A Project Report

on

TREE ENUMERATION AND EXTRACTING THE TREE HEIGHT USING UAV IMAGERY

submitted in partial fulfillment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE & ENGINEERING

by

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under the esteemed guidance of

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Department of Computer Science & Engineering

BVRIT HYDERABAD COLLEGE OF ENGINEERING FOR WOMEN

(NAAC Accredited-A Grade | NBA Accredited B.Tech (EEE, ECE, CSE, and IT))

(Approved by AICTE, New Delhi and Affiliated to JNTUH, Hyderabad)

Bachupally, Hyderabad – 500090

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CERTIFICATE

This is to certify that the Project Work report on “**TREE ENUMERATION AND EXTRACTING THE TREE HEIGHT USING UAV IMAGERY**” is a bonafide work carried out by **Ms. P Manasa (20WH1A0517), Ms. C Roshini (20WH1A0526), Ms. Ch Manasa (20WH1A0536)** in the partial fulfillment for the award of B.Tech. degree in **Computer Science & Engineering**, **BVRIT HYDERABAD College of Engineering for Women**, Bachupally, Hyderabad, affiliated to Jawaharlal Nehru Technological University Hyderabad, Hyderabad under my guidance and supervision. The results embodied in the project work have not been submitted to any other University or Institute for the award of any degree or diploma.

Internal Guide	**Head of the Department**
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DECLARATION

We hereby declare that the work presented in this project entitled **"TREE ENUMERATION AND EXTRACTING THE TREE HEIGHT USING UAV IMAGERY"** submitted towards completion of Project Work in IV year of B.Tech., CSE at 'BVRIT HYDERABAD College of Engineering for Women', Hyderabad is an authentic record of our original work carried out under the guidance of **Dr. M Indrasena Reddy**, Professor, Department of CSE.

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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 YOLO v8 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 tree heights 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 such as tree height, 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.

Keywords: *Unmanned Aerial Vehicle(UAV)*, *You Only Look Once(YOLO) v8*, *Density-Based Spatial Clustering of Applications with Noise(DBSCAN)*,*Orthomosaic Image*, *Canopy Height Model(CHM)*, *Digital Surface Model(DSM)*, *Digital Terrain Model(DTM).*

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LIST OF TERMS AND ABBREVIATIONS

- **UAV:** Unmanned Aerial Vehicle
- **DSM:** Digital Surface Model
- **DTM:** Digital Terrain Model
- **CHM:** Canopy Height Model
- **YOLO v8:** You Only Look Once Version 8
- **RGB:** Red Green Blue
- **NIR:** Near-Infrared
- **GPU:** Graphical Processing Unit
- **QGIS:** Quantum Geographic Information System (GIS)
- **DEM:** Digital Elevation Model
- **DBSCAN:** Density-Based Spatial Clustering of Applications with Noise
- **HSV:** Hue Saturation Value
- **NDVI:** Normalized Difference Vegetation Index
- **R-CNN:** Region-based Convolutional Neural Networks
- **HOG:** Histogram of Oriented Gradients
- **SVM:** Support Vector Machine
- **2D:** 2-Dimension
- **3D:** 3-Dimension
- **OpenCV:** Open Source Computer Vision Library
- **NumPy:** Numerical Python

CHAPTER 1

INTRODUCTION

1.1 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.

1.2 Problem Statement

Within the domains of precision agriculture and environmental monitoring, rising demand exists for an effective method to leverage multi-spectral UAV imagery for extraction of vital information of vegetation. Utilize multi-spectral UAV imagery for Tree Detection and Counting also extract Tree Height using GIS tools, advancing the fields of agriculture, ecology, environmental science.

1.3 Objective

Create a tree counting and analysis system leveraging UAV imagery, aiming to revolutionize orchard management. The project seeks to seamlessly integrate Advanced YOLOv8, OpenCV, and clustering techniques for efficient tree detection and counting, also use QGIS software for Tree Height Analysis in citrus fruit fields. Objectives include automating the counting process, enhancing operational efficiency, and exploring alternative methodologies for comparison. The integration of machine learning and computer vision technologies aims to provide a scalable solution, contributing to the advancement of precision agriculture.

1.4 Existing System

The existing system consists of detection of Citrus and other crop trees from UAV images using a simple Convolutional Neural Networks (CNN) algorithm. The workflow worked well for complex agricultural environments with an overall accuracy of 96.24%. The base paper lacks a dedicated tree counting modelwithin its existing framework. The adaptability of the CNN algorithm in handling diverse agricultural landscapes, varying lighting conditions, and different tree species. The diversity and size of the dataset used for training the CNN model, including information on labeled images and their relevance to different crop and citrus tree variations.

1.5 Proposed System

The proposed system aims to revolutionize tree counting in orchards by integrating two innovative methodologies. Firstly, through the implementation of Advanced YOLOv8, an advanced object detection model, we seek to develop an automated tree counting mechanism. Leveraging RGB and NIR band images captured by Unmanned Aerial Vehicles (UAVs), our system employs OpenCV and YOLO box annotation for precise tree identification. The outcome is a comprehensive tree count with extracted structural details, including the accurate Position of Trees in the Image. In parallel, the system explores alternative methodologies by incorporating clustering techniques. Using DBSCAN for clustering tree pixels based on density, we create a visually intuitive clustered image with distinct colors for different tree clusters. This approach significantly enhances accuracy, allowing for the identification and isolation of individual trees even in complex agricultural environments. The synergistic integration of these methodologies aims to provide a robust and versatile solution for accurate tree counting and analysis in orchards, contributing to the evolution of precision agriculture. The proposed system also includes Tree Height Extraction using QGIS software. By processing high-resolution Digital Surface Models (DSM) and Digital Terrain Models (DTM) to generate Canopy Height Models (CHM), we can accurately measure tree heights. This method enhances the automated tree counting system, offering a detailed analysis of tree structure and supporting better decision-making in precision agriculture.

CHAPTER 2

LITERATURE SURVEY

2.1 Review of literature

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].

Transitioning from the use of UAV-derived imagery, 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].

Continuing with the theme of improving agricultural efficiency through advanced imaging techniques, 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].

Expanding on the use of high-resolution imagery for environmental monitoring, this study focuses on the detection and enumeration of trees using high-resolution imagery from the Cartosat-2 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].

Following the exploration of satellite imagery, 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].

Transitioning to a focus on specific agricultural applications, 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].

Extending the focus to forestry management, 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].

Transitioning to innovative approaches for tree height estimation, 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].

Building on the theme of agricultural efficiency, 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].

Continuing with the focus on citrus orchards, 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[9].

Transitioning to a different crop type, 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[10].

Expanding the scope to species classification, 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[11].

Shifting focus to mangrove ecosystems, 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[12].

Following the theme of forest management, 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[13].

Moving to agricultural applications, 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[14].

Continuing with UAV-based agricultural assessments, 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[15].

Extending the application of UAVs to forest health monitoring, 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[16].

Transitioning to the use of thermal imaging for agricultural management, 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[17].

Focusing on nutrient management, 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[18].

Continuing with biomass estimation, 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[19].

Moving to a multi-task learning framework, 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[20].

Expanding on tree crown monitoring, 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[21].

Continuing with the accuracy of UAV-derived products, 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[22].

Transitioning to crop management, 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[23].

Continuing with the theme of plant health, 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[24].

Shifting focus to soil analysis, 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. Soil organic matter (SOM) is a crucial indicator of soil health, influencing various physical, chemical, and biological soil properties.

Traditional methods of SOM measurement are labor-intensive and time-consuming, necessitating the exploration of remote sensing technologies for rapid and cost-effective assessment. This study compares two advanced models—the optimal band algorithm and the Grey Relational Analysis-Artificial Neural Network (GRA-ANN)—in estimating SOM content using multispectral satellite data. By assessing the performance of these models against ground-truth soil samples, the research aims to identify a reliable and accurate method for SOM estimation, thus enhancing land management strategies and promoting sustainable agricultural practices. The methodology of this study involves several key steps: data acquisition, preprocessing, model implementation, and validation. Multispectral satellite data was acquired from a satellite platform, capturing images across various spectral bands. The study area, characterized by diverse soil types and land use patterns, was selected to ensure comprehensive model testing. Ground-truth soil samples were collected simultaneously with the satellite data, and laboratory analyses were conducted to determine the actual SOM content in these samples. Preprocessing of satellite data included atmospheric correction, geometric rectification, and normalization to ensure consistency and comparability of the spectral information. The optimal band algorithm seeks to identify the most informative spectral bands for SOM estimation. Initially, correlation analysis was performed between the spectral bands and SOM content of the ground-truth samples. Bands showing the highest correlation with SOM were selected. These optimal bands were then used to develop a regression model that predicts SOM content from the multispectral data. The algorithm's performance was evaluated using standard statistical metrics such as the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The Grey Relational Analysis-Artificial Neural Network (GRA-ANN) model integrates Grey Relational Analysis (GRA) and Artificial Neural Networks (ANN) to enhance predictive accuracy. GRA was employed to analyze the relational degree between the spectral bands and SOM content, identifying significant bands that were then used as inputs for the ANN. The ANN, a computational model mimicking the human brain, was trained using the identified spectral bands and corresponding SOM values. The network's architecture, including the number of hidden layers and neurons, was optimized through a series of experiments to minimize prediction error. Both models were validated using a subset of the collected soil samples that were not used in the training phase. Predictive accuracy was assessed by comparing the model outputs against the ground-truth SOM values. Statistical measures such as R^2, RMSE, and MAE were used to quantify the models' performance. The study also employed cross-validation techniques to ensure the robustness and generalizability of the models. The results indicated that the GRA-ANN model outperformed the optimal band algorithm in estimating SOM content. The GRA-ANN model demonstrated higher predictive accuracy, with a significantly higher R^2 and lower RMSE and MAE compared to the optimal band algorithm. The superior performance of the GRA-ANN model can be attributed to its ability to capture complex nonlinear relationships between spectral bands and SOM content, which the optimal band algorithm, relying on linear regression, could not achieve. The study's findings underscore the potential of integrating advanced machine learning techniques with traditional remote sensing methods for soil analysis. Accurate estimation of SOM through remote sensing can substantially improve land management practices by enabling precise nutrient management and monitoring of soil health. This approach supports sustainable farming by reducing the need for extensive field sampling and laboratory analyses, thus saving time and resources. The comparative analysis of the optimal band algorithm and the GRA-ANN model demonstrates the latter's superiority in estimating SOM content from multispectral satellite data. The GRA-ANN model's enhanced predictive accuracy highlights its potential as a valuable tool for soil quality assessment and sustainable agricultural management. Future research could explore the integration of additional spectral bands and advanced preprocessing techniques to further improve the accuracy and applicability of remote sensing-based SOM estimation models[25].

