

University of California, Merced

**Autonomous Robotic Systems and Data-Driven Models
For Smart Farming**

by

Mehrad Mortazavi

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Committee in charge:

Professor Ricardo Pinto de Castro, Chair
Professor Francesco Danzi
Professor Stefano Carpin
Professor Reza Ehsani, Advisor

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The dissertation of Mehrad Mortazavi, titled Autonomous Robotic Systems and Data-Driven Models For Smart Farming, is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

_____ Professor Ricardo Pinto de Castro	Date	_____
_____ Professor Francesco Danzi	Date	_____
_____ Professor Stefano Carpin	Date	_____
_____ Professor Reza Ehsani	Date	_____

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Contents

Contents	iv
List of Figures	vi
List of Tables	ix
List of Algorithms	x
Curriculum Vita	xii
1 Agriculture 4.0	1
2 Introduction	4
2.1 Objectives	4
2.2 Using Machine Learning to Detect Water Stress	7
2.3 Robotic Manipulation Unit for Leaf Grasping and Hyperspectral Sensing	10
2.4 Autonomous Navigation in Orchard Environments	15
3 A Practical Data-driven Approach for Precise Stem Water Potential Monitoring in Pistachio and Almond Orchards Using Supervised Machine Learning Algorithms	24
3.1 Introduction	25
3.2 Materials and Methods	30
3.2.1 Experimental Sites	30
3.2.2 Ground Measurements	30
3.2.3 Aerial Imaging	32
3.2.4 Weather Sensors	33
3.2.5 Feature Selection	33
3.2.6 Machine Learning Models	38
3.2.7 Model Evaluation	39
3.2.8 Data splitting	41
3.3 Results and Discussion	42
3.3.1 Collected Data	42

3.3.2	Classification using Machine Learning	46
3.3.3	Classification and Regression using RF	53
3.4	Conclusions	55
4	RoMu4o: A Robotic Manipulation Unit For Orchard Operations Automating Proximal Hyperspectral Leaf Sensing	64
4.1	Introduction	65
4.2	Related Work	68
4.3	System Overview	69
4.3.1	Hardware Components	69
4.3.2	Experimental Setup	70
4.4	Leaf Grasping Pipeline	73
4.4.1	Perception	74
4.4.2	Robotic Manipulation	78
4.5	Results and Analysis	80
4.5.1	Leaf Manipulation Performance	81
4.6	Conclusions	84
4.7	Acknowledgment	85
5	Conclusion	89
5.1	Contributions	89
5.2	Challenges and future work	91

List of Figures

1.1	Envisioning an IoT infrastructure for a model orchard. IoT sensors along with aerial and ground robots are deployed to continuously monitor crops and manage the orchard.	2
2.1	Overview of research projects. 1) drone imaging and remote sensing for water stress detection 2) enabling autonomous navigation in orchard environments 3) ground level monitoring for 4D orchard monitoring 4) leaf detection, segmentation, and 6D pose estimation 5) physical intervention for proximal hyperspectral measurement from leaf samples.	5
2.2	Stem water potential prediction using a data-driven approach. Fusing multi-spectral, thermal and weather data using machine learning models for precise predictions.	9
2.3	RoMu4o, a robotic manipulation unit for orchard operations effectively automating ground-based crop mintoring and hyperspectral leaf sensing.	15
2.4	Navigation software developed for our custom-made agricultural robot. a,b) SLAM in a simulated orchard environment c) example of a real orchard environment d) robust navigation allowing for precise localization and hybrid path-planning e) universal robot description model f) crawler-type ground vehicle.	17
3.1	Test sites located in Merced, California. A total of 18 pistachio trees and 17 almond trees were considered for the experiments. The location of trees under assessment are shown using red markers and bounding boxes. . . .	31
3.2	Pearson correlation heatmap for Pistachio (PO). (left) represents the Pearson correlation heatmap with all 15 inputs (right) filtered Pearson correlation heatmap with 6 inputs that were used in ML models for SWP prediction. T, P, RH refer to weather temperature, pressure, and relative humidity reflecting minimum, mean, and maximum values measured on each day of experiment. T_c is the canopy temperature, NDVI, GNDVI, OSAVI, LCI, NDRE are vegetation indices (VIs), which are measured for each tree individually throughout the season.	36

3.3	Pearson correlation heatmap for Almond (AO). (left) represents the Pearson correlation heatmap with all 15 inputs (right) filtered Pearson correlation heatmap with 6 inputs that were used in ML models for SWP prediction. T, P, RH refer to weather temperature, pressure, and relative humidity reflecting minimum, mean, and maximum values measured on each day of experiment. T_c is the canopy temperature, NDVI, GNDVI, OSAVI, LCI, NDRE are vegetation indices (VIs), which are measured for each tree individually throughout the season.	37
3.4	Binary classes of collected stem water potential (SWP) data where 25% of the total dataset is set aside as test set to evaluate the performance of ML models. n denotes the total number of dataset in (a) the pistachio orchard with $n = 126$ and (b) the almond orchard with $n = 111$	42
3.5	Collected stem water potentials (ψ) during the 2022 season versus the corresponding day of year (DOY) for the (a) pistachio orchard (b) almond orchard.	43
3.6	Collected weather data during each day of experiment in (a) pistachio (PO) and (b) almond orchard (AO). Each weather data is illustrated for 24h cycles starting at midnight 00:00 (12am).	44
3.7	Selected thermal and multispectral (MS) features throughout the season versus absolute SWP ($ \psi $) values in (a) pistachio orchard and (b) almond orchard. T_c represents the canopy temperature and OSAVI, NDVI, and NDRE represent the MS vegetation indices.	46
3.8	Performance of ML classifiers namely Random Forest (RF), Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Decision Tree (DT), K-Nearest Neighbors (KNN), and Artificial Neural Network (ANN) predicting SWP in pistachio (PO) and almond orchard (AO). The gray patch represents the accuracy of each fold during the cross-validation phase and the black patch shows the prediction accuracy of the best trained model on the test set.	47
3.9	Confusion matrices representing the results of ML classifiers predicting SWP in (a) pistachio orchard (b) almond orchard.	50
3.10	Feature importance provided by the Random Forest (RF) classifier for (a) pistachio orchard and (b) almond orchard.	51

4.1	(a) RoMu4o, our proposed robotic manipulation unit for orchard operations aimed for autonomous proximal hyperspectral leaf sensing. The system is comprised of 1) 6-DoF robotic manipulator 2) RGBD camera 3) two-finger gripper integrated with a hyperspectral sensing system 4) an independent VIS-NIR light source for referencing and self-calibration 5) crawler-type ground robot 6) electric and control boxes, hardware drivers, portable batteries, processing unit, Ethernet hub, other devices used for the UGV's navigation. (b) Pistachio leaves used for field experiments (c) and Magnolia for lab experiments.	66
4.2	Flowchart for the autonomous proximal hyperspectral leaf sensing process. The workflow consists of a perception pipeline for image processing and 6D pose estimation followed by a robotic manipulation pipeline for precise leaf grasping and hyperspectral data collection.	71
4.3	Difficulty with leaf candidate identification, segmentation, and depth matching in field trials as outdoor light intensity increased.	72
4.4	Perception pipeline for leaf manipulation. (a,e) the RGB image as seen by the RealSense depth camera. (b,f) leaf detection and segmentation using pre-trained instance segmentation deep-learning networks (c,g) extracting the 3d structure of identified target leaves by aligning the ordered depth channel to RGB pixels (d,h) noise elimination and 6D pose estimation for each target.	74
4.5	Leaf manipulation process in action. Pistachio trees representing field experiments on the <i>top row</i> , and magnolia shrub representing lab experiments on the <i>bottom row</i> . (a,e) a batch of foliage is observed by the camera for the perception pipeline to generate 6D poses for leaf targets (b,f) pose estimates are processed through the robotic manipulation workflow for path planning and trajectory execution while hyperspectral sensor is calibrated (c,g) first target is approached and grasped with hyperspectral data collected and stored (d,h) planning to the next target for leaf grasping and spectroscopy.	80
4.6	Leaf hyperspectral data collected using our proposed robotic system. (left) spectral transmittance of magnolia leaves used as a plant model for indoor lab experiments (right) spectral transmittance of pistachio leaves representing our outdoor field experiments.	82
4.7	Success rate of leaf grasping using the robotic manipulator in different experimental settings.	84

List of Tables

3.1	Final selection of input variables used in machine learning models to predict stem water potential.	34
3.2	Quantitative analysis on the performance of ML classifiers predicting SWP in the pistachio (PO) and almond orchard (AO).	49
3.3	Using the Random Forest (RF) model for comparison between various inputs. The units for RMSE and MAE are <i>bars</i>	54
4.1	Number of available tests.	82
4.2	Success rate of leaf grasping using the robotic manipulator in different experimental settings.	83

List of Algorithms

1	Perception Pipeline	77
2	Robotic Manipulation Workflow	79

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And to the land of free...

Curriculum Vitae

Doctor of Philosophy (Ph.D.) – Mechanical Engineering 2020 – 2024
University of California, Merced, Merced, California

Master of Science (M.Sc) – Mechanical Engineering 2018 – 2020
University of California, Merced, Merced, California

Bachelor of Science (B.Sc) – Mechanical Engineering 2013 – 2017
Sharif University of Technology, Tehran, Iran

Abstract

Autonomous systems are transforming various domains of our daily lives. Intelligent robots have been meticulously engineered and widely adopted across industries to improve efficiency or automate repetitive tasks — and the agricultural industry is no exception. To increase food production and meet the demands of a rapidly growing population, adopting autonomous systems equipped with flexible and context-aware decision-making capabilities has become essential in agriculture. Labor-dependent practices may provoke inefficiency, greater waste of resources, and financial loss. Such inefficiencies can be addressed using robust computer models that are customized based on the type of crop and its environment, and through proper infrastructure and sophisticated physical systems that allow for timely action. Developing and utilizing these integrated solutions would result in efficient field management and higher yields at lower costs. With a focus on practical utility for end-users, we developed engineering solutions across different phases and scales to automate, enhance, and transform a range of agricultural tasks. We established an Internet of Things (IoT) infrastructure to enable connectivity between sensor systems allowing for real-time monitoring of model orchards. We employed machine learning algorithms and created comprehensive data-driven models to facilitate optimal water management in orchards. This approach represents a significant step forward toward enabling precise, per-tree irrigation. In a distinctive contribution, we presented RoMu4o, a robotic manipulation unit tailored for operation in orchard environments. We developed a robust computer vision algorithm that enables the robot to identify target leaves within a batch of foliage for precise robotic manipulation. RoMu4o, was tested both in the lab and in the real orchard environment to autonomously grasp leaves and collect their hyperspectral data. We developed software packages for autonomous navigation of a custom-built mobile platform, designed for high maneuverability in unstructured agricultural terrains. Furthermore, we presented a 4D metric-semantic multi-modal mapping algorithm capable of tracking crops across seasonal growth stages. These efforts represent our contribution toward the next agricultural revolution.

Chapter 1

Agriculture 4.0

Population of the world is projected to reach 9.8 billion by 2050. The rapid growth in population has coincided with limited availability of arable land, water, and energy resources which are integral elements for food production. Nowadays, 70% of global water use is allocated to agricultural practices, energy costs represent the highest expense on a farm, and the ecological footprints of agrochemicals jeopardize humans health. To ensure food, energy, and water security, new agricultural technologies need to be developed to create sustainable and efficient approaches for agricultural practices. Recent technological advancements have paved the way for transforming solutions, addressing the inefficiencies of traditional farming while enabling precision and scalability to meet the growing demands of the global population. This transition is referred to as *Agriculture 4.0*, representing the fourth major revolution in agriculture. Agriculture 4.0 is characterized by the integration of artificial intelligence, robotics, internet of things (IoT) sensors and data-driven techniques to address modern challenges with food production (Kagan et al., 2022). Although it has been four decades since the concept of precision agriculture first emerged, it is the recent advancements in artificial intelligence and robotics, coupled with their growing accessibility and declining costs, that have enabled another revolution in agriculture.

