies for citrus tree identification and enumeration using Unmanned Aerial Vehicle (UAV) imagery, focusing on YOLOv8 object detection and segmentation with clustering techniques. While our approaches have demonstrated promising results in improving precision agriculture practices, several challenges were encountered that warrant discussion. These challenges underscore the complexities involved in applying UAV imagery and advanced image processing techniques in agricultural settings.

Challenges Faced During YOLO v8 Model Training:

During the training process of the YOLO v8 model, one of the key requirements is to annotate objects of interest within images. In our case, we focused on annotating citrus trees within the farm using a popular annotation tool called LabelImg. However, we encountered a notable challenge during this annotation process. In some images, the citrus trees appeared dense and bushy, resembling bushes rather than individual trees. This made it difficult for us to accurately draw bounding boxes around these tree-like structures. As a result, we faced limitations in properly annotating these ambiguous tree-like features in the images. Consequently, these images could not be included in the training dataset for the YOLO v8 model. This challenge highlights the complexity of annotating objects with similar visual characteristics, where the distinction between citrus trees and bushes becomes blurred. Addressing such challenges is crucial for ensuring the accuracy and reliability of the trained model in detecting citrus trees within the farm environment.

Challenges in Differentiating Trees from Non-Tree Elements:
One of the significant challenges encountered was the difficulty in distinguishing citrus trees from surrounding non-tree elements, such as fences, within orthomosaiced images. Both entities shared similar color characteristics and pixel sizes, complicating the automated differentiation process. This issue highlights the need for more sophisticated feature extraction techniques that can more accurately discern between different objects based on a broader range of attributes beyond color and size.

Noise Removal from Orthomosaiced Images:
The task of noise removal from orthomosaiced images proved to be particularly challenging. The similarity in color between the ground and the tree canopy made it difficult to isolate and remove noise without affecting the integrity of the tree data. This issue underscores the importance of developing more advanced noise reduction algorithms that can effectively differentiate between the target object (trees) and background noise based on contextual and spatial information.

Blob Detection for Tree Counting:
Our initial approach to count trees involved creating blobs around the trees and counting these blobs. However, this method was only partially successful, with blobs forming around a limited number of trees despite adjustments in image processing parameters, image quality, and resolution enhancements. This challenge points to the limitations of blob detection methods in complex environments where the target objects do not have uniform shapes or are closely spaced. It suggests the necessity for more adaptive and

context-aware algorithms capable of handling the diversity and complexity of orchard scenes.

Bounding Box Detection for Individual Trees:
An alternative approach involved using a mask to identify trees, drawing bounding boxes around detected trees, and overlaying these on the original image. This method aimed to visually indicate tree locations. However, it often resulted in bounding boxes encompassing groups of trees rather than individual ones. This outcome highlights the difficulty in segmenting closely spaced or overlapping canopy areas into distinct \entities, indicating a need for more refined segmentation techniques that can accurately separate individual trees within dense orchard layouts.

Challenges Encountered with Contour Drawing for Tree Detection:
In our effort to detect trees within the citrus farm using contour drawing, we faced a significant hurdle. The goal was to outline the contours of tree canopies, similar to edge detection, to identify individual trees. However, we encountered difficulty in accurately drawing contours around the tree canopies due to a specific issue. In some parts of the farm captured in the orthomosaic image, the tree canopies were interconnected, appearing as a single mass rather than distinct individual trees. This connectivity made it challenging to precisely delineate the contours of each tree canopy. Consequently, while the contour drawing method worked effectively in areas where tree canopies were separate and distinct, it struggled to perform accurately in rows where the canopies were intertwined or connected. This challenge underscores the complexity of tree detection in areas where tree canopies merge, highlighting the need for alternative approaches or techniques to effectively identify and delineate individual trees within such regions.

Canopy Height Model (CHM) Data Interpretation:
Our exploration into extracting tree heights using the Canopy Height Model (CHM) encountered data interpretation challenges. The extracted CHM data, processed through rasterio and rioxarray libraries, displayed only NaN values, indicating potential issues with data reading, processing, or the handling of no data values. This problem illustrates the complexities involved in working with high-dimensional spatial data and emphasizes the necessity for robust data preprocessing and validation frameworks to ensure the reliability and accuracy of derived metrics.

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