Continuing with disease management in crops, 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. Wheat yellow rust, caused by the fungus Puccinia striiformis f.sp. tritici, is a devastating disease that significantly impacts wheat yields worldwide. Early detection and precise monitoring are critical for effective disease management. Traditional scouting methods are often laborious and prone to human error, prompting the need for innovative approaches leveraging remote sensing technology. This study explores the use of multispectral imagery collected by unmanned aerial vehicles (UAVs) combined with machine learning techniques to detect and monitor wheat yellow rust, aiming to enhance disease management practices and reduce crop losses. The methodology encompasses several stages: data collection, image processing, machine learning model development, and validation. Multispectral images of wheat fields were captured using UAVs equipped with multispectral cameras. The UAVs flew at predetermined altitudes and patterns to ensure comprehensive coverage of the study area. Field data on yellow rust incidence was collected concurrently, with infected and non-infected areas marked for validation purposes. The spectral data obtained included several bands, such as visible, near-infrared, and red-edge, known for their sensitivity to vegetation health and stress. Preprocessing of the multispectral images involved several steps to ensure data quality and accuracy. These steps included radiometric correction to account for sensor-specific biases, atmospheric correction to mitigate the effects of atmospheric interference, and geometric correction to align the images accurately with the field coordinates. Normalization techniques were applied to standardize the spectral reflectance values across different flight sessions. The processed images were analyzed using machine learning techniques to identify spectral signatures associated with yellow rust. The study employed several machine learning algorithms, including Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN), to develop a robust detection model. Feature extraction was conducted to identify the most relevant spectral bands and indices for disease detection. The models were trained using a dataset comprising labeled samples of infected and healthy wheat plants. The training process involved optimizing the models' parameters to enhance their predictive performance. The trained models were validated using a separate dataset of field samples not included in the training phase. Model performance was assessed based on metrics such as accuracy, precision, recall, and the F1 score. Additionally, spatial accuracy was evaluated by overlaying the predicted infection maps on the ground-truth maps and calculating the area under the receiver operating characteristic (ROC) curve. The results demonstrated that the machine learning models, particularly the CNN, exhibited high accuracy in detecting yellow rust in wheat fields. The CNN model outperformed the RF and SVM models, achieving an accuracy rate exceeding 90%. The high spatial resolution of the UAV imagery, coupled with the advanced feature extraction capabilities of the CNN, enabled precise identification of infected areas. The study highlighted the potential of UAV-based multispectral imaging combined with machine learning for early detection and monitoring of wheat yellow rust. The approach allows for timely and targeted disease management interventions, reducing the reliance on broad-spectrum fungicides and minimizing environmental impact. By identifying infected areas early, farmers can implement localized treatments, thereby conserving resources and enhancing overall crop health. The integration of UAV technology with machine learning also offers scalability and adaptability to different crop types and diseases. The automated nature of the detection process ensures consistent and objective monitoring, reducing the variability associated with human scouting. This method can be further refined by incorporating additional data sources, such as hyperspectral imagery and weather data, to improve the accuracy and reliability of disease detection models. This study demonstrates the effectiveness of using UAV-based multispectral imagery and machine learning for the detection and monitoring of wheat yellow rust. The high accuracy of the developed models underscores their potential for revolutionizing disease management practices in agriculture. By enabling early detection and targeted interventions, this approach supports sustainable farming practices, reduces crop losses, and minimizes chemical inputs. Future research could focus on extending this methodology to other crop diseases and integrating additional data layers to enhance model performance and applicability[26].

Expanding the application of remote sensing to forest management, 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[27].

Transitioning to water use efficiency in orchards, 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[28].

Shifting focus to rice cultivation, 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[29].

Finally, addressing UAV stability, 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 [30].

CHAPTER 3

REQUIREMENTS

3.1 Hardware Requirements

3.1.1 Unmanned Aerial Vehicles

3.1.1.1 High-resolution Cameras

Essential for capturing RGB and NIR imagery to cover various lighting conditions, tree densities and orchard layouts effectively.

3.1.2 Computing Infrastructure

3.1.2.1 High-Performance Computers

Necessary for processing large datasets, running complex image processing tasks, and deep learning models.

3.1.2.2 Graphics Processing Units

GPUs are specifically required for running the YOLOv8 model efficiently, catering to its computational demands for real-time object detection.

3.2 Software Requirements

3.2.1 Image Processing and Annotation Tools

- **OpenCV:** Used for image normalization, data cleansing, and other initial image processing tasks.
- **LabelImg Annotation Tool:** Employed for precise annotation of UAV-captured images, which is critical for training the detection models.

3.2.2 Deep Learning and Object Detection Frameworks

- **YOLOv8 Algorithm:** Utilized for object detection tasks, optimized for speed and accuracy in identifying and classifying trees in UAV imagery.
- **Deep Learning Libraries:** Such as TensorFlow or PyTorch, likely used to implement and operate the YOLOv8 model.

3.2.3 GIS and Remote Sensing Software

- **QGIS:** Plays a crucial role in visualizing and extracting data from the Canopy Height Model (CHM) and handling other spatial analysis tasks.
- **Pix4D Mapper:** Used for generating high-resolution orthomosaic images by stitching together hundreds of UAV-captured images, transforming individual images into a comprehensive visual map of each orchard.

3.2.4 Scripting and Automation

- **Python:** Primary scripting language for automating data processing workflows, including running the DBSCAN algorithm and processing images for tree height calculations.

3.2.5 User Interface Development

- **Gradio:** Used to develop user-friendly interfaces, enabling easy interaction with the deep learning model outputs and other data visualization tools.

CHAPTER 4

METHODOLOGY

The methodology of this study integrates cutting-edge technologies in UAV imagery and machine learning to enhance tree detection and structural analysis in citrus orchards. This approach utilizes a dual-method strategy involving YOLOv8 object detection and segmentation with clustering techniques. Each method is developed and evaluated independently to assess its effectiveness in tree identification, enumeration, and structural property extraction.

4.1 Architecture

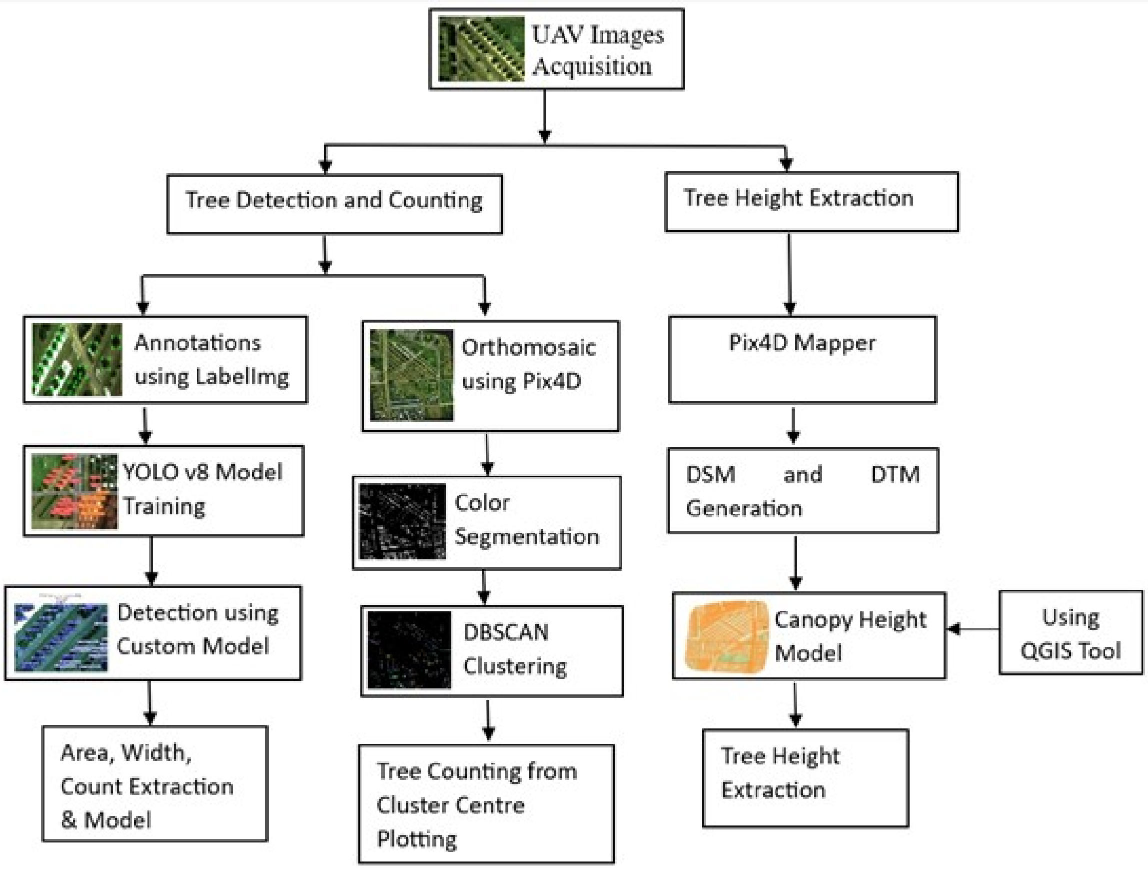


Fig. 4.1 Workflow diagram for the proposed methodology

Figure 4.1 depicts the workflow diagram for the proposed methodology, which outlines the sequential steps involved in processing and analysis, integrating both YOLOv8 detection and clustering techniques for a comprehensive assessment of orchard health and structure.

4.1.1 Tree Detection and Counting

YOLOv8 Object Detection:

The YOLOv8 model, recognized for its speed and precision, is specifically adapted to meet the unique challenges of citrus orchard monitoring. The workflow begins with extensive data annotation facilitated by OpenCV and YOLO box tools, which are instrumental in capturing the diverse dimensions and shapes of trees within the orchards. This step is crucial as it establishes the ground truth for training the model.

The annotated data undergo a series of preprocessing steps including normalization and data cleansing to ensure that the input data fed into the model is of high quality and free of anomalies that could affect learning outcomes. Following preprocessing, the model undergoes a fine-tuning phase where orchard-specific parameters are adjusted to optimize the detection of canopy variations and tree heights. This tailored training process is essential for adapting the model to the intricacies of orchard environments, enhancing its ability to recognize and classify different tree types accurately.

A separate testing dataset is used to validate the model's performance, ensuring that it not only performs well on the training data but also generalizes effectively to new, unseen data. This testing phase is critical for assessing the model's reliability and robustness in real-world orchard surveillance scenarios.

Segmentation and Clustering Approach:

In parallel with the YOLOv8 detection, the study employs a segmentation and clustering methodology that analyzes UAV-derived orthomosaic images. These high-resolution images are processed to convert their color space, isolating the green spectrum of citrus tree foliage, which is a critical indicator of vegetation.

The DBSCAN algorithm is then applied to these segmented images. This algorithm groups tree pixels based on density, effectively differentiating individual trees from each other and from the background. This pixel clustering is instrumental in providing a visual representation of tree distribution across the orchard, which aids in accurate tree enumeration and enhances understanding of the orchard's structural layout.

4.1.2 Tree Height Extraction

A significant aspect of the study focuses on extracting crucial structural properties, such as tree height, which has profound implications for orchard management. The Canopy Height Model (CHM) is employed for this purpose, derived from the integration of the Digital Surface Model (DSM) and the Digital Terrain Model (DTM).