To increase food production to the level that meets global needs, it is important to adopt innovative and automated strategies for agricultural practices. These

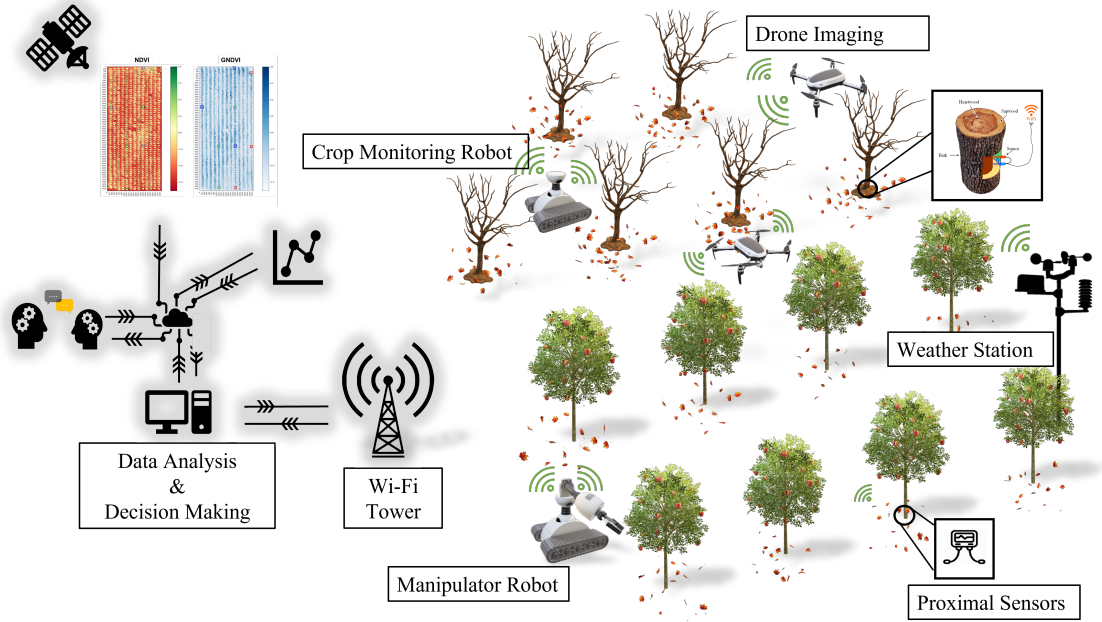


Figure 1.1: Envisioning an IoT infrastructure for a model orchard. IoT sensors along with aerial and ground robots are deployed to continuously monitor crops and manage the orchard.

practices include but are not limited to crop health monitoring, stress detection, irrigation, fertilization, harvesting and weed control. Non-automated solutions can lead to inefficiency, greater waste of resources, increased environmental footprints, and financial losses. Some reasons for such inefficiencies include; the absence of robust computer models customized to the type of crop and its environment, and a lack of infrastructure and physical systems that enable rapid response and timely action. Tackling these issues would result in efficient field management and higher yields at lower costs. In certain areas, such as crop monitoring and stress detection, automated solutions are either unavailable or not widely adopted, as many farmers still rely on manual labor for these tasks. This reliance creates financial and operational challenges, particularly due to the ongoing decline in the agricultural workforce.

Autonomous ground robots offer advanced solutions for intelligent automation in

agriculture. Equipped with specialized tools and sensors, these robots can navigate through agricultural fields, identify and locate crops, and precisely execute tasks such as crop health monitoring, data collection and phenotyping, resource allocation, harvesting, and pruning. This capability enables them to perform targeted actions with high efficiency and accuracy. Additionally, unmanned aerial vehicles (UAVs) complement these systems by rapidly scouting large areas, providing valuable insights into field conditions at scale and on a per-tree basis. The data gathered by UAVs can then guide ground robots for detailed investigations and precise interventions, creating a synergistic approach to agricultural field management. Such integrated approach forms a vital foundation for smart farming but necessitates the establishment of a robust infrastructure.

Recognizing the need for a cohesive framework, we envisioned and developed IoT infrastructure for a model orchard as seen in Figure 1.1, tailored to tackle technical challenges inherent in implementing smart farming solutions. We laid the groundwork for a cohesive blend of automation using data-driven insights and precision robotic interventions. In the next chapters of this dissertation, I explain how we turned our vision as seen in Figure 1.1 into reality Figure 2.1, by leveraging enabling technologies in robotics and machine learning to deliver innovative solutions for crop monitoring, yield estimation, and stress detection.

References

Kagan, C. R., Arnold, D. P., Cappelleri, D. J., Keske, C. M., and Turner, K. T. (2022). Special report: The internet of things for precision agriculture (iot4ag). *Computers and Electronics in Agriculture*, 196:106742.

Chapter 2

Introduction

This chapter is an introduction to innovative engineering solutions we pioneered to automate, enhance, and transform a range of agricultural practices, as depicted in Figure 2.1. We established an internet of things (IoT) infrastructure in two model orchards to enable connectivity between sensors allowing for real-time monitoring of the status of the orchards. We adopted an engineering approach to tackle some of the fundamental problems in agriculture in different phases and at various scales. In certain instances, advanced technologies in artificial intelligence were employed to address specific challenges in agricultural practices. In scenarios where existing solutions were inadequate or nonexistent, we innovated IoT sensors, engineered robotic systems, and developed novel algorithms to bridge these technological gaps. Some examples of these solutions are discussed below.

2.1 Objectives

Phase one focused on water status detection on a per-tree basis through machine learning and multi-modal sensor data. We deployed six machine learning algorithms to detect stem water potential (SWP) for each individual tree in pistachio and almond orchards. SWP is a physiological indicator that provides a reliable measure of crop water status. Measuring SWP, however, requires a manual process that is

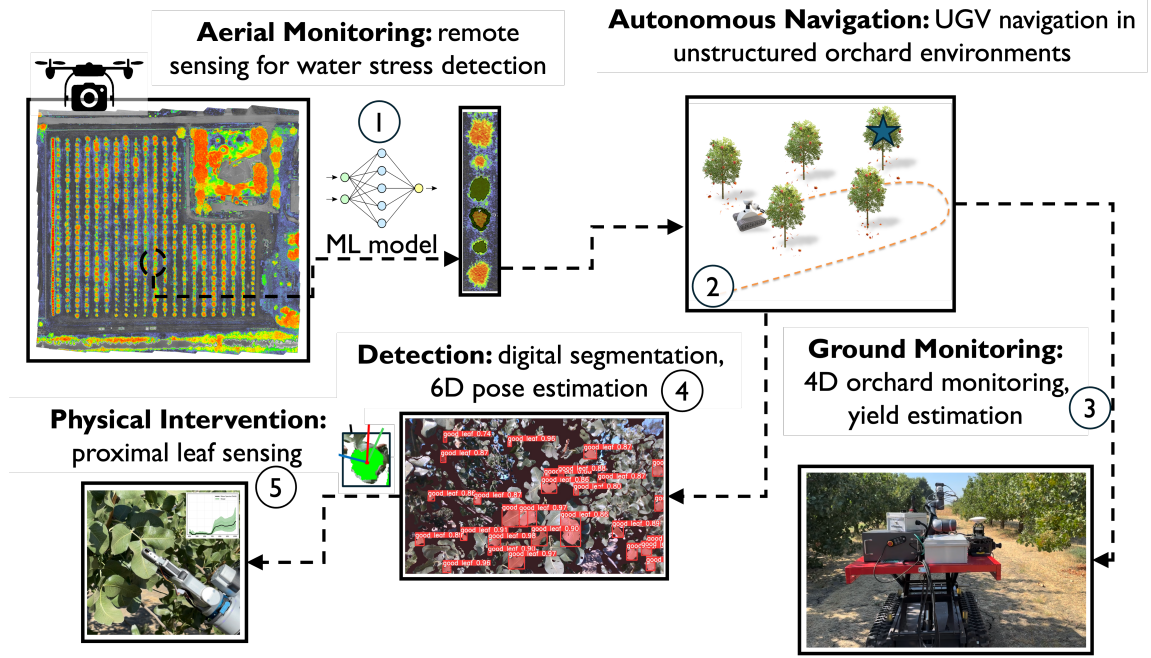


Figure 2.1: Overview of research projects. 1) drone imaging and remote sensing for water stress detection 2) enabling autonomous navigation in orchard environments 3) ground level monitoring for 4D orchard monitoring 4) leaf detection, segmentation, and 6D pose estimation 5) physical intervention for proximal hyperspectral measurement from leaf samples.

both labor- and time-intensive. This limitation makes it impractical to collect SWP measurements for all trees within a single day, restricting data collection to a small subset of trees, which may not fully capture field-wide variability. To address this challenge, we harnessed the power of machine learning to predict SWP values using non-destructive methods. This approach represents a significant step forward toward enabling precise, per-tree irrigation strategies, leading to efficient water management in orchards (Mortazavi et al., 2023).

In the second phase, we enabled autonomous navigation for a ground vehicle designed to operate in unstructured orchard environments. This unmanned ground vehicle (UGV) is capable of precise localization and mapping with collision-free hybrid planning capabilities in agricultural settings. This agricultural robot (AgBot) is

equipped with RTK-GNSS/IMU system for centimeter-level localization and precise odometry. The vehicle is a crawler-type mobile platform with two tracking sides. The vehicle is designed for locomotion in agricultural settings with high maneuverability due to its high traction capabilities. Additionally, the system includes a vertically adjustable overhead plate, which enhances its functionality by extending the field of view for data collection and enabling access to the upper sections of the tree canopy for leaf manipulation. Open-source software packages are developed and made available online for wide access. Additionally, the system is tested in simulation environment to streamline the debugging process (Mortazavi, 2024).

In the third phase, we developed a 4D spatio-temporal metric-semantic mapping approach to monitor fruit growth throughout an entire growing season. Although some studies have performed automated fruit detection in 3D with reasonable accuracy, they fail to provide insights into fruit development across multiple time intervals. To bridge this gap, we extended the 3D detection framework to a 4D fruit monitoring approach, enabling precise detection, tracking, and analysis of fruits across multiple timestamps throughout the entirety of a growth season. Multiple sensors: 3D LiDAR, 9-axis IMU, RGBD module, and GPS were assembled into a sensor suite to gather extensive data from the experimental orchards. The goal of this work extends beyond estimating yield. Our customized tracking algorithm was developed to track fruit growth across time and space, enabling a detailed understanding of how individual fruits develop within the orchard environment. By capturing temporal and spatial dynamics, the system provides valuable insights into fruit growth patterns and offers potential for optimized resource allocation. One potential application of 4D fruit monitoring is in precision irrigation and fertilization, as the quality of fruits such as grapes and peaches is highly influenced by the timing and amount of water or fertilizer they receive during critical growth stages. By providing continuous and detailed insights into fruit development over time, this approach can help optimize application of resources to enhance fruit quality and yield. Therefore, growers are likely to adopt this technology to enhance both their crop quality and profitability.

The datasets used for this study were constructed from diverse orchard types, including apple, peach, pear, cherry, and pistachio (Lei et al., 2024). This work is the result of a collaborative effort between the University of California, Merced, and the University of Pennsylvania, conducted under the auspices of the IoT4Ag engineering research center.

Phase four and five are the key contributions of this work, resulting in the development of RoMu4o, a robotic manipulation unit for orchard operations automating proximal hyperspectral leaf sensing. This robotic unit provides an automated solution for ground-level orchard monitoring by enabling high-resolution and non-invasive data acquisition for applications such as phenotyping, crop health assessment, and detecting water stress. Featuring a 6DOF robotic arm and a vision system, RoMu4o identifies target leaves, reconstructs their 3D structure, and autonomously performs hyperspectral measurements with a 70% overall success rate during field experiments in a pistachio orchard. Moreover, it achieved 95% and 79% success rates for 1-leaf-per-batch sampling on indoor (magnolia) and outdoor (pistachio) plant models, respectively. RoMu4o, marks a significant step toward autonomous, ground-based agricultural monitoring (Mortazavi, 2024).

2.2 Using Machine Learning to Detect Water Stress

California is one of the world’s leading agricultural producers, but its agricultural industry faces significant challenges due to water scarcity. From 2020 to 2022, California experienced the driest three-year period on record, with precipitation amounting to just 68% of the 20th-century’s average (Medellín-Azuara et al., 2022). Frequent droughts and water shortages pose a significant threat to agricultural industries in drought-prone regions. These conditions jeopardize California’s \$60 billion agricultural industry (CFDA, 2023) and intensify the need for efficient water management practices. Efficient irrigation management can be challenging due to variations in wa-

ter needs across species and cultivars (Scalisi et al., 2020). This highlights the need for scalable, reliable approaches to assess water stress for better agricultural water management (Pinter Jr et al., 2003; Garofalo et al., 2023). With the introduction of new regulations in California such as the Sustainable Groundwater Management Act (SGMA) (Langridge and Van Schmidt, 2020), farmers are increasingly seeking efficient strategies for precision irrigation (Abioye et al., 2020) that are adaptable to severe drought conditions while minimizing labor and time demands. One widely used approach is measuring stem water potential (SWP) (Chone et al., 2001; Abrisqueta et al., 2015), which helps determine the optimal timing for irrigation. This method involves cutting sample leaves from trees and placing them in a pressure chamber, where pressure is gradually increased until water is released from the leaf stem Figure 2.2. The pressure required for water release serves as an indicator of the tree water requirement. The tedious and time-consuming nature of obtaining SWP data has significantly limited its use in commercial settings Savchik et al. (2024). As a result, many crop growers are discouraged from adopting this method and instead rely on traditional irrigation practices, which apply water uniformly across the field rather than tailoring it to the specific per-tree or per-block water needs.

We recognized the limitations of traditional methods in assessing crop water status and identified the need for a more efficient, scalable approach that could be widely adopted. To address this, we proposed leveraging advanced data processing technologies to generate detailed, per-tree insights while significantly reducing the time required for data collection. This approach provides growers with precise, actionable information about the specific water needs of their fields, empowering them to make informed decisions tailored to their crops. By bridging the gap between labor-intensive measurements and scalable, practical solutions, this method offers the potential to optimize irrigation strategies and enhance resource management.

Building on this foundation, we explored the integration of remote sensing technology and machine learning to advance the prediction of stem water potential (SWP).