CHM Calculation: The CHM represents the vertical distance between the ground surface (DTM) and the top of tree canopies (DSM). It is calculated using the equation 4.1.

$$CHM = DSM - DTM \tag{4.1}$$

Where the DSM includes all objects on the earth's surface, and the DTM represents the bare earth surface without any objects. This difference provides the height of the trees, which is critical for assessing their growth patterns and health.

Data Visualization and Analysis: QGIS software plays a pivotal role in visualizing and extracting data from the CHM. This GIS tool allows for detailed spatial analysis and is complemented by custom Python scripts that automate the processing of large datasets and perform binary image analyses to assess tree coverage. This comprehensive landscape analysis not only provides metrics on tree height but also offers insights into canopy density and overall orchard health.

Combined Methodological Approach: While each methodology-YOLOv8 object detection and segmentation with clustering—operates independently, their integration provides a robust framework for comparative analysis. This strategic combination highlights the strengths and potential limitations of each approach within the context of precision agriculture. It enriches the understanding of effective UAV-based monitoring strategies and opens avenues for further technological advancements and methodological enhancements in agricultural research

4.2 Dataset

The dataset utilized in this project originates from the Yatshiro Mikan Research Center, Japan. It comprises images captured by Unmanned Aerial Vehicles (UAVs) over a citrus farm. The dataset includes imagery from three distinct sites, each site providing two sets of images: one set in RGB format and another set in NIR (Near Infrared) band format. These images serve as a comprehensive resource for analyzing the structural properties of vegetation within the citrus farm.

4.2.1 Site 1

Site 1 encompasses a total of 408 RGB and NIR band images. These images are essential resources for understanding the vegetation within the citrus farm. RGB images capture visual information, aiding in the identification of different vegetation types and assessing their health. Meanwhile, NIR band images provide valuable data on vegetation density, health, and stress levels, significantly enhancing the analysis of vegetation structure and condition.

Maintaining a 70% overlap between images is crucial for Site 1. This overlap ensures sufficient coverage of the area and allows for accurate reconstruction of both terrain and vegetation, which is vital for precise analysis.

The speed of the UAV during image capture, set at 3 m/s, significantly influences the spacing between images. This speed ensures a consistent and adequate coverage of the area, impacting the resolution and detail of the captured imagery.

Site 1's imagery boasts a Ground Sample Distance (GSD) of 0.7 cm/px. This high-resolution detail enables precise measurements and analysis, providing valuable insights into the structure and health of the citrus farm's vegetation.

4.2.2 Site 2

Site 2 encompasses a total of 300 RGB and NIR band images, which play a crucial role in analyzing the vegetation within the citrus farm. Like Site 1, RGB images in Site 2 provide visual data essential for identifying different vegetation types and their health status. Meanwhile, NIR band images offer deeper insights into vegetation health and density, aiding in comprehensive analysis.

The importance of overlap cannot be overstated, with Site 2 maintaining a 70% overlap between images. This ensures continuity in the image data, facilitating accurate stitching and reconstruction of the terrain and vegetation. This overlap is vital for creating seamless mosaics and ensuring consistency in the dataset.

Operating at a speed of 3 m/s, the UAV captures images efficiently, ensuring sufficient coverage and detail across the area. This speed influences the spacing between images, which in turn affects the resolution and coverage of the imagery. Moreover, Site 2's imagery has a Ground Sample Distance (GSD) of 0.9 cm/px, providing detailed information necessary for precise analysis and measurement of the citrus farm's vegetation structure and health.

4.2.3 Site 3

Site 3 consists of a total of 172 images, each contributing to the comprehensive understanding of the vegetation within the citrus farm. The dataset includes both RGB images, which offer visual data crucial for vegetation analysis, and NIR band images, providing additional insights into vegetation health and structure. This combination allows for a detailed examination of the vegetation's condition and density.

The importance of maintaining a 70% overlap between images cannot be overstated. This overlap ensures comprehensive coverage of the area and aids in accurate reconstruction of the terrain and vegetation. By ensuring sufficient overlap, the dataset facilitates precise analysis and interpretation of the imagery.

The UAV's speed of 3 m/s plays a crucial role in the spacing and coverage of the captured images. This speed ensures that the images are evenly distributed, contributing to the overall resolution and detail of the dataset. The consistent speed of the UAV helps in capturing uniform and detailed imagery, essential for accurate analysis.

Site 3's imagery boasts a Ground Sample Distance (GSD) of 0.9 cm/px, providing highly detailed information for precise analysis. This level of detail enables researchers to make accurate measurements and observations, further enhancing the understanding of the vegetation's characteristics and distribution within the citrus farm.

4.2.4 Significance of Overlap, GSD, UAV Speed, and Altitude Variation in Citrus Farm Analysis

The significance of maintaining a 70% overlap between images in the dataset from Site 3 cannot be overstated. This overlap ensures comprehensive coverage of the citrus farm area, allowing for accurate reconstruction of the terrain and vegetation. By ensuring sufficient overlap, researchers can minimize data gaps and distortion, facilitating precise analysis and interpretation of the imagery.

Ground Sample Distance (GSD) plays a vital role in understanding the level of detail captured in the images. With a GSD of 0.9 cm/px, Site 3's imagery provides highly detailed information essential for precise analysis of the citrus farm. The smaller the GSD, the higher the resolution of the imagery, enabling researchers to make accurate measurements and observations of vegetation characteristics and distribution.

The speed of the UAV during image capture directly impacts the coverage and quality of the imagery. Operating at a speed of 3 m/s, the UAV ensures even spacing between images, contributing to the overall resolution and detail of the dataset. Consistent UAV speed helps in capturing uniform and detailed imagery, essential for accurate analysis and interpretation of the citrus farm's vegetation.

Variation in altitude also plays a crucial role in the study of the citrus farm. With altitudes ranging from 26 m to 30 m across Site 3, researchers can analyze the citrus farm from different perspectives, capturing variations in elevation and terrain. This variation allows for a comprehensive understanding of the citrus farm's topography and vegetation distribution, aiding in effective management and decision-making processes.

4.3 Implementation

4.3.1 Tree Detection and Counting

4.3.1.1 YOLO v8 Approach

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. Figure 4.2 shows a collage of RGB band images from the dataset. Figure 4.3 shows a collage of NIR band images from the dataset.

Fig. 4.2 Collage of RGB Band UAV Images

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. Figure 4.4 shows a sample image of annotations made in LabelImg tool.

We defined four specific classes for annotation:

- **Tree (RGB)**: Mature trees in RGB band.
- **Small Tree (RGB)**: Younger, smaller trees in RGB band.
- **Tree (NIR)**: Mature trees in NIR band.

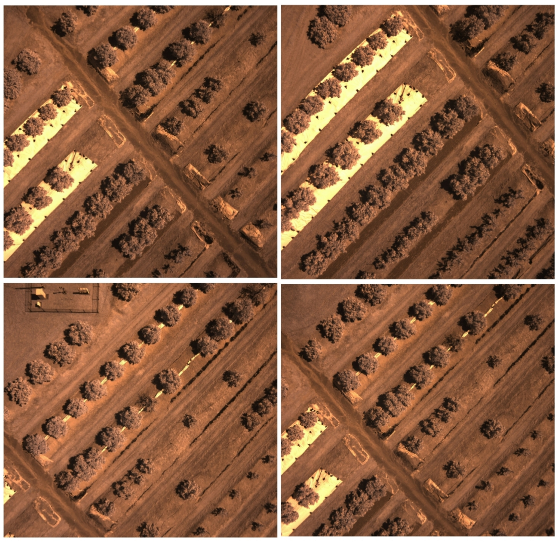


Fig. 4.3 Collage of NIR Band UAV Images

- **Small Tree (NIR)**: Smaller trees in NIR band.

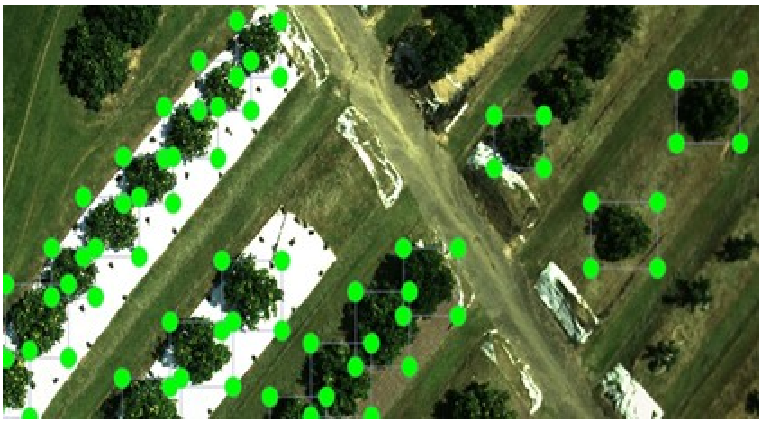


Fig. 4.4 Annotations in LabelImg Tool

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.

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 4.5 shows training batch image of YOLO v8.

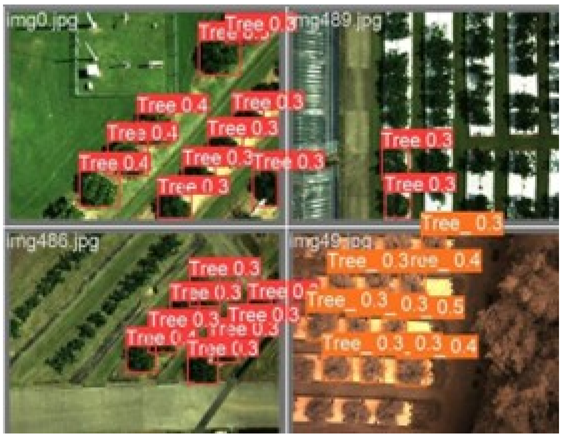
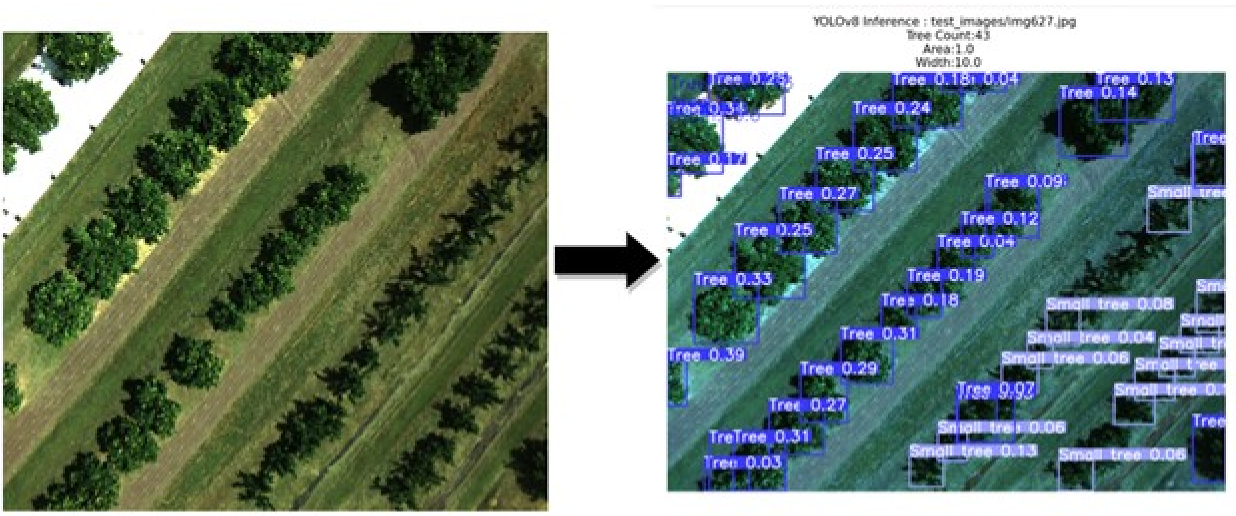


Fig. 4.5 YOLO v8 Model Training

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 test image given for YOLO v8 model is shown in Figure 4.6.



a

b

Fig. 4.6 Visualization of YOLOv8 predictions with annotations highlighting tree count, area coverage, and canopy width. **a.** Input RGB Band Image **b.** Output of YOLO v8

4.3.1.2 Color Segmentation and Clustering

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 orthomosaic and rectified image served as the basis for our segmentation analysis. Figure 4.7 shows the Orthomosaic and Rectified image obtained from Pix4DMapper Software.

Fig. 4.7 Orthomosaic and Rectified Image

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.

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.

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.

4.3.2 Tree Height Extraction

4.3.2.1 Acquiring UAV Imagery

UAV (Unmanned Aerial Vehicle) imagery is collected using a drone equipped with multi-spectral sensors. Multi-spectral sensors capture data across different wavelengths, providing valuable information about vegetation health and structure.

4.3.2.2 Generating DSM and DTM using Pix4D Mapper

DSM (Digital Surface Model), represents the Earth's surface and includes all objects and features on it, such as vegetation, buildings, and terrain. DTM (Digital Terrain Model), represents the bare ground surface without any objects like buildings or vegetation. It represents the elevation of the ground level. These models are created from the UAV imagery using Pix4D Mapper software. DSM and DTM are crucial for extracting canopy height information because they provide the baseline terrain and surface elevation.

4.3.2.3 Calculating Canopy Height Model (CHM) in QGIS

CHM is generated by subtracting the DTM from the DSM. This results in a raster dataset where each cell value represents the height of the vegetation above the ground. The CHM highlights the vertical structure of vegetation, making it a key input for tree height extraction. This calculation is performed in QGIS using raster algebra where the subtraction of DTM from DSM is done using subtraction operation.

4.3.2.4 Tree Height Extraction in QGIS

In QGIS, tree height extraction from the Canopy Height Model (CHM) involves various tools to analyze and extract height information. Various tools in QGIS to extract height information are:

- **Identify Features:** This tool directly retrieves height information by clicking on points in the CHM raster layer. Clicking on a specific point returns the value of the CHM raster at that location, representing the height of the vegetation above the ground.
- **Raster Calculator:** The Raster Calculator in QGIS enables mathematical operations on raster layers, useful for creating new layers based on certain conditions.
- **Zonal Statistics:** Zonal Statistics calculates statistics for raster layers within specified

vector zones, aiding in analyzing vegetation height across different areas.

- **Point Sampling:** Point Sampling Tool extracts raster values at predefined point locations, such as tree coordinates collected in the field.
- **Contour Extraction:** Contour Extraction generates contour lines from the CHM raster, providing a visualization of elevation changes and vegetation height.

As the 'Identify Features' tool directly retrieves height information by clicking on points in the CHM raster layer, thus it simplifies the process by directly providing height information of individual trees or vegetation patches, aiding in further analysis and interpretation. We have extracted the heights of the individual trees by pointing on the tree tops to note the height value. The Coordinate Reference System(CRS) is in meters for the DSM, DTM and CHM as well. Thus the extracted tree heights are in meters.

CHAPTER 5

TECHNOLOGY STACK

5.1 Ultralytics

Ultralytics is a Python library dedicated to facilitating the use of state-of-the-art deep learning models, especially in the realms of object detection, classification, and segmentation. It simplifies the process of working with complex models like YOLO (You Only Look Once) and Faster R-CNN, making them more accessible to developers and researchers.

The YOLO model, in particular, is a groundbreaking architecture for real-time object detection. YOLO processes images in a single pass through a neural network and directly predicts bounding boxes and class probabilities for the objects present in the image. This approach is highly efficient and capable of detecting objects in real-time video streams, making it ideal for a wide range of applications.

In our work, the YOLO() function from Ultralytics is used to load a YOLOv8 model. This model has been trained to recognize citrus trees in images. Once the model is loaded, the predict() function is utilized to perform inference on an input image.

5.1.1 YOLO Function

- The YOLO() function is essential for loading a pre-trained YOLO model. This step is critical because training such a model from scratch requires massive amounts of data and computational resources. Ultralytics provides pre-trained YOLO models, allowing users to leverage the expertise of the model developers without needing to train their own from scratch.
- In this specific case, the YOLOv8 model loaded by the YOLO() function has been trained to detect citrus trees in images. The model has learned to identify the visual features associated with citrus trees, such as their shape, color, and texture.

5.1.2 Predict Function

- Once the YOLO model is loaded, the predict() function is used to perform inference on an input image. This means the model is applied to the image to detect citrus trees.
- The YOLO model predicts bounding boxes around the detected objects along with the corresponding class labels and confidence scores. These bounding boxes indicate where the objects are located in the image, while the class labels specify what type of objects they are in our case it is citrus trees.
- The confidence scores represent the model's confidence in its predictions. Higher scores indicate greater confidence that the detected object is indeed a citrus tree. After inference, the results are returned, which include the bounding boxes, class labels, and confidence scores for each detected citrus tree in the image.

5.1.3 Importance of YOLO and Ultralytics in Object Detection

- YOLO, with its real-time processing capability, is crucial in applications where fast and accurate object detection is required, such as surveillance systems, autonomous vehicles, and robotics.
- Ultralytics simplifies the process of working with YOLO models, providing an easy-to-use interface for loading pre-trained models and performing inference. This accessibility accelerates the development of applications that rely on object detection.

5.2 OpenCV

OpenCV (Open Source Computer Vision Library) is a powerful open-source computer vision and machine learning software library. It provides various functions for image processing, computer vision, and machine learning tasks, making it a fundamental tool for developers, researchers, and hobbyists in the field of computer vision.

- **cv2.imread():** This function plays a pivotal role in loading input images for processing. In the context of the provided code, it reads the input image of a citrus tree from a specified file path. By using cv2.imread(), the image data is loaded into memory and represented as a NumPy array, which allows for further processing. This function is the starting point of many computer vision tasks, providing access to the raw image data. For instance, in the code, it reads the input image of a citrus tree from the specified file path, providing the necessary data to the subsequent processing steps.

- **cv2.cvtColor():** Color space conversion is a common requirement in image processing tasks, and cv2.cvtColor() fulfills this purpose. It is used to convert the color space of an image, which is often necessary for various preprocessing tasks. Although commented out in the provided code, this function might be utilized for converting the color space of the input image if needed. For example, converting from the default BGR (Blue, Green, Red) color space to RGB (Red, Green, Blue) format. Color space conversion is crucial for ensuring compatibility with different algorithms and models, and it's a standard preprocessing step in computer vision workflows.

- **cv2.putText():** Annotating images with text is essential for visualizing results, adding labels, or providing information about the content of the image. cv2.putText() is used for precisely this purpose. In the provided code, it is used to annotate the count of detected trees onto the annotated frame before displaying it. This function allows for customization of the text appearance, including font size, color, and thickness. In object detection tasks, annotating the detected objects with labels and counts enhances the interpretability of the results and aids in understanding the performance of the algorithm.

- **cv2_imshow():** When working in Google Colab, traditional OpenCV functions like cv2.imshow() do not function as expected. Instead, cv2_imshow() is specifically designed for displaying images in the Colab environment. It plays a crucial role in visualizing images, particularly when working with notebooks or interactive environments like Colab. After annotating the image with detected objects and counts, it's essential to display the annotated image for analysis and evaluation. cv2_imshow() facilitates this process by rendering the annotated image directly within the Colab notebook.

5.3 Google.colab.patches

Google Colab patches is a module that provides utility functions tailored to the Google Colab environment, specifically designed to enhance compatibility with the Jupyter Notebook interface. It contains functions to facilitate various tasks and interactions within the Colab's interactive notebook environment.

- **cv2_imshow():** This function is a part of the google.colab.patches module and is crucial for displaying images within the Google Colab environment. It is specifically designed to overcome the limitations of traditional OpenCV functions like cv2.imshow() in Colab, where direct image display is not supported. The cv2_imshow() function is essential for visualizing annotated images, particularly when working with object detection results.

5.4 Gradio

Gradio is a Python library designed for building interactive web-based interfaces for machine learning models. It simplifies the process of creating UI components for inputs and outputs of machine learning models, making them accessible and easy to use. Gradio allows developers and data scientists to quickly create user-friendly interfaces without extensive knowledge of web development. Gradio is used to create a simple web interface for the object detection model. This interface allows users to upload an image and obtain the count of detected objects (in this case, citrus trees) in the image.

- **Interface:** The Interface() function in Gradio is a crucial tool for creating interactive web-based interfaces for machine learning models. It allows you to define the input and output components of the interface, along with additional details like title and description, making the interface more user-friendly and informative.
- **Launch:** The launch() function in Gradio is an essential part of the process for deploying an interface created with Interface(). It starts a server and makes the interface accessible through a web browser. This function simplifies the deployment process, making it easy to share machine learning models with others and obtain input from users.

5.5 Matplotlib

Matplotlib is a powerful plotting library in Python used for creating static, interactive, and animated visualizations. It provides a wide range of functions for creating plots, charts, histograms, and more. Matplotlib is widely used in various fields, including data science, machine learning, and scientific research, for data visualization and analysis. Matplotlib is a vital tool for displaying images, particularly annotated images generated after object detection. Its plt.imshow() function is used to visualize the images, while plt.show() is used to display the plot with the image. Matplotlib simplifies the process of visualizing detection results, enabling effective analysis and interpretation.

- **plt.imshow():** The plt.imshow() function in Matplotlib is crucial for displaying images within a plot. In the provided code, this function is utilized to visualize the annotated image generated after object detection. The annotated image, which contains bounding boxes or other visual indicators of detected objects, is passed as an argument to plt.imshow(). This function then renders the image within the Matplotlib plot.

- **plt.show():** The plt.show() function in Matplotlib serves to display the plot containing the image after it has been rendered using plt.imshow(). This function is essential as it renders the plot containing the displayed image, making it visible to the user.