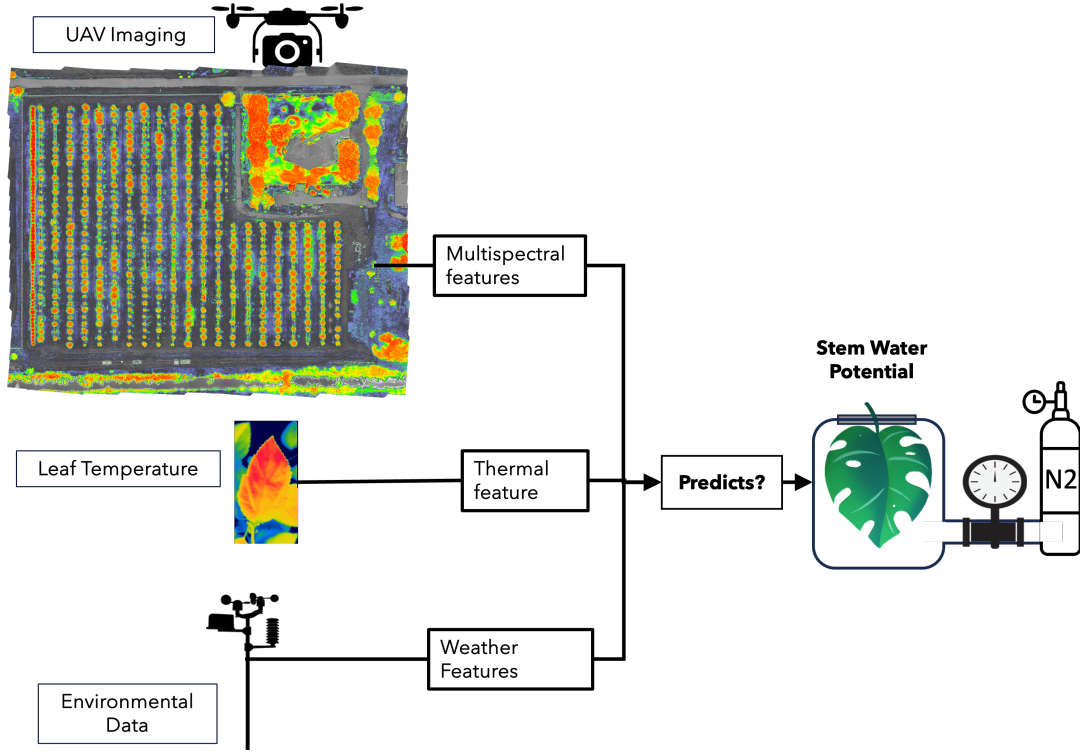


Figure 2.2: Stem water potential prediction using a data-driven approach. Fusing multi-spectral, thermal and weather data using machine learning models for precise predictions.

These technologies offer a logical progression by combining the extensive coverage of aerial imaging with the analytical power of data-driven algorithms. We developed a predictive model that balances minimal data requirements with high accuracy, aiming to provide practical utility for orchard irrigation management. Using six machine learning classifiers and deploying weather, thermal, and multispectral variables, we predicted SWP categories for individual trees in almond and pistachio orchards. Additionally, we evaluated the prediction performance of random forest (RF) regression and classification models with various feature sets. This work demonstrates a practical and cost-effective approach for tree-specific water status detection, allowing growers to implement and automate precise irrigation practices at scale. This approach is discussed in detail in Chapter 3, (Mortazavi et al., 2023).

Furthermore, we continued this analysis and developed a robust stochastic decision tree (SDT) model aimed specifically at enhancing SWP prediction in pistachio and almond trees. The SDT model addresses the limitations of traditional SWP measurement techniques, which are often labor-intensive and reliant on costly equipment. By integrating accessible environmental data, such as weather variables and multispectral vegetation indices, the SDT model delivers precise SWP predictions with minimal data requirements. Our results show that the SDT model can outperform established machine learning algorithms such as Random Forest and Support Vector Machines, achieving higher accuracy. The stochastic nature of this model eliminates the need for rigorous feature selection, makes it robust against data variability, and enables practical application in diverse agricultural settings. By reducing the reliance on manual processes, this approach provides growers with a scalable and cost-effective solution for precision irrigation contributing to sustainable water management and ultimately higher yields. This study underscores the potential of integrating data-driven models into agricultural practices and is aligned with the broader goal of precision irrigation in smart farming (Alizadeh et al., 2024).

2.3 Robotic Manipulation Unit for Leaf Grasping and Hyperspectral Sensing

The future of agriculture is significantly dependent on the deployment of robotic platforms for various agricultural practices such as harvesting, crop monitoring, transportation, weed management, plant breeding, and more (Lytridis et al., 2021; Vougioukas, 2019). The application of agricultural robots is of great importance globally and especially in the United States due to severe labor shortages and regular increases in farm labor wages. Robots have the capability for automation, unmanned navigation, and consistent performance under harsh conditions (Ju et al., 2022; Wang et al., 2021). Moreover, limiting the intervention of humans in demanding agricultural tasks will reduce the risk of injury and fatality. High performance, cost reduction,

and safety improvement in the long-term have been major reasons for the agricultural industry to deploy autonomous robotic systems in field operations (Rondelli et al., 2022).

Unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) have been used extensively for research and commercial purposes in agriculture. UGVs and UAVs have remarkable potential for scalability, manipulation, and rapid data collection (Ju et al., 2022). UAVs can quickly survey and rapidly acquire data over large areas of land. Large-scale UAV information can be combined with ground measurements to be used for plant health monitoring and crop management (Fan et al., 2021). Remote sensing is the most common application of UAVs. Agricultural UAVs are extensively used for: weed mapping, plant growth monitoring, crop yield estimation, plant health monitoring and diseases detection, irrigation management, and rarely for crop spraying and harvesting (Tsouros et al., 2019). UGVs are one of the most integral parts of a smart farm since they can be trained to perform a variety of labor-intensive tasks. Development of UGVs in agriculture can be divided into two main categories: automation of conventional agricultural vehicles such as tractors and designing autonomous mobile platforms for agricultural-specific purposes (Ju et al., 2022; Gonzalez-De-Santos et al., 2020). Application of agricultural UGVs include but are not limited to harvesting (Zhou et al., 2022; Yoshida et al., 2022), seeding and planting (Blender et al., 2016), weed detection and killing (Albani et al., 2017), physical sampling (Kim et al., 2022), precision irrigation and fertilization (Thayer et al., 2018; Minßen et al., 2011), phenotyping (Gao et al., 2018), and pruning (You et al., 2022; Ju et al., 2022). There are specific examples of robotic platforms developed to perform various agricultural tasks both on farms and in orchards. Here, we will review some studies in which a robotic arm is deployed to perform to physically interact with crops and perform specific agricultural tasks.

In a study by Wang et al. (2022), a mobile manipulation platform was designed to detect and harvest apples. In this study, a geometry-aware network is proposed that

performs segmentation and grasping pose estimation. The success rate of field experiments for this study ranged between 70% to 85%. In another study (You et al., 2022), an integrated robotic system was developed to autonomously detect and cut pruning targets in a sweet cherry orchard. A Real-Sense D435 RGB-D camera is used for branch detection and segmentation. A pruning end effector attached to a 6 degree-of-freedom collaborative arm is mounted on a linear slider and receives signals from the RGB-D camera to perform precision cuts. The foreground masks of branches are first extracted using semantic segmentation algorithm followed by a mask R-CNN-based instance segmentation model to detect pruning points. In the final step, a closed-loop hybrid/vision interaction controller is used to reach the target branches and cut them. The pruning success rate of 58% was achieved in the field trials. Kim et al. (2022), designed a novel agricultural robotic platform named Purdue-AgBot which is capable of autonomous crop monitoring and physical sampling of corn and sorghum. Due to unreliable global navigation satellite system (GNSS) signals under dense vegetation environments, an adaptive Monte Carlo localization with an extended Kalman filter (EKF) is used to facilitate the localization of the robot. A 2D Light detection and ranging (LiDAR) sensor is then used for navigation and collision avoidance through the field. The crop shape monitoring is performed through a 3D LiDAR, while the manipulation and leaf physical sampling are guided through an RGB-D sensor. As a result, the crop monitoring experiments, which entail height and stalk diameter estimation, were performed with less than 10% error and the physical sampling and manipulation tasks achieved approximately 80% of success rate. Subsequent versions of P-AgBot introduced improved vision (Deb et al., 2023) and navigation (Kim et al., 2024) performance.

As demonstrated in these examples, autonomous ground robots integrated with robotic manipulators are alternative solutions for in-person scouting and manual work in agriculture. Ground-based vehicles equipped with robotic manipulators serve as platforms carrying various sensors capable of rapid and consistent data collection (Atefi et al., 2021). UGVs are capable of autonomously navigating through agricul-

tural fields for monitoring or interacting with specific areas of interest within the canopy. While most existing systems are designed for crop harvesting there has been limited focus on physical intervention with leaves for sensing and sampling. Mueller-Sim et al. (2017); Campbell et al. (2022); Ahlin et al. (2016); Motokura et al. (2020); Kim et al. (2022); Chen et al. (2021, 2023) are among the studies in this domain. Autonomous systems for leaf grasping and sensing have primarily been tested in controlled environments, with few addressing the complexities of real orchard conditions. This gap highlights the need for robotic systems capable of operation in unstructured field or orchard settings, where challenges such as varying lighting, wind, and temperature conditions demand robust algorithms and hardware integration.

The early identification of biotic and abiotic stresses in plants is crucial for mitigating severe damage and avoiding yield losses. In agricultural settings such as orchards, remote sensing technologies, including satellite and UAV imagery, have proven effective for detecting plant stress. Hyperspectral data collected from individual trees can be analyzed to identify issues such as disease, water stress, and nutrient deficiencies. While UAV hyperspectral imagery is an efficient method for covering large areas in a short amount of time, they have high operational cost, require specific calibration process, and can not operate under cloudy or varying lighting conditions. A robotic manipulation system equipped with a portable hyperspectral sensor offers a practical solution, providing high-fidelity data while minimizing labor-intensiveness and enhancing scalability for precise crop monitoring. Ground robots can also benefit from an independent lighting source to streamline the calibration process for the hyperspectral sensors, which reduces the operational constraints.

Our work introduces a ground robotic system, RoMu4o, which is specifically designed for proximal hyperspectral leaf sensing in orchard environments. By integrating advanced vision-guided algorithms with a 6DOF robotic manipulator, our system enables precise detection, segmentation, and grasping of target leaves. The compact and innovative design of the end-effector, which combines a hyperspectral sensor with

an independent lighting source, ensures consistent and high-fidelity data acquisition while streamlining calibration processes. This feature addresses a common limitation associated with aerial hyperspectral imaging systems, which are often affected by outdoor lighting variability and require extensive calibration. Additionally, the crawler-type UGV platform ensures reliable mobility and adaptability in unstructured orchard terrains.

Our system bridges the gap between high-resolution data acquisition and operational scalability, addressing the limitations associated with manual sampling and aerial imaging approaches. While aerial platforms excel at identifying stress regions at scale, they require ground verification to determine the underlying causes of stress, necessitating labor-intensive and time-consuming sampling. By automating leaf-level hyperspectral sensing, RoMu4o as seen in Figure 2.3, eliminates the need for manual work, providing growers with actionable, tree-specific insights to enhance irrigation and crop health management.

Our work prioritizes real orchard conditions and diverse tree species, including pistachios and almonds. The integration of deep-learning-based perception algorithms allows our system to navigate and operate in the noisy and dynamic environment of a typical orchard. By addressing challenges such as complex crop structures, environmental noise, our system represents a significant advancement towards automation in agriculture. While prior research laid important groundwork, our contribution lies in combining robust perception and manipulation pipelines with practical field-deployable hardware. RoMu4o, offers a scalable and cost-effective solution for hyperspectral sensing, and provides a transformative approach to crop health monitoring. Detailed contributions of this work are discussed thoroughly in Chapter 4.



Figure 2.3: RoMu40, a robotic manipulation unit for orchard operations effectively automating ground-based crop mintoring and hyperspectral leaf sensing.

2.4 Autonomous Navigation in Orchard Environments

In agricultural settings, navigation is a non-trivial task due to unstructured field conditions and the absence of consistent physical landmarks (Radcliffe et al., 2018). Various agricultural environments require customized algorithms to ensure both safety and performance. Localization, mapping, route planning, and motion control are the fundamental components of an autonomous robotic navigation system (Santos et al., 2020). Localization involves determining the position and orientation of a robot relative to its surrounding environment, while mapping creates an operational map of an unknown environment that the robot can perceive and utilize. Initially, these two processes were studied independently. However, as robotic applications expanded into dynamic and unpredictable environments, localization and mapping became in-

creasingly interdependent, leading to the development of Simultaneous Localization and Mapping (SLAM), originally proposed by Smith and Cheeseman (1986). Navigation in agricultural environments faces unique challenges due to uneven terrain, dense vegetation, and variable lighting conditions (Aguilar et al., 2020).

GNSS signals offer a viable solution for robot localization in agricultural fields. However, their reliability is influenced by factors such as signal availability, vegetation texture, and canopy density. In GNSS-denied environments, visual odometry (VO) can be used as an alternative. VO estimates the motion of a robot by analyzing sequential images but its performance can suffer from drift over time, as well as environmental challenges such as shadows and intense sunlight, which impair visual signals (Shalev and Degani, 2020). To overcome these limitations, lidar odometry (LO) or lidar-inertial odometry (LiO) has been introduced as a more robust navigation solution. Equipped with loop closure algorithms, drift can be minimized and accurate maps can be obtained. Such techniques were presented as lidar odometry and mapping (LOAM) (Zhang et al., 2014), or Semantic-LOAM (Chen et al., 2020). When signals are available, RTK-GNSS based positioning provides centimeter-level accuracy. GNSS data can be fused with other sources of data such as inertial measurement units (IMUs), and wheel encoders to reliably localize the robotic vehicles. Extended Kalman Filter is a widely used probabilistic algorithm that fuses multiple sensors information to enable autonomous navigation of robots through orchards (Blok et al., 2019; Shalev and Degani, 2020).