5.6 sklearn.cluster

The sklearn.cluster module from scikit-learn provides various clustering algorithms, among which Density-Based Spatial Clustering of Applications with Noise (DBSCAN) stands out. DBSCAN is particularly useful for clustering spatial data based on density, as it can identify clusters of points in high-density regions, while marking points in low-density regions as noise.

5.6.1 DBSCAN

DBSCAN operates by grouping together closely packed points as members of the same cluster, while marking points in low-density regions as noise. It does this by defining two parameters: epsilon (eps) and min_samples. Epsilon determines the maximum distance between two samples for them to be considered as part of the same neighborhood, while min_samples specifies the minimum number of samples required for a region to be considered as a cluster.

DBSCAN starts by randomly selecting a point from the dataset. If there are enough neighboring points within epsilon distance, the point is labeled as a core point, and a cluster is formed by recursively expanding the neighborhood. If a core point has fewer than min_samples neighboring points, it is labeled as a border point and added to the cluster. Points that do not meet the criteria to be core or border points are considered noise.

The ability of DBSCAN to identify clusters of arbitrary shapes and handle noise points makes it robust to various types of datasets. It is particularly effective for datasets with non-uniform density distributions and clusters of varying shapes and sizes. Additionally, DBSCAN can handle outliers well, as noise points are not assigned to any cluster. This makes it suitable for tasks such as anomaly detection and clustering in datasets with noisy or sparse regions.

5.7 NumPy

NumPy is a fundamental package for scientific computing in Python, providing support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays. NumPy is widely used in various fields, including mathematics, physics, engineering, and data science, due to its efficient handling of numerical data and extensive mathematical functions. NumPy plays a crucial role in various aspects of data manipulation and array operations.

- **Array Manipulation:** NumPy is used extensively for manipulating arrays representing image data and pixel coordinates. For example, the np.column_stack() function is used to stack the row indices and column indices of non-zero pixels obtained from the mask to form a 2D array of pixel coordinates. This stacked array of pixel coordinates is essential for inputting data into the DBSCAN clustering algorithm.
- **Mathematical Operations:** NumPy provides a rich set of mathematical functions that are utilized for various operations on arrays. In our work, mathematical operations are performed on arrays to calculate cluster centers, means, and other statistical properties. For instance, the np.mean() function is used to calculate the mean coordinates of pixels within each cluster, which are then used to draw cluster centers on the clustered image.
- **Array Indexing and Slicing:** NumPy's powerful indexing and slicing capabilities are used to extract subsets of arrays. In our work, array slicing is utilized to crop the orthomosaic image based on specified coordinates. For example, the cropped image is obtained by slicing the resized orthomosaic image using the specified crop coordinates.
- **Statistical Calculations:** NumPy provides functions for various statistical calculations, which are used for analyzing and processing image data. In our work, statistical functions are used to compute properties of clusters, such as mean coordinates. These statistical calculations aid in visualizing and interpreting the results of the DBSCAN clustering algorithm.

5.8 Digital Surface Model

In the context of tree height extraction, DSM, or Digital Surface Model, is a fundamental component. Accurate estimation of tree height is essential for numerous applications, including forestry management, urban planning, and environmental monitoring. DSM provides valuable information about the surface terrain, encompassing features like buildings, vegetation, and ground elevation. By leveraging DSM data, analysts can derive precise measurements of tree heights, which in turn assist in tasks such as forest inventory assessments, habitat mapping, and estimation of carbon sequestration levels.

5.8.1 Use of DSM

DSM is utilized in conjunction with other geospatial data sources such as LiDAR (Light Detection and Ranging) or photogrammetry to create 3D models of the terrain. In tree height extraction, DSM helps differentiate between tree canopies and the surrounding landscape, providing a baseline for height measurements. Various algorithms and techniques, such as watershed segmentation or region growing, are applied to DSM data to detect and delineate individual trees and estimate their heights accurately.

5.8.2 Features

High-resolution DSM data offer detailed surface information, enabling precise delineation of tree canopies and accurate height measurements. DSM datasets may incorporate multiple spectral bands, allowing for the differentiation between vegetation and other surface features. Advanced DSM processing techniques, such as filtering for noise removal and interpolation for enhancing spatial resolution, contribute to more accurate tree height extraction. Integration with other geospatial datasets, such as Digital Terrain Models (DTMs) or aerial imagery, enhances the accuracy and reliability of tree height estimation by providing additional context and reference points.

5.9 Digital Terrain Model

Digital Terrain Models (DTMs) are foundational datasets crucial for understanding terrain morphology and its impact on various applications. These models represent the bare-earth surface, devoid of surface features such as vegetation, buildings, and other structures. Accurate tree height estimation relies on distinguishing between terrain elevation and the height of vegetation above it, a task where DTMs play a pivotal role. By providing baseline elevation information, DTMs serve as a reference surface against which tree heights can be accurately measured. This understanding of terrain morphology is vital for applications like flood modeling, land development, and infrastructure planning.

5.9.1 Use of DTM

In tree height extraction, DTMs are utilized in conjunction with Digital Surface Models (DSMs) to differentiate between ground elevation and tree canopy height. By subtracting the DTM from the DSM, analysts can derive the heights of objects (e.g., trees, buildings) above the ground level. DTMs help create a reference surface against which tree heights can be accurately measured, enhancing the precision of tree height estimation algorithms.

5.9.2 Features

DTMs represent the bare-earth surface, typically derived from LiDAR data, photogrammetry, or other remote sensing techniques. These models provide elevation data with high spatial resolution, enabling detailed analysis of terrain morphology. DTMs may incorporate attributes such as slope, aspect, and curvature, which are valuable for understanding terrain characteristics and their influence on vegetation distribution and growth. Integration with other geospatial datasets, such as DSMs and aerial imagery, enhances the accuracy and reliability of tree height estimation by providing comprehensive information about the terrain and its features.

5.10 Canopy Height Model

Canopy Height Models (CHMs) are integral components in the accurate estimation of tree heights, crucial for various applications such as forest inventory assessment, habitat mapping, and environmental monitoring. CHMs provide a precise representation of vegetation canopy height above the ground level, offering insights into forest structure and biomass estimation. They are invaluable datasets for understanding vegetation dynamics, species distribution, and overall ecosystem health.

In tree height extraction, CHMs are derived from Digital Surface Models (DSMs) by subtracting Digital Terrain Models (DTMs). This process isolates the heights of objects such as trees and vegetation above the ground surface. CHMs offer clear visualizations of canopy height variations across a landscape, facilitating the identification and delineation of individual trees or vegetation patches. Various algorithms and techniques, including thresholding, segmentation, and object-based image analysis, are applied to CHMs to detect and measure tree heights accurately. CHMs represent the vertical structure of vegetation, providing information about height and spatial distribution. They offer high-resolution data with pixel-level height values, enabling detailed analysis of canopy structure and vertical vegetation profiles.

5.11 QGIS

QGIS (Quantum GIS) is a powerful open-source Geographic Information System (GIS) software that plays a crucial role in tree height extraction processes. It offers a user-friendly platform equipped with a range of tools and capabilities for geospatial analysis, data visualization, and map creation. One of its primary applications is in processing and analyzing geospatial data relevant to tree height extraction, including Digital Elevation Models (DEMs), Digital Surface Models (DSMs), and other remote sensing datasets.

5.11.1 Use of QGIS

QGIS offers a wide range of tools and plugins specifically designed for processing and analyzing raster and vector geospatial data, which are essential for tree height extraction. Users can import and visualize DSMs, DTMs, and other relevant datasets within QGIS, allowing for visual inspection and exploration of terrain morphology and vegetation characteristics. Various algorithms and techniques for tree height extraction, such as differencing DSM and DTM, segmentation, and classification, can be implemented using QGIS tools and plugins. QGIS provides the flexibility to integrate data from different sources and formats, enabling comprehensive analysis and visualization of tree height data in a single platform.

5.11.2 Features

QGIS offers a comprehensive set of tools for raster and vector data analysis, including terrain analysis, image classification, and spatial statistics, which are applicable to tree height extraction. The software supports a wide range of data formats, including raster (e.g., GeoTIFF, DEM) and vector (e.g., Shapefile, GeoJSON), allowing users to work with diverse geospatial datasets. QGIS provides advanced visualization capabilities, including customizable symbology, labeling, and map layouts, facilitating the creation of informative maps and visualizations of tree height data. The QGIS community actively develops and maintains a vast repository of plugins and extensions, offering additional functionality for specific tasks such as LiDAR data processing, vegetation analysis, and 3D visualization, which can be leveraged for tree height extraction projects.

5.11.3 Identify Features Tool

The "Identify Features" tool in QGIS plays a crucial role in our work, particularly in the extraction of tree heights from Canopy Height Models (CHMs) derived from Digital Surface Models (DSMs) and Digital Terrain Models (DTMs). This tool offers a powerful and interactive way to retrieve information about specific features or locations within a map, which is essential for our analysis.

Firstly, the basic functionality of the Identify Features tool allows us to click on individual pixels within the CHM layer to retrieve information about the corresponding tree heights. By activating the tool and clicking on a pixel representing a tree canopy, we can obtain attribute information such as the height of the selected tree, its feature ID, and any other relevant metadata stored in the attribute table of the layer.

The tool's use cases align perfectly with our requirements for tree height extraction. It enables us to explore the CHM data interactively, allowing us to visually inspect and analyze the heights of individual trees across the landscape. This interactive exploration is crucial for verifying attribute values and spatial relationships between tree canopies, ensuring the accuracy of our height measurements.

In our workflow, the Identify Features tool serves as a key component in the validation and decision-making processes. By providing real-time access to spatial data attributes, it empowers us to make informed decisions based on accurate tree height information. This tool also facilitates efficient data validation and quality assurance, allowing us to quickly identify and rectify errors or discrepancies in the tree height data derived from CHMs.

CHAPTER 6

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.

6.1 YOLO v8 Results

6.1.1 Performance Metrics

The results from the YOLO v8 approach on individual UAV images show notable differences in precision scores between RGB-based and NIR-based classes. The RGB-based classes, specifically "Tree (RGB)" and "Small Tree (RGB)," exhibited lower precision scores of 0.429 and 0.366, respectively. This variance underscores the challenges in accurately distinguishing tree features within the visible spectrum captured by RGB imagery.

In contrast, the NIR-based classes, "Tree_ (NIR)" and "Small Tree_ (NIR)," demonstrated significantly higher precision scores, with values of 0.649 and 0.643, respectively. These results highlight the model's enhanced capability in utilizing the Near Infrared (NIR) spectrum to detect and classify trees with greater accuracy. NIR imagery provides additional information on vegetation health and structure, making it particularly useful for tree detection and classification tasks.

The mean Average Precision (mAP) across all classes at an Intersection over Union (IoU) threshold of 0.5 was calculated to be 0.522. This metric indicates the overall performance of the model in identifying and classifying trees within the orchard environment. A higher mAP value signifies better accuracy and consistency in object detection and classification. In this case, an mAP of 0.522 indicates a solid performance of the YOLO v8 approach in accurately identifying trees within the orchard environment, considering the challenges posed by variations in tree appearance and environmental conditions. Figure 6.1 illustrates the Precision-Recall Curve graph, providing an overview of the precision and recall values for all four classes.