Our contribution focused on developing software packages for a custom-built non-commercial mobile platform to enable reliable navigation in an orchard environment. Given the minimally cluttered nature of our experimental testbed, we relied on GNSS-based navigation, as high signal-to-noise ratio provided stable and accurate localization. Recognizing the importance of robustness in agricultural environment, we designed the navigation software from the ground up by fusing RTK-GNSS, IMU, and wheel encoder data and ensured its adaptability to orchard conditions. We also de-

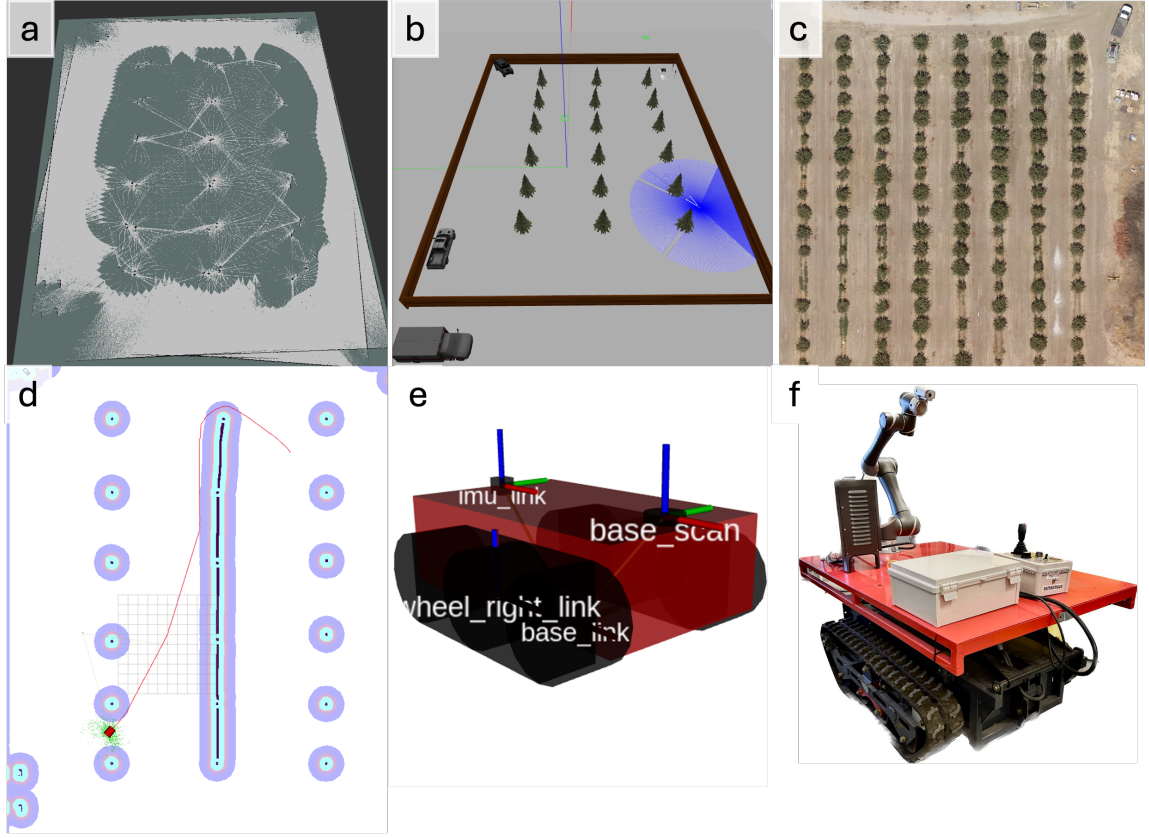


Figure 2.4: Navigation software developed for our custom-made agricultural robot. a,b) SLAM in a simulated orchard environment c) example of a real orchard environment d) robust navigation allowing for precise localization and hybrid path-planning e) universal robot description model f) crawler-type ground vehicle.

veloped a simulation environment, which allowed us to test the navigation algorithms in virtual environments Figure 2.4. This approach not only ensured reliable operation in the field but also provided a foundation for refining the system’s capabilities to meet the demands of real-world applications in orchard settings.

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Chapter 3

A Practical Data-driven Approach for Precise Stem Water Potential Monitoring in Pistachio and Almond Orchards Using Supervised Machine Learning Algorithms

Abstract: *The advent of machine learning technologies in conjunction with the advancements in UAV-based remote sensing pioneered a new era of research in agriculture. The escalating concern for water management in drought-prone areas such as California underscores the urgent need for sustainable solutions. Stem water potential (SWP) measurement using pressure chambers is one of the most common methods used to directly determine tree water status and the optimal timing for irrigation in orchards. However, this approach is inefficient due to its labor-intensive nature. To address this problem, we used weather, thermal and multispectral data as inputs to the machine learning (ML) algorithms to predict the SWP of pistachio and almond trees. For each crop, we first deployed six supervised ML classification models: Random Forest (RF), Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Decision Tree (DT), K-Nearest Neighbors (KNN), and Artificial Neural Network (ANN). All classifiers provided more than 79% of accuracy while RF showed high performance in both pistachio and almond orchards at 88% and 89%, respectively. The feature importance results by the RF model revealed that the weather features were the most influential factors in the decision-making process. In both crops, canopy temperature T_c was the next important feature closely followed by OSAVI in pistachios and NDVI in almonds. RF regression model predicted SWPs with R^2 of 0.70 in pistachio and R^2 of 0.55 in the almond orchard. Our results demonstrate that ML classification models are practical tools for irrigation scheduling decisions. This study offered a data-driven approach that effectively balances minimal data requirements with accuracy to facilitate optimal water management for end-users.*

3.1 Introduction

The state of California is a major crop producer in the world (Hong et al., 2020). California’s agricultural exports achieved a value of \$22.5 billion in 2021, showing a 20% percent growth over the span of 10 years. The foundation of this success rests on the state’s almond and pistachio industries that contribute to about 30% of these

exports in value according to CFDA reports. However, crop production in California is subject to substantial uncertainty due to high vulnerability to drought and water shortage (Medellín-Azuara et al., 2022). In 2014, California adopted the Sustainable Groundwater Management Act (SGMA) regulations to mitigate groundwater overdraft, especially in agriculture (Espinoza et al., 2023). These regulations aim to optimize water allocation and reduce wastage. Guidelines cover aspects such as irrigation scheduling and water application methods. With these regulations in effect, the need for efficient irrigation methods become more important (Escriva-Bou et al., 2020). The escalation in crop water requirements is urging growers to explore new irrigation strategies that can accommodate severe drought conditions. It is crucial to seek solutions that are not labor-intensive and time-consuming to allow for efficient water management under challenging circumstances (Kagan et al., 2022).

Stem water potential (SWP) is a direct measure of tree water level. SWP measurement has been exclusively used in the field of horticulture and viticulture for irrigation scheduling and high-quality crop production (Carrasco-Benavides et al., 2022). However, manual SWP measurement is labor-intensive and not practical for evaluating the water status of all trees within a large-scale orchard (Giménez-Gallego et al., 2021). To address the limitations associated with ground measurements, remote sensing using unmanned aerial vehicles (UAVs) has emerged as a promising solution for predicting SWP to provide rapid and efficient assessments. Remote sensing can leverage spectral data to facilitate the identification of crop water status (Gautam and Pagay, 2020; Romero et al., 2018). Supplementary information such as soil water content (SWC), local weather data, and evapotranspiration (ET) can synergistically be used along with spectral measurements to enhance the accuracy of SWP predictions.

Various studies have investigated thermal and multispectral UAV imagery to assess tree water status. UAV-based Normalized difference vegetation index (NDVI) and crop water stress index (CWSI) were compared with water status indicators includ-

ing SWP to detect water stress in almond cultivars (Gutiérrez-Gordillo et al., 2021). CWSI was measured using high- and low-resolution UAV thermal imaging to estimate midday SWP and stomatal conductance in cherry cultivars (?). Thermal and multispectral UAV imaging using a high-end all-in-one camera was conducted to establish a relationship between VIs and crop quality in Pistachios (Martínez-Peña et al., 2023). While both NDVI and CWSI were capable of detecting water stress, CWSI exhibited higher sensitivity. CWSI value of 0 represents a crop with no stress and a value of 1 indicates non-transpiring crops that are under severe water stress. Studies have offered various approaches to compute the CWSI (Idso et al., 1981; Egea et al., 2017; Kirnak et al., 2019; Liu et al., 2022). The main difference between various methods is often found in the computation of the lower and upper limits. For instance, a widely used approach offered by (Idso et al., 1981), also referred to as the empirical approach, is to determine the lower limit as a linear function of vapor pressure deficit (VPD). The upper boundary can be calculated either by taking the maximum observed difference between the canopy and air temperatures or through a linear relationship the vapor pressure gradient (VPG), as described by (Katimbo et al., 2022). Some studies have discussed the use of constant values (e.g 5°C) for the calculation upper baselines (Ben-Gal et al., 2009). One limitation of CWSI calculation is that it requires specific adjustments according to the lower and upper limits for the difference between canopy temperature and air temperature (González-Dugo et al., 2014). Its reliance on experimental data to establish lower or upper baselines can be significantly affected by changes in weather conditions. This variability raises concerns about its applicability for real-time irrigation scheduling and the adaptability of the established baseline across different climate zones (Katimbo et al., 2022).

The utilization of machine learning (ML) in remote sensing has been on the rise over the past decade (Virnodkar et al., 2020). These ML-powered technologies are actively deployed to automate the process of data exploration and address information deficits across spatial and temporal dimensions (Benos et al., 2021; Sun and Scanlon, 2019; Marques Ramos et al., 2020). ML algorithms excel in capturing complex

and nonlinear interactions between multiple input variables to predict desired outputs. They can effectively utilize fundamental components as inputs to reduce the dependency on carefully engineered features or variables with high potential correlations to the target output. This capability allows ML models to identify intricate patterns in the data and offers a more flexible data-driven approach compared to traditional methods that often require significant feature engineering. Several studies have used ML algorithms to predict plant water status and more exclusively SWP. Hyperspectral imageries from grape leaves were analyzed using Random Forest (RF) and Extreme Gradient Boosting (XGBoost) to classify water-stressed leaves based on their SWP values with %84 accuracy (Loggenberg et al., 2018). Multiple ML models were deployed to predict olive SWP using various multi-spectral vegetation indices and spectral bands with RF outperforming other models with $R^2 = 0.78$ (Garofalo et al., 2023). Normalized difference red edge index (NDRE), SWC, and ET were used to predict raw SWP values in an almond orchard using RF and Artificial Neural Networks (ANN). Together, all models resulted in an average $R^2 = 0.73$ and $RMSE = 2.5bars$ for SWP prediction in almond (Savchik et al., 2024). SWP, along with SWC and atmospheric features, have also been used as input variables to predict the leaf temperature as an indicator of almond water status. In this study, ANN was able to predict the target with $R^2 = 0.78$ (Meyers et al., 2019). Currently, there are limited studies in almonds and especially pistachios where ML is used to predict direct indicators of tree water status such as SWP.

There remains an opportunity to carve out a pathway toward a simplified, cost-effective, and non-destructive approach to remotely determine SWP and facilitate its adoption by the end-users. The motivation for such an approach emerges from the necessity to integrate emerging technologies into current field practices, particularly for large-scale orchard water management, where precise monitoring of tree water status forms an integral component of efficient irrigation. Tree water status has been estimated by an array of direct and indirect methodologies, ranging from sap flow sensors (Mobe et al., 2020; Alizadeh et al., 2021), soil moisture sensors (Vera et al.,

2019; Millán et al., 2020), and dendrometers (Celedón et al., 2012) to hyperspectral and multispectral sensors (Ballester et al., 2018; Zhao et al., 2017; Zhou et al., 2021). Although these techniques have demonstrated effectiveness in assessing crop water status, those of which require ground installation or measurement, typically involve intrusive procedures and can impose significant financial and labor burdens, especially in large commercial orchards. Moreover, conventional techniques might not sufficiently capture the spatial and temporal heterogeneity of SWP within the tree and across the orchard.

The current infrastructures in most orchards are not designed for tree-specific irrigation. Instead, they allow for the control of irrigation on a block-by-block basis. By gaining insights into specific stress levels of trees, growers could make more informed decisions. This would enable them to prioritize irrigation in blocks with higher numbers and greater severity of water stress. Given the rapid advancements in remote sensing technology and machine learning, there is an opportunity to leverage these developments to enhance SWP prediction. The adoption of a predictive model predominantly reliant on remotely sensed and weather data, unites the power of aerial imaging technology with the sophistication of data-driven algorithms, representing a logical progression in this domain. In this study, our objective was to develop a data-driven model that balances minimal data requirements with accuracy while enabling practical utility for end-users in managing orchard irrigation scheduling. We used six ML classifiers and deployed weather, thermal, and multispectral variables to predict SWP categories of each tree in almond and pistachio orchards. Additionally, RF regression and classification models were used to determine the SWP prediction performance using different features. Here, we present a practical and cost-effective approach for tree-specific water status detection in orchards.

3.2 Materials and Methods

3.2.1 Experimental Sites

The study sites include a 2.5-ha (6.1 acres) pistachio orchard (PO) and a 3-ha (7.4 acres) almond orchard (AO) situated in Merced County, within California’s San Joaquin valley as shown in Figure 3.1. This region is known for its Mediterranean climate, characterized by hot and dry summers and mild and wet winters. The pistachio variety was Kerman, and the trees were 9 years old. The almond was a nonpareil variety and trees were 12 years old. The average maximum and minimum temperatures in Merced, CA, between June and August 2022 were 36°C (97°F) and 12°C (54°F), respectively. The PO was irrigated through a double-line drip irrigation system, while the almond orchard was irrigated through a macro jet irrigation system. A total of 14 data collection field trips were conducted between June and August 2022. These data collections trips were evenly split between PO and AO, with seven experiments in each orchard. For PO these days were: June 7, June 21, July 5, July 13, July 26, August 2, August 12 representing day of year (DOY) 158, 172, 186, 194, 207, 214, 224, respectively. For AO these days were: June 8, June 23, July 8, July 15, July 30, August 3, August 31 representing day of year (DOY) 159, 174, 189, 196, 211, 215, 243, respectively. A total of 18 trees in the PO and 17 trees in the AO were selected as sample trees from which stem water potential (SWP), leaf temperature, and aerial multispectral images were collected. In each field, the sample trees were randomly chosen in blocks of three or four across the fields to account for the possible variability in the orchards.

3.2.2 Ground Measurements

Throughout each day of experiment, stem water potential (SWP) measurements were collected within 1-2 hours of solar noon, approximately around 1 PM. To account for variability in SWP measurements within target trees, three leaves from the lower shaded canopy of each sample tree were chosen for SWP measurements. The resultant data was averaged to produce a mean SWP value per tree for subsequent

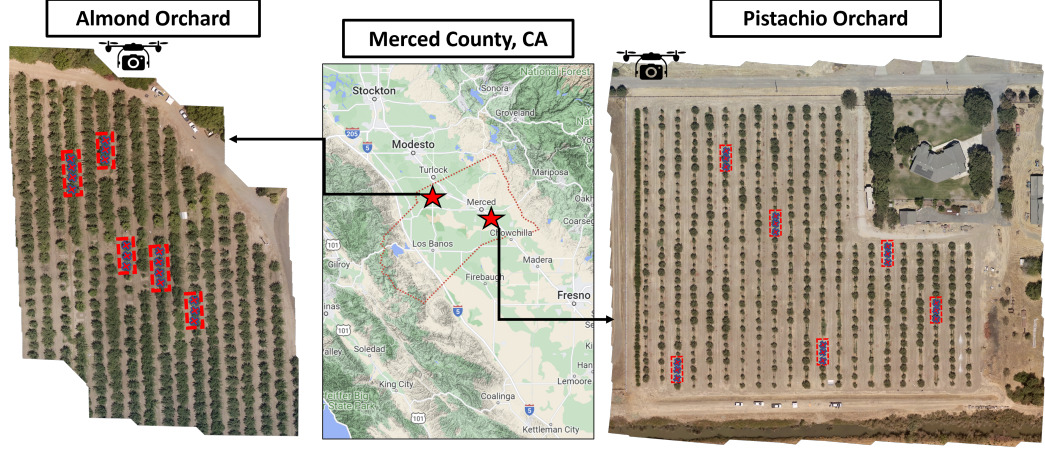


Figure 3.1: Test sites located in Merced, California. A total of 18 pistachio trees and 17 almond trees were considered for the experiments. The location of trees under assessment are shown using red markers and bounding boxes.

analysis. These measurements were performed using the PMS-615 pressure chamber (PMS Instrument Company, Albany, OR, USA). Prior to being detached from the tree and analyzed in the pressure chamber, the leaves were sealed in aluminum bags for a minimum duration of 15 minutes. Encasing the leaves in bags before conducting the SWP measurements is crucial for obtaining precise results. This procedure guides the leaf toward an equilibrium state and mitigates discrepancies that could arise from continuous photosynthesis and transpiration within the leaves (Lampinen et al., 2015).

Concurrently with the collection of SWP measurements (± 1 hour of solar noon), leaf temperature was recorded from three distinct leaves located at three different sides of each tree on the lower canopy. The recorded measurements were subsequently averaged to represent the canopy temperature T_c for each sample tree. The leaf temperature data was measured using a TM0866 non-contact infrared thermometer (PerfectPrime, Barbican, UK) with 0.1°C resolution and $\pm 1\%$ accuracy. Each temperature measurement was conducted at a 5-10cm distance from the leaf center and perpendicular to its surface.

3.2.3 Aerial Imaging

Flights were conducted within an hour of the solar noon, which occurred approximately at 1 pm local time, to minimize issues related to canopy shading. Aerial imaging is performed using DJI P4 multispectral agricultural drone (SZ DJI Technology Co., Ltd., Shenzhen, China) equipped with RTK-GNSS system for precise georeferencing. The built-in imaging system is composed of an RGB camera and a five-band multispectral camera array, all of which are mounted on a 3-axis stabilized gimbal. The multispectral array encompasses five distinct bands: blue (B: 450 nm $\pm$ 16 nm), green (G: 560 nm $\pm$ 16 nm), red (R: 650 nm $\pm$ 16 nm), red edge (RE: 730 nm $\pm$ 16 nm), and near-infrared (NIR: 840 nm $\pm$ 26 nm). Each band was captured by a dedicated 2 MP camera with a global shutter.

During each flight mission, images were captured from an altitude of approximately 100 meters above the ground providing $4\text{cm}/\text{pixel}$ resolution. Additionally, the integrated upward looking sunlight sensor records solar irradiance during the flight, which allows for instantaneous referencing of spectral reflectance. The collected spectral data were processed through the computer software DJI Terra version 3.7.0 to create orthomosaic maps for each orchard. The DJI Terra software was utilized for radiometric correction to produce one color composite along with five indexed maps for specific vegetation parameters: Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Optimized Soil-Adjusted Vegetation Index (OSAVI), Leaf Chlorophyll Index (LCI), and Normalized Difference Red Edge (NDRE). The spectral indices were calculated as follows: NDVI was computed as $(R_{nir} - R_{red}) / (R_{nir} + R_{red})$, GNDVI as $(R_{nir} - R_{green}) / (R_{nir} + R_{green})$, OSAVI as $(R_{nir} - R_{red}) / (R_{nir} + R_{red} + 0.16)$, LCI as $(R_{nir} - R_{rededge}) / (R_{nir} + R_{red})$, and NDRE as $(R_{nir} - R_{rededge}) / (R_{nir} + R_{rededge})$. We utilized the Computer Vision Annotation Tool (CVAT) to manually extract the location of selected canopies from the orthomosaic maps. NDVI maps were utilized for annotation due to their enhanced clarity in identifying canopy boundaries. With the aid of these annotated NDVI maps, precise locations of the target tree canopies were determined. Subsequently, these geoloca-

tions were leveraged to automate the extraction of index values from all the other maps. Image processing and all subsequent analysis were carried out using Python. Upon extraction of the index values from each tree canopy, the median of all values was used to represent the corresponding vegetation index for each sample tree.

3.2.4 Weather Sensors

Local weather stations were installed in both orchards to collect the ambient temperature, barometric pressure, and relative humidity. These weather data were collected every ten minutes during the 2022 growing season. The availability of a wireless network in the PO allowed for real-time monitoring and cloud storage of the data. In contrast, the lack of a reliable internet network in the AO prevented us from transferring data to an internet-connected cloud server. Therefore local data storage was adopted in this area. Weather stations include a BME688 sensor (Bosch Sensortec, Kusterdingen, Germany) and an ESP8266 chip (Espressif Systems, Shanghai, China) with IEEE 802.11 b/g/n Wi-Fi and built-in TCP/IP networking software. The BME688 sensor measures temperature, humidity, pressure, and gas resistance, providing a comprehensive environmental data. The ESP8266 chip enables wireless connectivity and allows the weather stations to transmit data to a central server for real-time monitoring and analysis. In the PO, two ordinary D size 1.5 V batteries connected in series could provide the required energy to each weather station. The weather station in AO relied on solar cells as a sustainable energy source.

3.2.5 Feature Selection

Initially, we considered a total of 15 features for the prediction of SWP in both PO and AO. Out of these, nine were derived from weather features, representing minimum, maximum, and mean values of air temperature $T(^{\circ}C)$, air pressure $P(hPa)$, and relative humidity $RH(\%)$ calculated for each day of the experiment. The remaining features included five vegetation indices, NDVI, GNDVI, OSAVI, LCI, NDRE, and a thermal feature T_c representing the canopy temperature, which are all calculated

individually for each sample tree.

Table 3.1: Final selection of input variables used in machine learning models to predict stem water potential.

	Selected Input Features						Output
Pistachio	T_{mean}	P_{min}	RH_{min}	T_c	$OSAVI$	$NDRE$	SWP (ψ)
Almond	T_{max}	P_{min}	RH_{min}	T_c	$NDVI$	$NDRE$	SWP (ψ)
Unit	[°C]	[hPa]	[%]	[°C]	–	–	[bar]
Input type	weather	weather	weather	thermal	MS	MS	

The correlation heatmaps based on the Pearson method were generated and are illustrated in Figure 3.2 and Figure 3.3. Before deploying machine learning models for SWP prediction, inputs were filtered and checked for potential multi-collinearity. For each weather feature (T, P, RH) represented by minimum, mean, and maximum values on each day of experiment, we selected the one with highest correlation with the SWP. This choice was made to avoid redundancy in inclusion of weather features. As a result one representative weather feature was chosen from each group, resulting in ($T_{mean}, P_{min}, RH_{min}$) for PO, and ($T_{max}, P_{min}, RH_{min}$) for AO, as seen in Table 3.1. Then, a cutoff value of 0.75 was applied to remove features that are highly correlated with other features. This means that one out of the two features with absolute correlation coefficients greater than $|r| > 0.75$, was subsequently excluded from the analysis. Among those two features, the one with lower correlation with SWP is eliminated. The cutoff value of $|r| > 0.75$ was selected as it falls within the range commonly associated with strong collinearity, ensuring the removal of redundant features while preserving the most valuable ones. By applying this cutoff, the average absolute correlation between input features was reduced to 0.25 for PO and 0.30 for AO, placing them in a range generally characterized by weak correlations. This approach effectively eliminated multi-collinearity while maintaining a diverse and independent set of predictors for SWP prediction. From Figure 3.2 and Figure 3.3 it can be observed that in both crops, T_c was not highly collinear with any other feature. Additionally

in PO, NDVI and GNDVI with OSAVI, and LCI with NDRE were highly correlated thus eliminated from the input features. In AO, GNDVI and OSAVI with NDVI, and LCI with NDRE were highly correlated thus eliminated from the input features. Filtering the features based on correlation coefficients led to the establishment of a final collection of predictors. Consequently, six input features, as demonstrated in Table 3.1, were selected to be used for SWP prediction in PO and AO using machine learning. These features were T_{mean} , P_{min} , RH_{min} , T_c , $OSAVI$, $NDRE$ for PO, and T_{max} , P_{min} , RH_{min} , T_c , $NDVI$, $NDRE$ for AO.

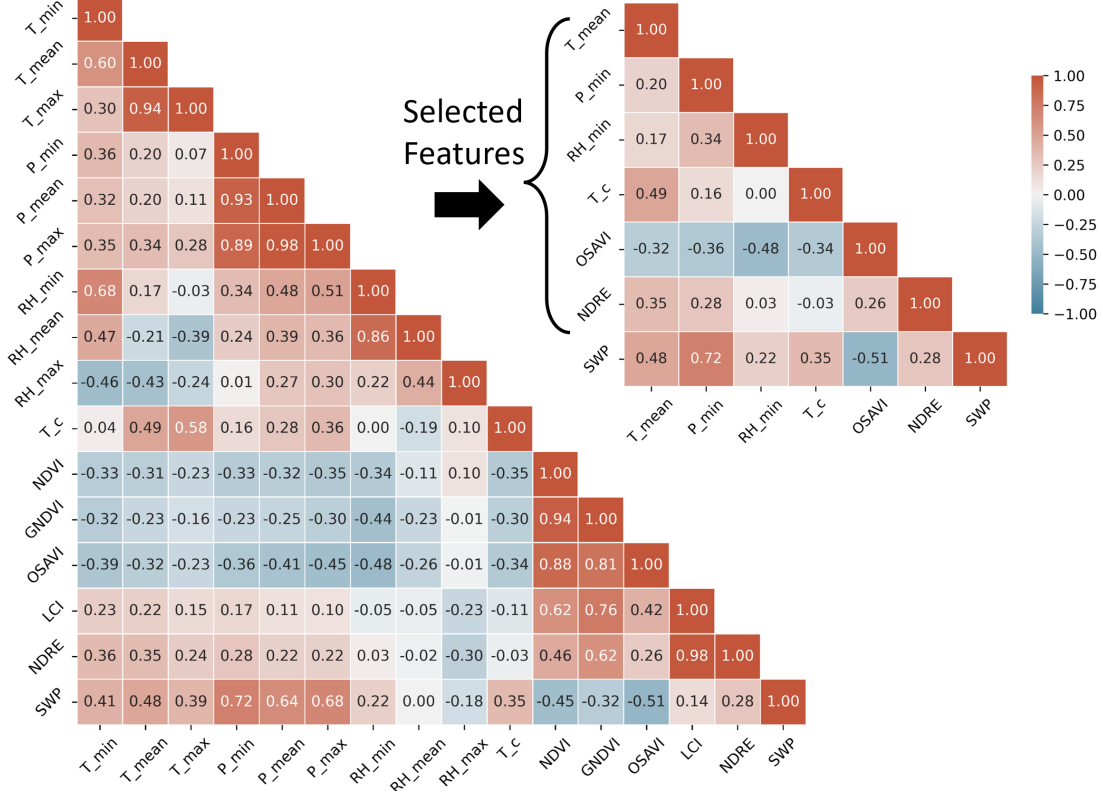


Figure 3.2: Pearson correlation heatmap for Pistachio (PO). (left) represents the Pearson correlation heatmap with all 15 inputs (right) filtered Pearson correlation heatmap with 6 inputs that were used in ML models for SWP prediction. T , P , RH refer to weather temperature, pressure, and relative humidity reflecting minimum, mean, and maximum values measured on each day of experiment. T_c is the canopy temperature, NDVI, GNDVI, OSAVI, LCI, NDRE are vegetation indices (VIs), which are measured for each tree individually throughout the season.