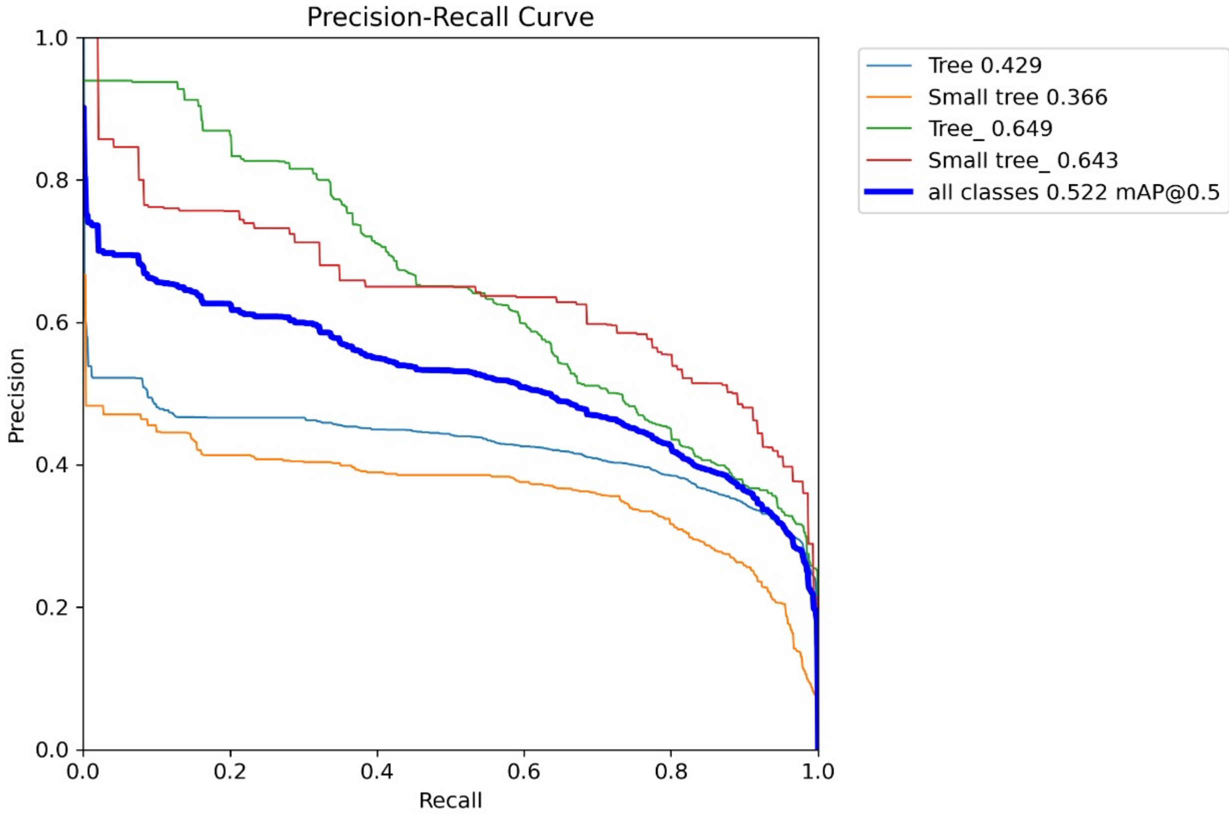


Fig. 6.1 YOLO v8 Precision-Recall Curve

6.1.2 Confidence in Predictive Accuracy

The results reveal a remarkable level of confidence in the predictive accuracy of the model, particularly at a confidence threshold of 0.857. At this threshold, the model achieved peak precision of 1.00 across all classes. This means that the model correctly identified and classified all instances of tree-related features with absolute precision. Such a high level of precision emphasizes the model's robustness and reliability in accurately detecting tree-related features from UAV imagery.

This peak performance underscores the model's ability to effectively discriminate between different objects within the orchard environment, particularly trees, with a high degree of certainty. It showcases the model's potential as a dependable tool for orchard monitoring, where precision and reliability are paramount. Figure 6.2 presents the Precision-Confidence Curve graph, offering a visual representation of precision values across varying confidence thresholds for all four classes.

By achieving perfect precision at a confidence threshold of 0.857, the model demonstrates an exceptional level of confidence in its predictions. This confidence is crucial for decision-making processes in orchard management, where accurate identification and monitoring of trees are essential for optimizing agricultural practices and ensuring crop health.

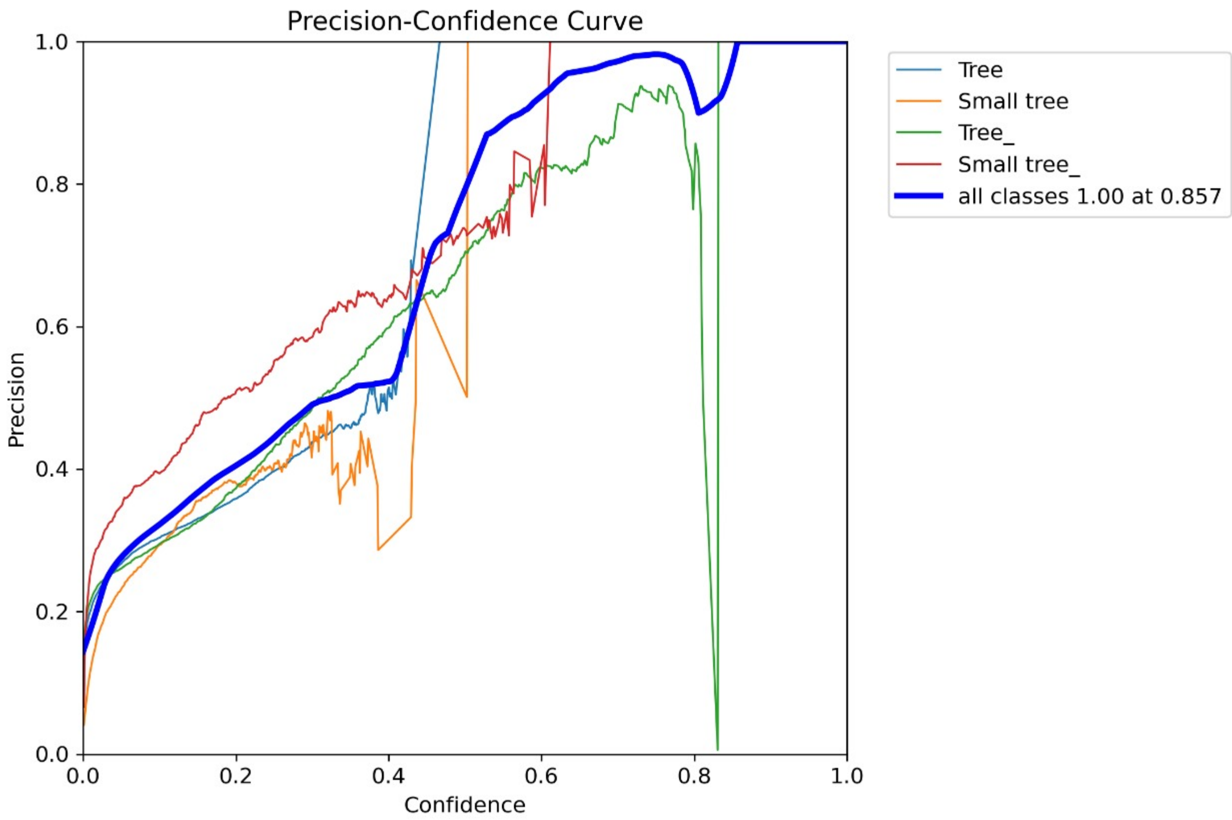


Fig. 6.2 YOLO v8 Precision-Confidence Curve

Overall, these results highlight the effectiveness of the model in accurately detecting tree-related features from UAV imagery and showcase its potential as a reliable tool for orchard monitoring, providing valuable insights for farmers and agricultural practitioners.

6.1.3 YOLO v8 Test Image Result

In the evaluation process below, we utilized a test image captured in RGB band, containing a total of 27 manually counted citrus trees. The model, which was trained using the best weights obtained from all trained epochs, predicted the presence of 22 trees in this RGB image. Figure 6.3 shows the RGB image test result. Similarly, an NIR input image containing 26 trees was processed by the same model, resulting in a prediction of 20 trees. Figure 6.4 shows the NIR image test result.

It's noteworthy that no ground truth values were available for comparison; hence, the number of trees was determined through manual counting and verification. This meticulous approach ensured accuracy in assessing the model's performance.

The model's prediction of 22 trees in the RGB image and 20 trees in the NIR image demonstrates its effectiveness in identifying citrus trees from UAV imagery. Despite the absence of ground truth values, the manual verification process validated the model's predictions.

The utilization of the best weights obtained from all trained epochs suggests a comprehensive and optimized training process. By selecting the best-performing weights, the model was fine-tuned to achieve optimal performance, resulting in accurate tree detection.

Overall, these results indicate the model's reliability in identifying citrus trees from both RGB and NIR imagery, showcasing its potential as a valuable tool for orchard monitoring and management.

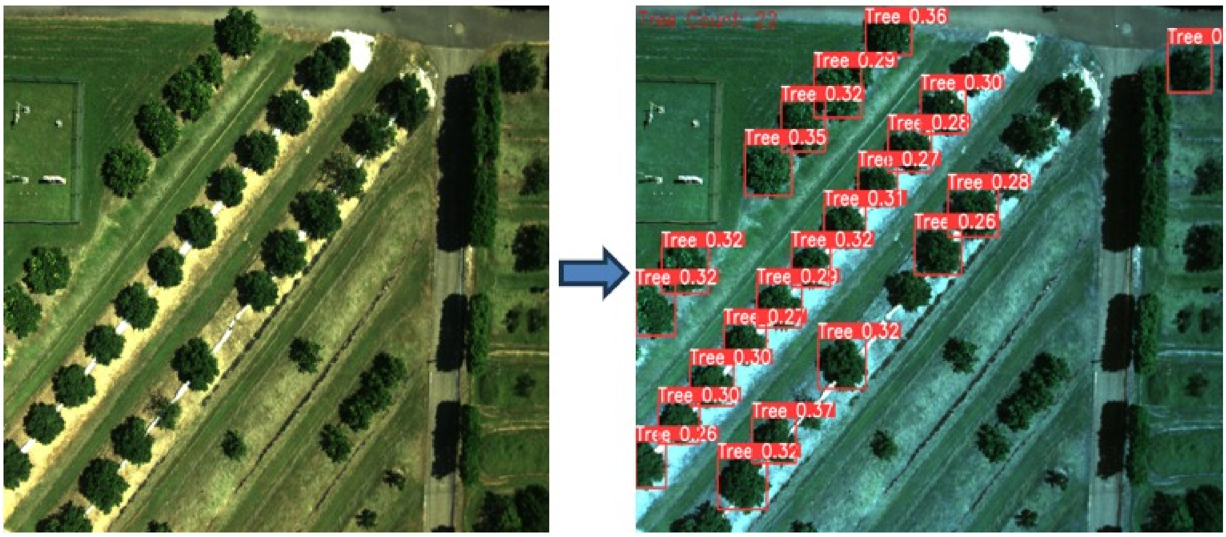


Fig. 6.3 YOLO v8 Test RGB Image Result

6.1.3.1 YOLO v8 Gradio Interface

We developed a user-friendly interface using Gradio to facilitate tree detection and counting using the YOLOv8 model. Users can upload an image through the interface, and upon submission, the image is processed by the YOLOv8 model to detect and count trees.