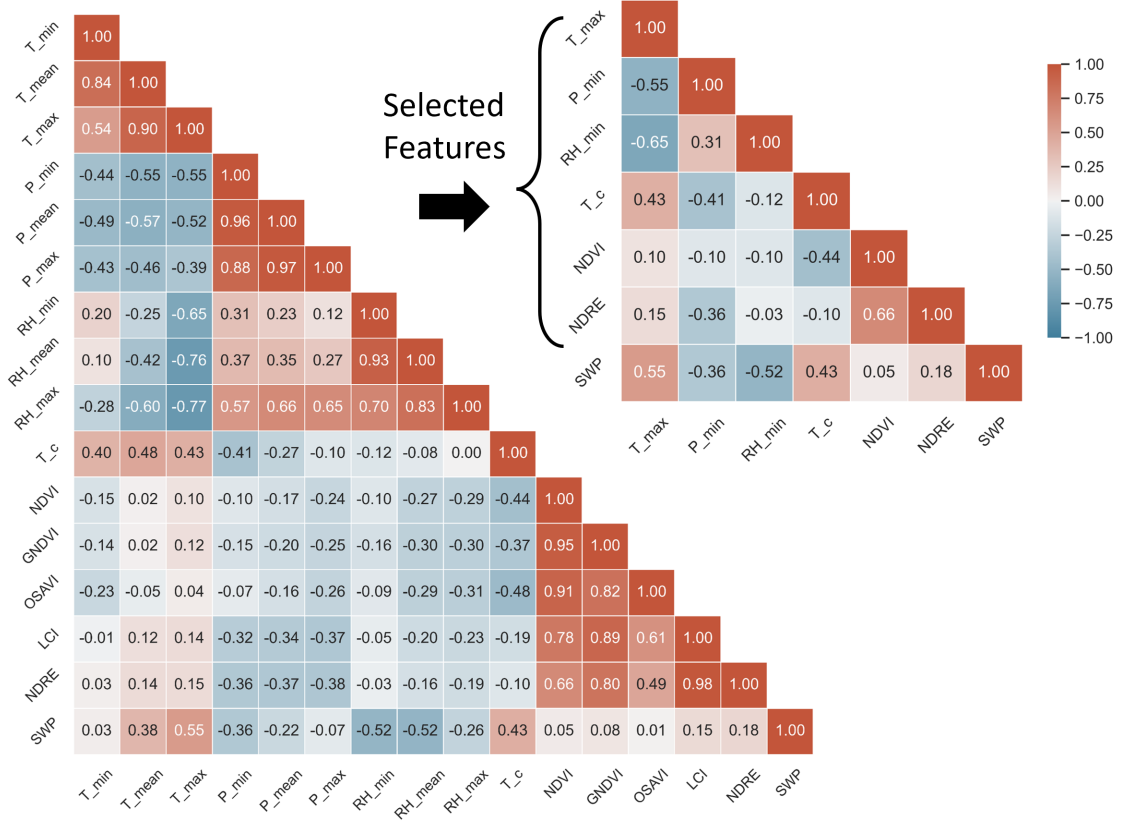


Figure 3.3: Pearson correlation heatmap for Almond (AO). (left) represents the Pearson correlation heatmap with all 15 inputs (right) filtered Pearson correlation heatmap with 6 inputs that were used in ML models for SWP prediction. T, P, RH refer to weather temperature, pressure, and relative humidity reflecting minimum, mean, and maximum values measured on each day of experiment. T_c is the canopy temperature, NDVI, GNDVI, OSAVI, LCI, NDRE are vegetation indices (VIs), which are measured for each tree individually throughout the season.

3.2.6 Machine Learning Models

We used six machine learning (ML) models, including Random Forest (RF), Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Decision Tree (DT), K-Nearest Neighbors (KNN), and Artificial Neural Network (ANN). These models were implemented using the Scikit-learn (Pedregosa et al., 2011), an open-source machine learning library developed for Python.

DT and RF possess distinct characteristics in handling classification and regression problems. DT functions by systematically dividing data into progressively smaller subsets. In the constructed tree-like diagram, every node symbolizes a comparison based on a specific feature, whereas the terminal leaves signify the final decision or prediction. RF stands as a prime example of ensemble learning, where the power of multiple decision trees is harnessed to form an aggregated predictive model. Ensemble learning methods aim to boost predictive performance by creating a composite model from a collection of simpler base models, each reflecting a unique hypothesis. This approach allows for integrating diverse hypotheses, often yield superior predictive results. RF offers robustness against noise and is less prone to overfitting thanks to the averaged predictions across multiple trees (Liakos et al., 2018; Quinlan, 1993). GNB belongs to the family of Bayesian models, which are probabilistic graphical models employed within the framework of Bayesian inference. This supervised learning model is applicable to both classification and regression problems. Despite its naive assumption of feature independence, the computational efficiency of GNB makes it an ideal choice for tasks necessitating quick and real-time predictions (Rish et al., 2001; Liakos et al., 2018). SVMs are key tools in ML, renowned for their adaptability in handling regression and classification tasks as well as clustering. They function by constructing a maximum margin hyperplane in a high-dimensional space, distinguishing between various classes while maximizing the margin between nearest points or support vectors (Chang and Lin, 2011; Zoppis et al., 2019). KNN is a supervised learning algorithm that works without any inherent assumptions about the underlying dataset. It is widely used for classification where it assigns classes to new data points

based on their proximity to existing labeled examples. The k in KNN represents the number of nearest neighbors the algorithm considers when making its prediction. Choosing an optimal k value is the key to its effectiveness and performance (Taunk et al., 2019; Ray, 2019). ANN is a computational model inspired by the biological neural networks, which offers a distinctive approach to handle intricate and highly non-linear problems. A specific type of ANN is the Multi-Layer Perceptron (MLP), which functions as a feed-forward network. The neurons in each layer are interconnected to the neurons of the subsequent layer through weighted connections. During the learning phase, these weights are adjusted using techniques such as backpropagation (Messikh et al., 2017; Delashmit et al., 2005). In this study, we used MLP for ANN analysis to map the complex relationships between the input data and the output predictions.

3.2.7 Model Evaluation

To evaluate the predictive capabilities of the machine learning algorithms, we partitioned the datasets from each orchard such that 75% was allocated for the training and validation of the models, while the remaining 25% was set aside for testing their performance. The test dataset was completely isolated from the training/validation dataset to avoid overfitting and data leakage. The dataset was then subjected to a standard scaling process, where each feature in the training set was normalized to have a mean of zero and a standard deviation of one. This step prevents features with larger values from dominating others during the training process, ensuring that each feature contributes proportionately to the final prediction. Next, each classifier was optimized to provide the highest performing predictive model, a strategy known as hyperparameter optimization. For the optimization process, we utilized a randomized search among the hyperparameters along with a 10-fold stratified cross-validation (CV) within the training dataset. This method partitions the original sample into ten equal-sized subsamples. In our study, the use of stratified CV was essential due to the imbalanced nature of the classes. This technique allows each fold to represent the overall class distribution accurately, thus preventing the model from being biased

toward the majority class. This enhances the robustness and generalization of the model as it accounts for the scarcity of minority class instances. Of the ten subsamples, one is retained as validation set and the remaining are used as training data. The cross-validation process is then repeated ten times, with each of the ten subsamples used once as validation data. The optimal set of hyperparameters was eventually determined based on the best average performance across all folds. Through the optimization process, it is ensured that the trained models are not exposed to the final test dataset to prevent data leakage and overfitting.

The optimized classifiers were subsequently utilized to evaluate the performance of test datasets. We used accuracy, F1-score, and Area Under Curve (AUC) of the Receiver Operating Characteristic (ROC) as metrics to assess the performance of each classifier. Accuracy is defined as the proportion of correct predictions relative to the total number of predictions. Consider class 0 as negative and class 1 as positive. The F1-score is first calculated on a per-class basis and defined as the harmonic mean of the precision and recall. Within each class, precision is the number of true positives (TP) or correctly identified positive instances by the model in the positive class, divided by all positively identified instances ($TP + FP$) (whether correct or incorrect), with FP denoting false positives. Recall is the number of true positives TP divided by all samples that should have been identified as positive $TP + FN$, where FN represents false negatives. As a result, the average of F1-scores calculated for each class are reported. The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various thresholds. The AUC is then computed by integrating the area under ROC curve. AUC provides a single scalar value representing the expected performance of the classifier. An AUC score close to 1 implies that the model has excellent ability to distinguish between classes, while an AUC score close to 0.5 indicates that the model is not classifying groups better than random classification. The regression model was similarly trained using a 10-fold CV and its performance was evaluated using the coefficient of determination R^2 , root mean square error $RMSE$, and mean absolute error MAE .

3.2.8 Data splitting

Tentative categories based on SWP values have been defined by the University of California Agricultural Extension (UCANR) for different type of crops. For instance, pistachio trees are considered non-stressed at -9 to -12 bars, moderately stressed at -12 to -14 bars, and severely stressed at values less than -15 bars. Almond trees are categorized as experiencing minimal stress at -6 to -10 bars, mild stress at -10 to -14 bars, moderate stress at -14 to -18 bars, high stress at -18 to -22 bars, and severe stress at values below -30 bars (Savchik et al., 2024).

For ML classification and given the total number of collected SWP readings and their distribution across these categories, we adopted a binary classification approach. This decision was primarily driven by the overall water levels observed in the experimental orchards and the specific conditions of the sampled trees. Upon examination of the SWP readings from the almond orchard (AO), we noted a significant level of water stress, with approximately 74% of the total SWP readings falling below -18 bars. Conversely, the pistachio trees in the corresponding orchard were observed to be well watered, with about 70% of the SWP readings exceeding -9 bars. To effectively categorize the orchards based on water levels, we defined thresholds for binary classification. In PO, a cutoff SWP value of -9 bars and in AO a cutoff of -18 bars were applied to separate trees with different stress levels. As illustrated in Figure 3.4, the total number of observations for the pistachio was $n = 126$, whereas for the almond, it was 119. Some incomplete data points within the almond dataset were identified and subsequently excluded from the analysis to get a total number of $n = 111$ observations in AO. As a result, 25% of the data in each orchard was used for testing and the remaining 75% was considered for training and validation of the ML models.

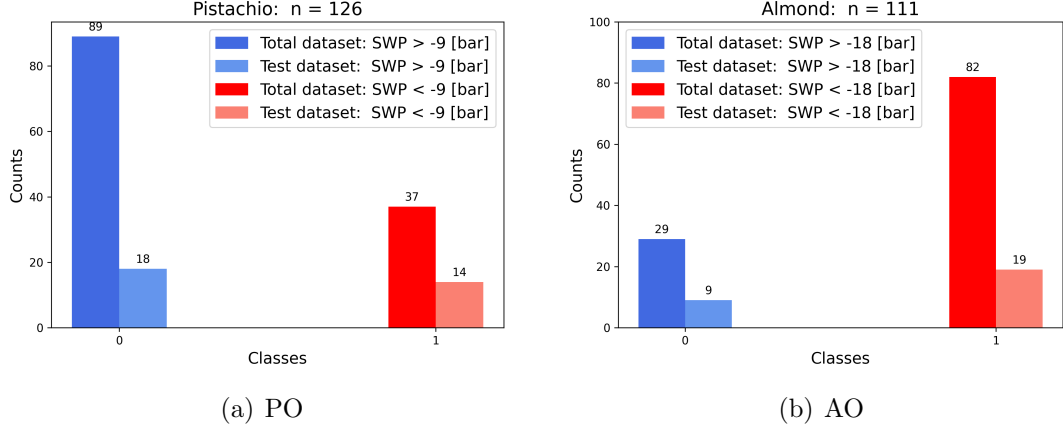


Figure 3.4: Binary classes of collected stem water potential (SWP) data where 25% of the total dataset is set aside as test set to evaluate the performance of ML models. n denotes the total number of dataset in (a) the pistachio orchard with $n = 126$ and (b) the almond orchard with $n = 111$.

3.3 Results and Discussion

3.3.1 Collected Data

Weather and MS data along with T_c and SWP (ψ), were recorded for PO and AO, during the 2022 growing season. SWP values for each DOY are illustrated in Figure 3.5. Among the seven days of experiment in PO, the lowest mean $|\psi|$ value was $|\psi| = 5.4 \text{ bars}$ with standard deviation of $\sigma = \pm 1.31 \text{ bars}$, observed on DOY 172, which corresponds to the second day of experiment. Conversely, the highest mean $|\psi|$ value was $|\psi| = 10.8 \text{ bars}$ with $\sigma = \pm 2.17 \text{ bars}$, observed on DOY 224, which corresponds to the last day of experiment. The standard deviations were ranged between $0.91 < |\sigma| < 2.17$ in PO. Among the seven days of experiment in AO, the lowest mean $|\psi|$ value was $|\psi| = 14.3 \text{ bars}$ with standard deviation of $\sigma = \pm 1.67 \text{ bars}$, observed on DOY 211, which corresponds to the fifth day of experiment. Conversely, the highest mean $|\psi|$ value was $|\psi| = 26.1 \text{ bars}$ with $\sigma = \pm 2.96 \text{ bars}$, observed on DOY 215, which corresponds to the sixth experiment. The standard deviations were ranged between $1.67 < |\sigma| < 4.37$ in AO. Considering all collected SWP data during the season, PO

had a mean of $|\bar{\psi}| = 8.0 \pm 2.41$ *bars* and AO had a mean of $|\bar{\psi}| = 21.0 \pm 4.70$ *bars*.

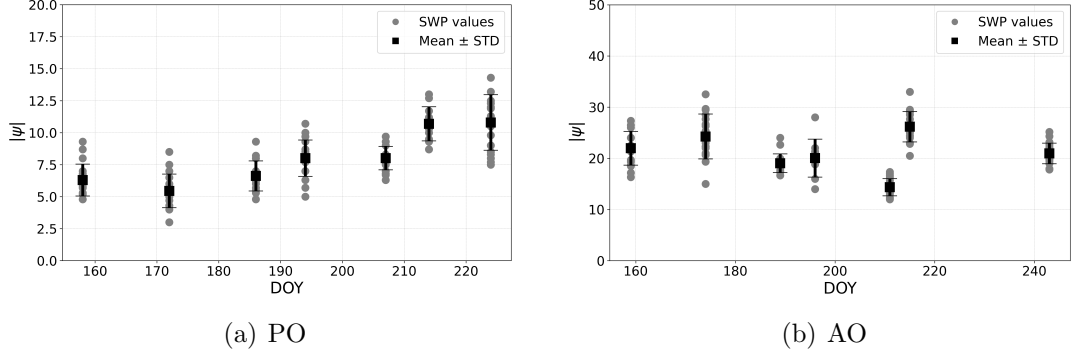


Figure 3.5: Collected stem water potentials (ψ) during the 2022 season versus the corresponding day of year (DOY) for the (a) pistachio orchard (b) almond orchard.

Weather data were continuously monitored through local weather stations installed in both orchards for which the results are demonstrated in Figure 3.6. As shown in Table 3.1, the final selection of weather features were T_{mean} , P_{min} , RH_{min} for PO, and T_{max} , P_{min} , RH_{min} for AO. During the seven days of experiment in PO, the lowest and highest average temperature T_{mean} were $25.5^{\circ}C$ and $31.4^{\circ}C$ representing the first (DOY 158) and sixth (DOY 214) experiments. The first and the third days of experiment corresponding with DOY 158 and 178 recorded the lowest and highest RH_{min} at 13.8% and 31.4%, respectively. The lowest and highest P_{min} were respectively observed on DOY 172 and 224 at 1002.4 *hPa* and 1006.0 *hPa*, which represent the second and the seventh days of experiment. During the seven days of experiment in AO, the lowest and highest average temperature T_{max} were $34.9^{\circ}C$ and $41.4^{\circ}C$ representing the fifth (DOY 211) and second (DOY 174) experiments. The second and the fifth days of experiment corresponding with DOY 174 and 211 recorded the lowest and highest RH_{min} at 23.2% and 48.3%, respectively. The lowest and highest P_{min} were respectively observed on DOY 174 and 189 at 1005.8 *hPa* and 1011.6 *hPa*, which represent the second and the third days of experiment. Considering the Pearson correlation coefficients among the weather features as seen in Figure 3.2 and Figure 3.3, P_{min} ($r = 0.72$) in pistachio and T_{max} ($r = 0.55$) in almond had the highest

linear correlation with SWP. The correlations $r = 0.48$ and $r = 0.22$ were respectively observed for T_{mean} and RH_{min} in PO, and $r = -0.52$ and $r = -0.36$ for P_{min} and RH_{min} in AO.

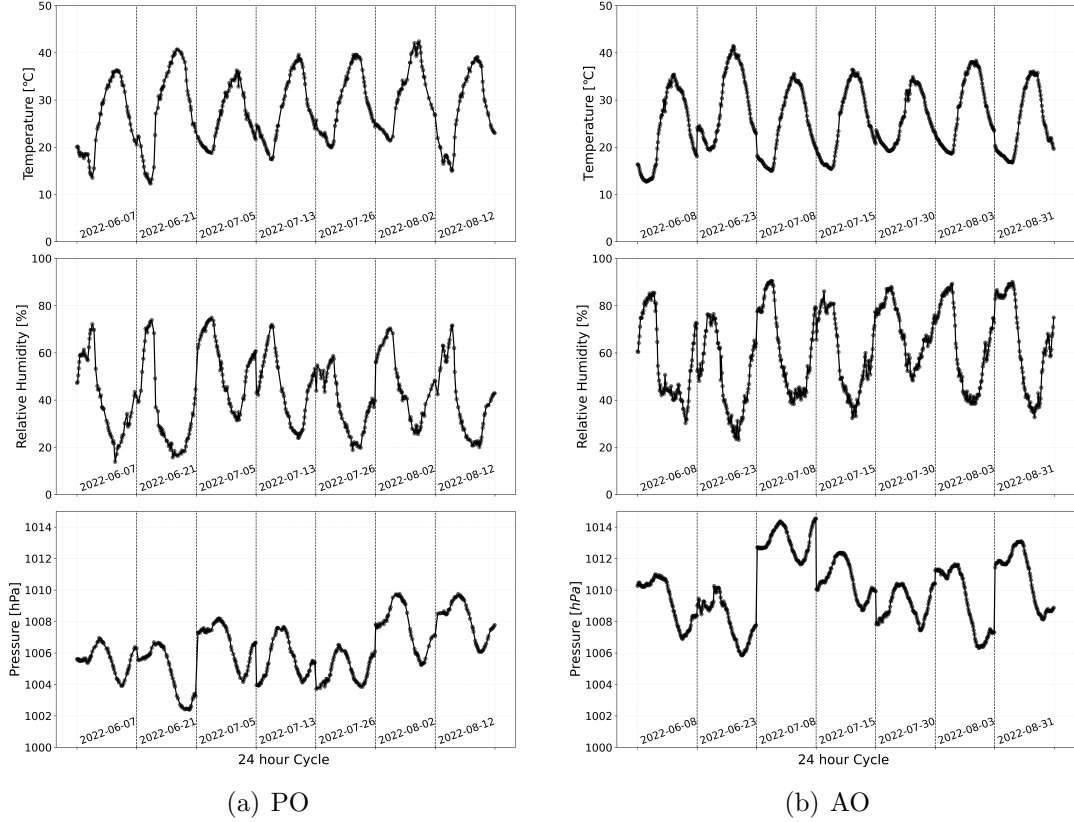


Figure 3.6: Collected weather data during each day of experiment in (a) pistachio (PO) and (b) almond orchard (AO). Each weather data is illustrated for 24h cycles starting at midnight 00:00 (12am).

The selected thermal and MS input features, as demonstrated in Table 3.1, were T_c , $OSAVI$, $NDRE$ for PO, and T_c , $NDVI$, $NDRE$ for AO. These features were plotted against absolute SWP ($|\psi|$) and the results along with their best fitted regression lines are demonstrated in Figure 3.7. In PO and AO, the correlations between T_c and SWP were $r = 0.35$ and $r = 0.43$, respectively. Among the VIs, $OSAVI$ in pistachio with $r = -0.51$ and $NDRE$ with $r = 0.18$ in almond exhibited higher linear

relationships with SWP. NDRE in PO with $r = 0.28$ and NDVI in AO with $r = 0.05$ had the weakest linear relationship with SWP among the selected thermal and MS features. In PO the trees had higher water levels while in AO the trees were mostly under water stress. This signifies that MS indices were more sensitive to SWP in the well-watered PO. Conversely, MS indices demonstrated lower sensitivity to SWP in the water stressed AO while T_c was more sensitive to the changes in SWP. In PO, OSAVI had the highest coefficient of determination with SWP at $R^2 = 0.26$ while in AO, $R^2 = 0.19$ was highest between T_c and SWP.

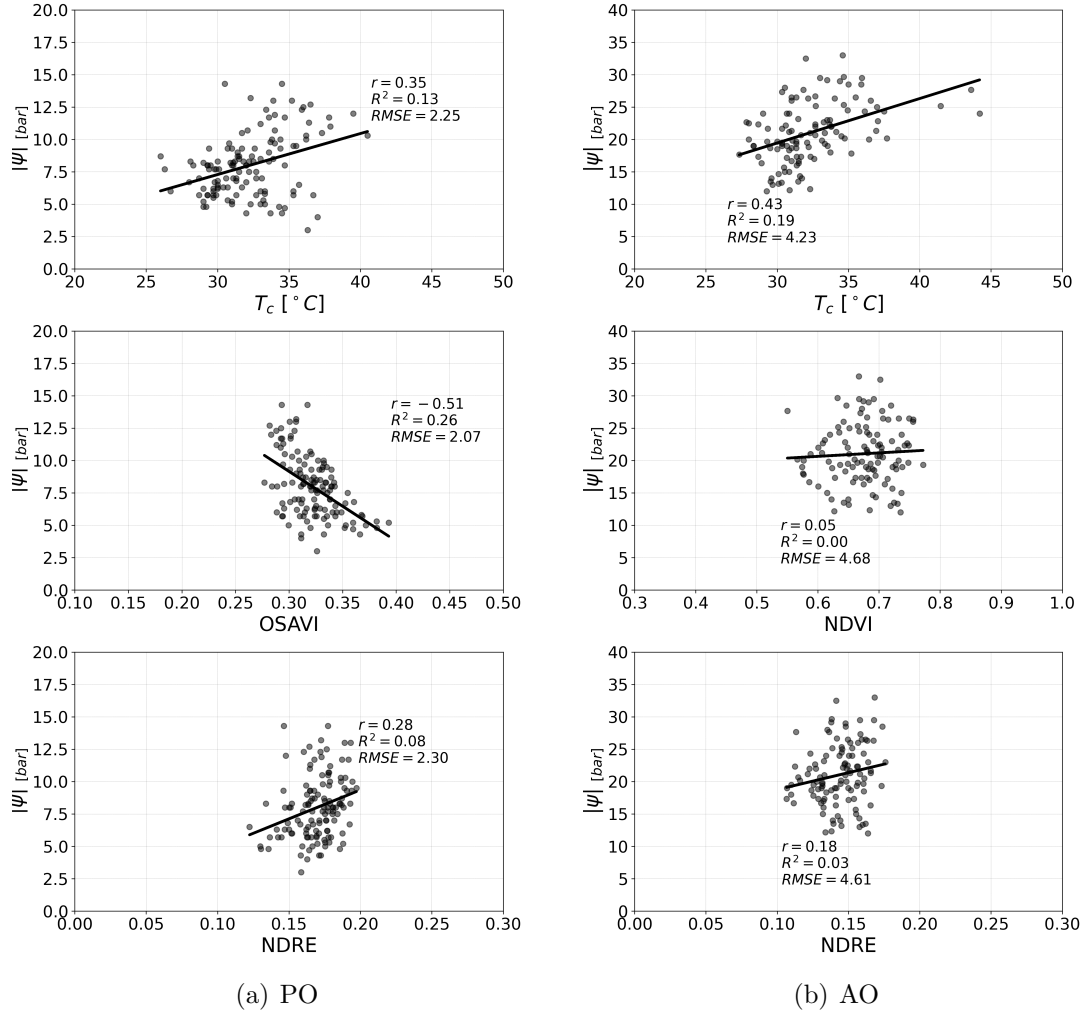


Figure 3.7: Selected thermal and multispectral (MS) features throughout the season versus absolute SWP ($|\psi|$) values in (a) pistachio orchard and (b) almond orchard. T_c represents the canopy temperature and OSAVI, NDVI, and NDRE represent the MS vegetation indices.

3.3.2 Classification using Machine Learning

The resulting optimized classifiers were subsequently deployed to predict the test dataset. Figure 3.8 illustrates the classification performance of the implemented machine learning models predicting SWP values in both the PO and AO. For each model, the classification accuracy of the test dataset along with their performance

across each fold of cross-validation during the training phase are elucidated. The accuracy of each classifier was obtained based on the ratio of correct predictions to the total number of predictions made by the model. All models provided accuracies higher than 79%. For the PO, the Random Forest (RF) and Decision Tree (DT) models delivered superior performance, each achieving an accuracy rate of 88%. In the AO, RF shared the highest accuracy rate of 89% with Support Vector Machine (SVM), K-nearest neighbors (KNN), and Artificial Neural Network (ANN) models.

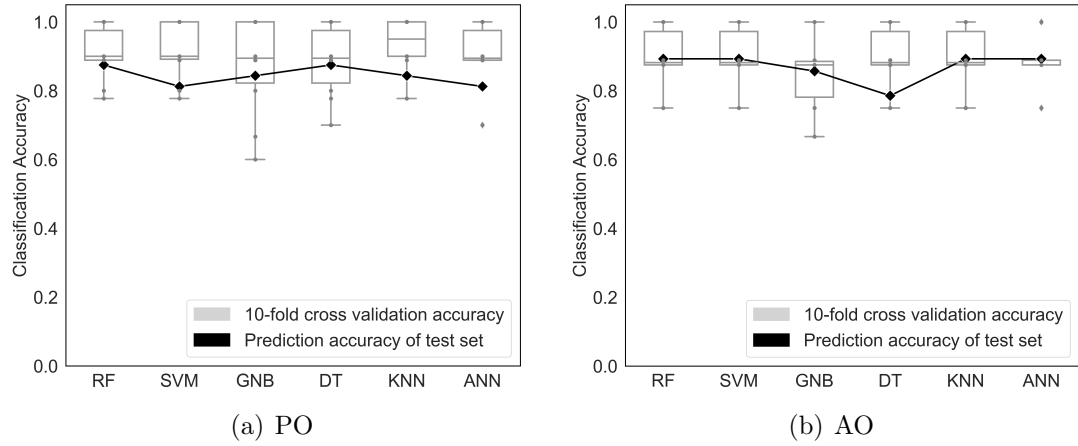


Figure 3.8: Performance of ML classifiers namely Random Forest (RF), Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Decision Tree (DT), K-Nearest Neighbors (KNN), and Artificial Neural Network (ANN) predicting SWP in pistachio (PO) and almond orchard (AO). The gray patch represents the accuracy of each fold during the cross-validation phase and the black patch shows the prediction accuracy of the best trained model on the test set.