The YOLOv8 model, integrated with the Gradio interface, accurately detects trees within the uploaded image. After detection, the model annotates the image, highlighting the detected trees, and displays the count of trees identified. Figure 6.5 shows the YOLO v8 Gradio Interface result.

Using the interface, users can conveniently upload images and receive immediate feed-

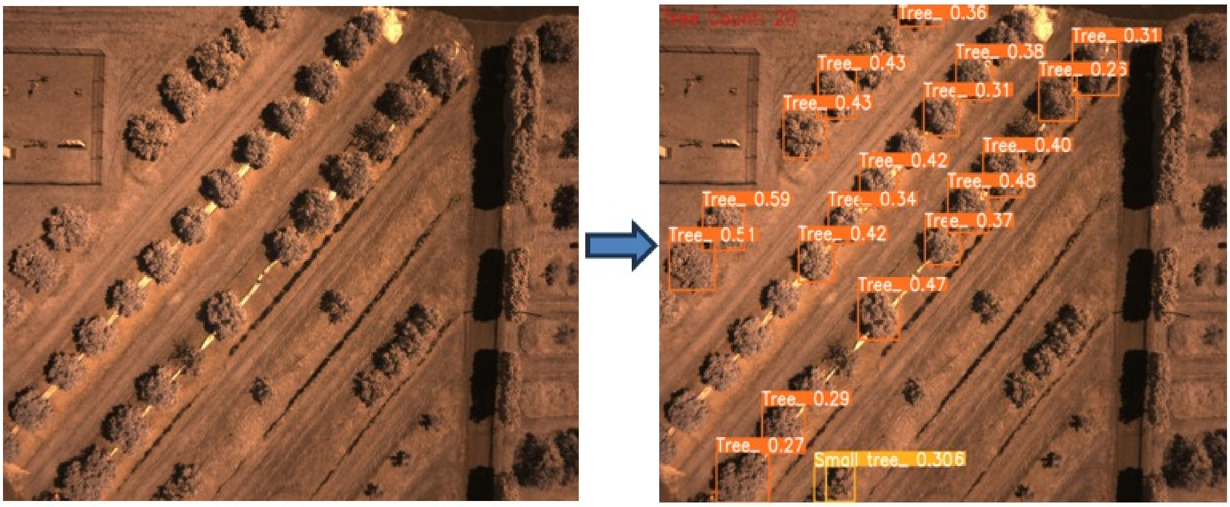


Fig. 6.4 YOLO v8 Test NIR Image Result

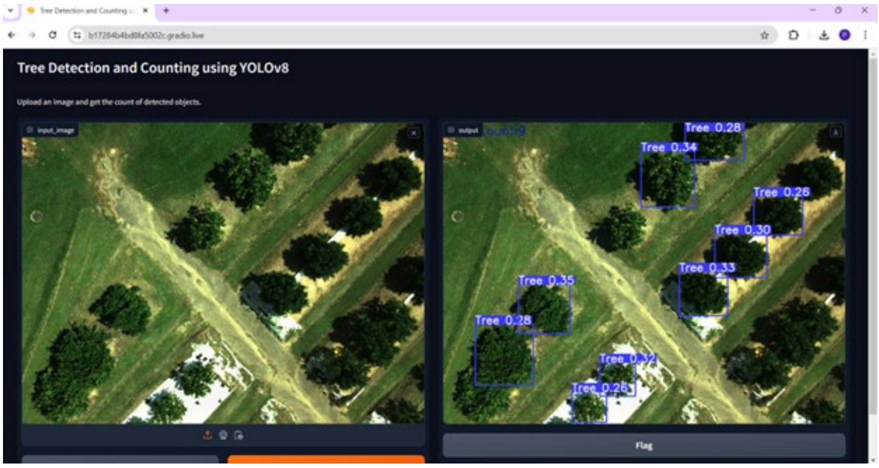


Fig. 6.5 Color Segmented and Clustered Orthomosaic Image

back on the number of trees detected. This enables efficient tree counting and monitoring in agricultural settings, such as citrus farms, aiding in orchard management and decision-making processes.

6.2 Color Segmentation and Clustering Results

6.2.1 Orthomosaic Results

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. The result of Color Segmented and Clustered Orthomosaic Image result is shown in Figure 6.6

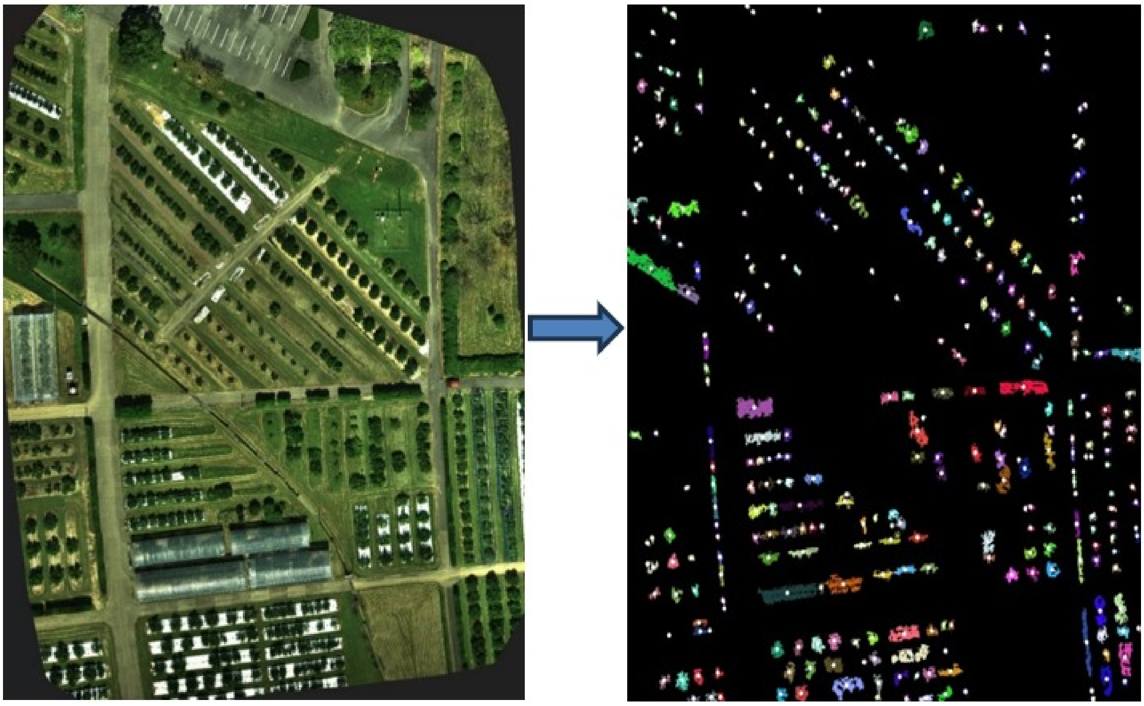


Fig. 6.6 Color Segmented and Clustered Orthomosaic Image

6.2.2 Plotwise Results of Orthomosaic Image

The orthomosaic image of the citrus farm was divided into 10 plots, each representing a specific area within the orchard. Utilizing color segmentation and clustering techniques, we applied the DBSCAN algorithm to each plot to detect and delineate individual trees.

In this process, we adjusted the parameter values of the DBSCAN algorithm, specifically epsilon and min_samples, for some plots to optimize tree detection and segmentation. By fine-tuning these parameters, we aimed to achieve better results in terms of accuracy and precision.

Subsequently, we manually counted the trees within each plot and compared the results with those obtained from the DBSCAN clustering. This manual verification process ensured the accuracy and reliability of the detected trees.

By comparing the manually counted trees with the results obtained from the clustering algorithm, we calculated the accuracies for each plot. These accuracies provided insights into the performance of the clustering algorithm in accurately identifying and delineating individual trees within the orthomosaic image.

Overall, this approach enabled us to assess the effectiveness of color segmentation and clustering techniques, particularly the DBSCAN algorithm, in accurately segmenting trees within the citrus farm. The fine-tuning of parameters allowed for optimization of results, resulting in improved accuracy and precision in tree detection and segmentation. The results of the plot-wise images before applying the technique and after the Color Segmentation and Clustering is shown in Figure 6.7

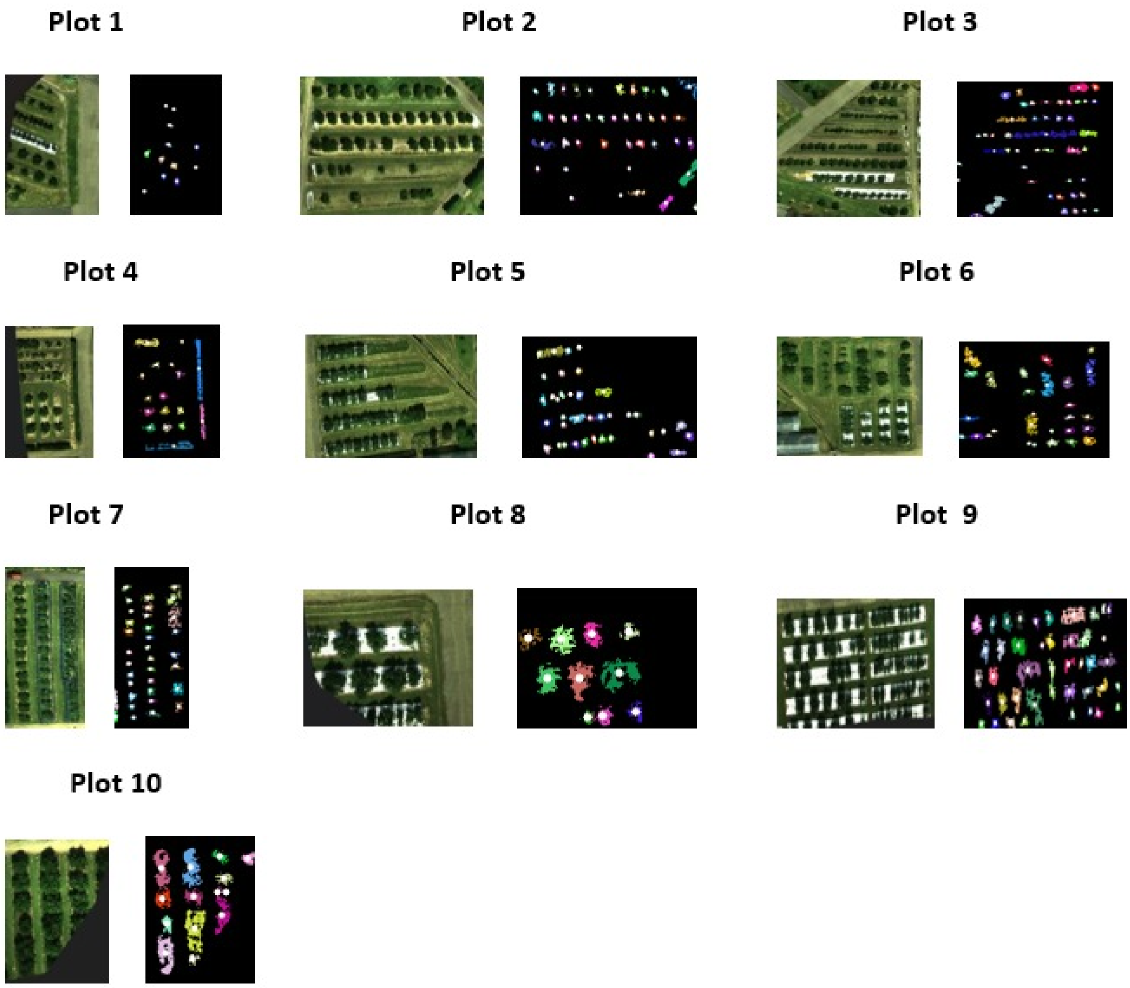


Fig. 6.7 10 Plots of Color Segmented and Clustered Orthomosaic Image

6.3 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. Figure 6.8 shows the CHM generated 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. The table 6.1 shows the results for each plot of Manual Count, Results of Tree Count, Minimum Height of Tree, Maximum Height of Tree, Mean Height of Tree, Accuracies for Tree Count.

Plot No.	Manual Count	Results	Min. Height	Max. Height	Mean Height	Accuracy
1	14	12	1.84	3.37	2.31	85.71
2	43	40	2.25	3.71	2.83	93.02
3	46	37	1.74	3.55	2.76	80.43
4	13	11	1.39	3.49	2.25	84.61
5	33	31	1.37	3.39	2.72	93.93
6	30	22	1.51	3.25	2.51	73.33
7	26	24	1.57	2.98	2.3	92.3
8	10	10	1.25	3.25	2.16	100
9	29	23	1.27	3.15	2.41	82.14
10	16	14	1.9	3.7	2.92	87.5

Table 6.1 Plotwise Info of Tree Count, Min, Max, Mean Height of tree and Accuracy

Fig. 6.8 Final CHM image generated using QGIS

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 6.2.

- **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.

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 6.2 Tree Heights for Plot 1 in Meters

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

The integration of advanced technological methodologies such as YOLOv8 Object Detection, Color Segmentation, and Clustering within UAV-based surveillance systems represents a significant leap forward in the management of citrus orchards. This study harnesses the precision of YOLOv8, particularly in NIR spectrums, to deliver highly accurate tree identification and classification. The effective deployment of the color segmentation and clustering techniques further refines the process of enumerating tree clusters, which is critical for assessing the orchard's spatial organization and health.

The combined use of these advanced methodologies contributes to several key improvements in orchard management:

- Improved Accuracy: The precision of tree detection and classification is paramount in monitoring orchard health and development. Accurate data capture helps in identifying diseased or underperforming sections of the orchard, enabling targeted interventions that conserve resources and enhance yield quality.
- Adaptability: The demonstrated robustness of the employed methodologies across varying orchard conditions—ranging from different tree densities and layouts to variable lighting conditions—ensures that our approach can be applied broadly across different agricultural settings. This adaptability fosters a comprehensive understanding of orchard dynamics, which is essential for adapting management practices to specific environmental conditions and tree health needs.
- Informed Management: Leveraging accurate tree counts and detailed structural analyses allows for more informed decision-making processes. By optimizing resource allocation based on precise data, orchard managers can implement more effective watering, fertil-

ization, and pest control programs, which are tailored to the actual needs of the orchard rather than based on estimates.

This holistic approach sets a new standard for operational efficiency and accuracy in orchard management, marking a significant advancement in agricultural technology application. It heralds a new era of data-driven agriculture, where decisions are informed by reliable data, leading to improved outcomes for orchard health, productivity, and sustainability.

7.2 Future Scope

While this study has made considerable advancements in precision agriculture, there remains substantial potential for further research and development in this domain. Future efforts could focus on several exciting and innovative directions:

- Enhanced Feature Discrimination: One of the challenges identified in this study is the difficulty in distinguishing non-citrus trees during the color thresholding and clustering processes. Future research could incorporate more sophisticated machine learning algorithms that are capable of learning a broader spectrum of citrus tree features. This would not only improve the accuracy of tree detection but also enhance the system's ability to classify different types of vegetation, which is critical in mixed-crop settings.

- Optimization of YOLOv8 Model: There is ongoing potential to further refine the YOLOv8 model to enhance its performance. Specifically, increasing the utilization of NIR band images, which have shown promise in improving tree classification accuracy, could be a fruitful area of focus. Enhancements might include adjusting the model architecture, optimizing the training process, or experimenting with different sets of hyperparameters to fine-tune the model's ability to discern subtle features in the NIR spectrum.

- Beyond Detection and Counting: Extending the scope of our methodologies to include more detailed analyses of tree structural properties such as canopy width and plant area coverage could revolutionize orchard management. Advanced imaging techniques and deeper machine learning analyses could uncover new insights into orchard dynamics, such as the identification of optimal tree spacing for sunlight exposure and growth, or the early detection of structural vulnerabilities that could predict future tree health issues.

- Integration with IoT Devices: The future of precision agriculture could also involve the integration of our methodologies with Internet of Things (IoT) devices. Real-time data collection and analysis facilitated by IoT technology could transform orchard management, allowing for continuous monitoring and more dynamic responses to emerging issues. This integration could pave the way for fully automated orchard management systems where decisions on watering, pesticide application, and harvesting are optimized without human intervention.

These future directions not only aim to refine current methodologies but also to explore new dimensions in precision agriculture. By driving innovation and improving efficiency, these advancements hold the promise of transforming orchard management practices and enhancing the sustainability and profitability of agriculture more broadly.

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Appendices

Appendix A

Appendices

Listing A.1: Python script for Gradio Interface with YOLO v8 Model .

```
!pip install gradio
!pip install ultralytics
import gradio as gr
from ultralytics import YOLO
import cv2
from matplotlib import pyplot as plt

# Define the font parameters

org = (20, 120)
font_face = cv2.FONT_HERSHEY_SIMPLEX
font_scale = 4
font_color = (0, 0, 255) # Red
font_thickness = 5
line_type = cv2.LINE_AA

# Load the YOLOv8 model
model = YOLO('/content/drive/MyDrive/Major Project YOLO
    v8/CitrusTrees_yolov8s_custom3/weights/best.pt')

def detect_objects(input_image):
    # Run YOLOv8 model inference
    results = model.predict(input_image)
    # Visualize the results on the frame
    annotated_frame = results[0].plot()
    Count = len(results[0])
    cv2.putText(annotated_frame, f"Tree Count:{Count}", org,
        font_face, font_scale, font_color, font_thickness, line_type)

    return annotated_frame
```

```python
# Define Gradio interface
gr.Interface(
    detect_objects,
    inputs="image",
    outputs="image",
    title="Tree Detection and Counting using YOLOv8",
    description="Upload an image and get the count of detected
        objects."
).launch()
```

Listing A.2: Python script for Color Segmentation and Clustering.

```
import cv2
import numpy as np
from sklearn.cluster import DBSCAN
from google.colab.patches import cv2_imshow
# Load the orthomosaic image
image_path = "/content/drive/MyDrive/IV Year Major
   Project/OrthomosaicImages/original_orthomosaic.png"
orthomosaic_image = cv2.imread(image_path)
#cv2_imshow(orthomosaic_image)

# Resize the image if needed
target_height = 1000 # specify your desired height
target_width = 1200 # specify your desired width

orthomosaic_image_resized = cv2.resize(orthomosaic_image,
    (target_width, target_height))
#cv2_imshow(orthomosaic_image_resized)

# Define the coordinates of the region to crop (format: (y_start,
   y_end, x_start, x_end))
crop_coordinates = (60, 950, 160, 950)

# Crop the image
cropped_image =
   orthomosaic_image_resized[crop_coordinates[0]:crop_coordinates[1],
   crop_coordinates[2]:crop_coordinates[3]]

# Display the cropped image using cv2_imshow
#cv2_imshow(cropped_image)

# Convert to HSV color space
hsv_image = cv2.cvtColor(cropped_image, cv2.COLOR_BGR2HSV)

# Define a range for green color (trees)
lower_green = (52, 40, 15) # Example values, adjust as needed
upper_green = (80, 255, 65)

# Threshold the image
mask = cv2.inRange(hsv_image, lower_green, upper_green)
```

```python
# Find non-zero pixels (tree pixels) in the mask
tree_pixels = np.column_stack(np.where(mask > 0))

# Apply DBSCAN to cluster tree pixels
eps = 4 # Adjust epsilon as needed
min_samples = 30 # Adjust min_samples as needed
dbscan = DBSCAN(eps=eps, min_samples=min_samples)
tree_labels = dbscan.fit_predict(tree_pixels)

# Create an image with colored clusters
clustered_image = np.zeros_like(cropped_image)

# Define a dictionary to map labels to colors
label_colors = {}

# Iterate over unique labels (excluding noise label -1)
for label in np.unique(tree_labels):
   if label == -1:
      continue # Skip noise points (label=-1)

   # Extract the pixels belonging to the current label
   cluster_mask = (tree_labels == label)
   cluster_pixels = tree_pixels[cluster_mask]

   # Check if there are any pixels with the current label
   if len(cluster_pixels) > 0:
      # Use a consistent color for each label
      if label not in label_colors:
         label_colors[label] = np.random.randint(0, 255, size=3)

      # Assign the color to the pixels in the clustered image
      clustered_image[cluster_pixels[:, 0], cluster_pixels[:, 1]] =
         label_colors[label]

      # Calculate and draw the cluster center
      cluster_center = np.mean(cluster_pixels, axis=0, dtype=int)
      cv2.circle(clustered_image, tuple(cluster_center[::-1]), 3,
         (255, 255, 255), -1) # Draw a white circle at the center

# Overlay the clustered image on the original cropped image
overlay = cv2.addWeighted(cropped_image, 0.7, clustered_image, 0.3,
```

```
    0)

# Display the original image, mask, and clustered result
cv2_imshow(cropped_image)
print()
cv2_imshow(mask)
print()
cv2_imshow(clustered_image)
print()

# Count the number of identified trees (excluding noise points)
tree_count = len(np.unique(tree_labels)) - 1 # Exclude noise point
    label -1
print(f"Number of trees: {tree_count}")

cv2.waitKey(0)
cv2.destroyAllWindows()
```