Table 3.2 further elucidate the performance of each classifier, detailing additional metrics, including Cross-Validation (CV) averages, F1-scores, and Area Under Curve (AUC) values. It is noteworthy that the classifiers also demonstrated consistent performance across the folds during the CV phase. In PO, the mean of CV values were ranged between 87-94% whereas in AO this values were ranged between 86-89%. With an exception to the F1-score of DT in AO, which was 75%, F1-scores in both PO and AO were ranged between 81-87%. The F1-score acts as a measure of a model's

performance in correctly identifying instances in each class. The F1-score takes into account both precision and recall, providing a more comprehensive picture of model performance across all classes. This is particularly critical when dealing with datasets with imbalanced class distributions, as it provides a more nuanced understanding of a model's performance than accuracy alone. Moreover, the AUC which is calculated from the ROC curve, provides further insights into the model's ability to distinguish between the classes at various thresholds. An AUC score of 0.5 represents a model with no discrimination capacity, effectively performing no better than random chance. On the other hand, an AUC of 1.0 (100%) signifies perfect classification. High values of AUC imply that the model is making correct classifications while avoiding misclassifications. In the PO, the F1-scores of the applied ML classifiers varied from 81% (ANN and SVM) to 87% (RF and DT). Meanwhile, the AUC values ranged from 82% (KNN) to 88% (GNB) underlying a satisfactory ability while distinguishing between the classes. In the AO, the F1-scores ranged from 75% to 86%. The lowest AUC value was 77% by DT and the highest values was achieved by SVM and ANN at 93%. Overall, these metrics represent relative reliability of the ML models employed for SWP prediction in this study.

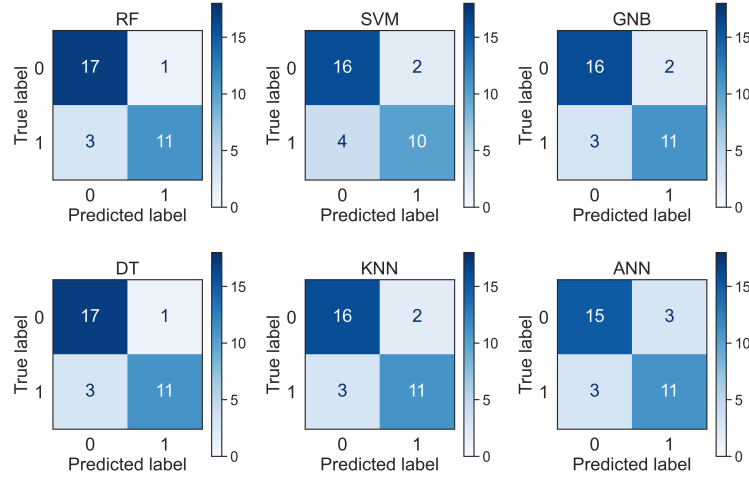
Confusion matrices were demonstrated in the Figure 3.9. The total number of test datasets in PO was $n_{test} = 32$ and in AO was $n_{test} = 28$ representing 25% of total dataset in each orchard. The RF and DT were the best classifiers in PO providing 28 correct and 4 wrong predictions. There were 17 *TN* and 11 *TP* as well as 1 *FP* and 3 *FN* in both RF and DT. This also reflects better prediction accuracy towards the majority class or class 0, in PO. Conversely, SVM and ANN had the lowest accuracies with 26 correct and 6 wrong predictions reflecting 16 *TN*, 10 *TP*, 2 *FP* and 4 *FN* in SVM, and 15 *TN*, 11 *TP*, 3 *FP* and 3 *FN* in ANN. In AO, RF, DT, SVM, and ANN were the best classifiers providing 25 correct and 3 wrong predictions. In all of these classifiers, there were 6 *TN* and 19 *TP* as well as 3 *FP* and 0 *FN*. This also reflects better prediction accuracy towards the majority class or class 1 in AO. Conversely, DT had the lowest accuracy with 22 correct and 6 wrong predictions reflecting 6 *TN*,

Table 3.2: Quantitative analysis on the performance of ML classifiers predicting SWP in the pistachio (PO) and almond orchard (AO).

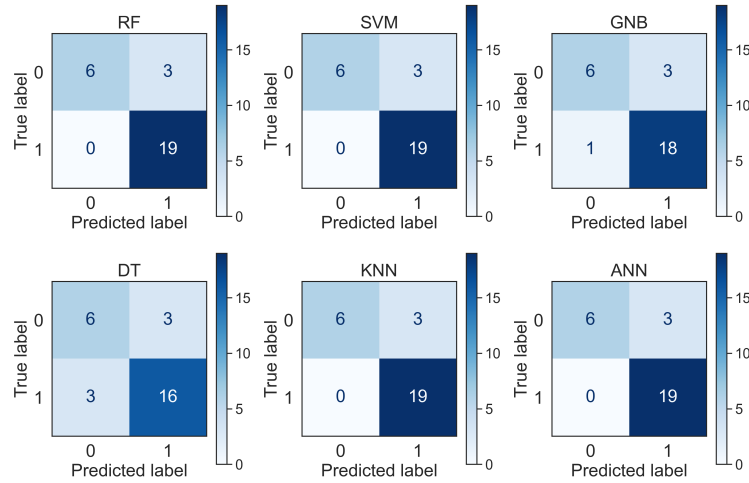
PO					
Models	Input	Accuracy	$\overline{CV}$	F1-score	AUC
RF	All	0.88	0.91	0.87	0.86
SVM	All	0.81	0.92	0.81	0.87
GNB	All	0.84	0.87	0.84	0.88
DT	All	0.88	0.89	0.87	0.86
KNN	All	0.84	0.94	0.84	0.82
ANN	All	0.81	0.91	0.81	0.83
AO					
		Accuracy	$\overline{CV}$	F1-score	AUC
		0.89	0.89	0.86	0.88
		0.89	0.89	0.86	0.93
		0.86	0.86	0.82	0.87
		0.79	0.89	0.75	0.77
		0.89	0.89	0.86	0.86
		0.89	0.88	0.86	0.93

16 *TP*, 3 *FP* and 3 *FN*.

RF provided high accuracy and more consistency classifying SWPs in both orchards. RF has been extensively explored and employed in numerous studies due to its high tolerance for outliers and noise, along with its resistance to overfitting (Fan et al., 2021; Benos et al., 2021; Pagano et al., 2023). An additional advantage of RF is its capacity to calculate feature importance percentages. Feature importance in RF provides a measure of the contribution each feature makes to the predictive power of the model. This is calculated using a combination of the mean decrease accuracy (MDA) and mean decrease Gini (MDG) metrics, allowing for a comprehensive understanding of the relevance of each feature. This characteristic can be particularly useful in understanding and interpreting the model’s decisions (Virnodkar et al., 2020). In the context of our study, the feature importance results offered by the RF model can illuminate the relative contribution of each feature to the SWP prediction. Such un-



(a) PO



(b) AO

Figure 3.9: Confusion matrices representing the results of ML classifiers predicting SWP in (a) pistachio orchard (b) almond orchard.

derstanding is instrumental in formulating data acquisition strategies for subsequent research studies related to tree water status assessment. Figure 3.10 demonstrates the importance of features used to determine SWP in almond and pistachio trees. Weather features contributed the highest to the SWP prediction. In the PO, the feature with the greatest influence was P_{min} , accounting for 30% of feature importance. In the AO, T_{max} was the most critical feature, with a contribution of 36%. The T_{max}

and RH_{min} collectively dominated nearly 68% of the decisions made by the RF model in the AO. In both PO and AO, T_c demonstrated a higher importance relative to individual MS VIs. It accounted for approximately 22% of the importance in PO and 10% in the AO. In terms of MS VIs, OSAVI (20%) in PO and NDVI (7.5%) in AO showed higher importance than NDRE in both crops. However, the disparity was more noticeable between OSAVI and NDRE in PO, which was about 10% compared to the minimal difference between NDVI and NDRE in AO at about 2-3%. The overall contribution of weather, thermal, and MS features to SWP classification in PO were, 48%, 22%, 30%. The overall contribution of weather, thermal, and MS features to SWP classification in AO were, 77%, 10%, 13%.

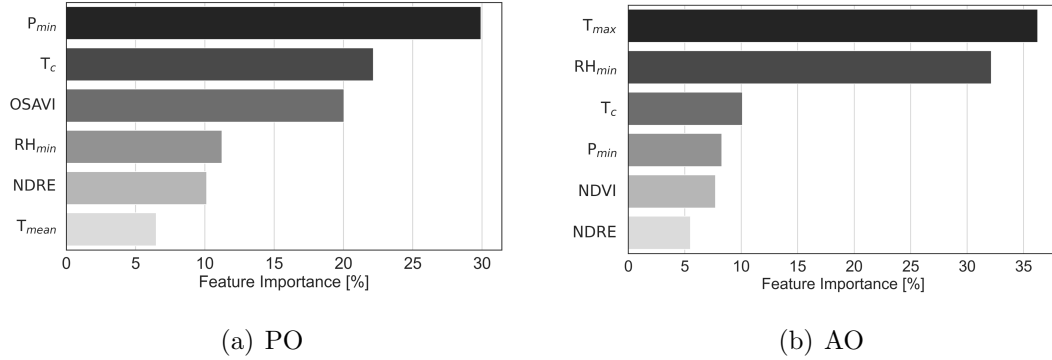


Figure 3.10: Feature importance provided by the Random Forest (RF) classifier for (a) pistachio orchard and (b) almond orchard.

Given the observations in this study, the AO was under considerable water stress, with nearly 74% of the SWP values registering below -18 bars. This is indicative of high stress and notable water deficiency in the almond trees (see Figure 3.4). In contrast, the PO demonstrated an entirely different watering profile with a predominantly hydrated state. About 70% of the SWP measurements were above -9 bars, highlighting an excessive hydration status for the pistachio trees. The difference in hydration profiles of the two orchards brings into focus the role of atmospheric features in SWP determination as seen in Figure 3.10. Given the distinct differences in

water stress levels between the two orchards, it appears that the importance of these atmospheric variables in SWP prediction fluctuates in accordance with the level of tree water status. Particularly, under conditions of high water stress, as observed in the almond orchard, atmospheric parameters like air temperature and air pressure may gain prominence towards the determination of SWP.

Environmental factors like micro-climate, soil variation, and root system differences significantly impact tree water status within an orchard. Micro-climate fluctuations influence water uptake, while soil properties affect moisture availability to roots. Understanding root system diversity is crucial. For precise irrigation, knowledge about spatial water variability and micro-climate are essential (Peters et al., 2010; Ntshidi et al., 2023). Given the complex interaction of various environmental factors within an orchard, a single atmospheric measure might not offer a comprehensive picture of tree water needs. While these parameters play a pivotal role in estimating the overall tree water status in an orchard, they are not able to determine the water status of an orchard on a per-tree basis. For a more precise prediction of SWP on a tree-by-tree basis, more individualized features may be required. Among these exclusive features, $CWSI(T_c, T_a, VPD)$ holds a distinct importance. In other studies, CWSI has also been found to have a good correlation with SWP both in pistachios (Jafarbiglu and Pourreza, 2022; Gonzalez-Dugo et al., 2015; Testi et al., 2008) and almonds (Gonzalez-Dugo et al., 2012; García-Tejero et al., 2012). This can be attributed to the heightened sensitivity of canopy temperature T_c to fluctuations in plant water stress. T_c is capable of identifying subtle changes in plant water status that other multispectral VIs often overlook. Its high sensitivity renders it a potentially powerful tool for monitoring plant water status and predicting SWP values at a tree-specific level. The ability to reconcile distinct but interconnected sources of information would be key to developing robust machine learning models for accurate and reliable prediction of SWP values.

3.3.3 Classification and Regression using RF

The RF classification and regression models were used to predict SWP with different input features, shown in Table 3.3. For PO with all inputs, the RF model demonstrated strong classification performance, achieving an accuracy of 88%, an average 10-fold cross-validation ($\overline{CV}$) score of 91%, a F1-score of 0.87, and an AUC of 0.86. The regression metrics were also satisfactory with R^2 value of 0.70, RMSE of 1.13, and MAE of 0.84, indicating good predictions. When the model inputs were limited to MS and thermal features only, the classification accuracy reduced to 78%, the $\overline{CV}$ score to 84%, F1-score to 0.72, and AUC to 0.78 along with noticeable declines in regression outcomes (R^2 of 0.46, RMSE of 1.54, and MAE of 1.29). A further reduction to only MS features led to further decreases in both classification and regression metrics, with classification accuracy dropping to 72%, $\overline{CV}$ to 83%, F1-score to 0.68, AUC to 0.73, as well as R^2 of 0.33, RMSE of 1.72, and MAE of 1.38. These results underscore the challenges in achieving high predictive accuracy for SWP with only MS used as input feature.

Similar trends were observed in AO although the effect of reduced features on model performance were higher. Utilizing all inputs, the RF model showed good classification accuracy at 89%, with a $\overline{CV}$ score of 89%, F1-score of 0.86, and AUC of 0.88. The regression metrics were less robust than in PO with R^2 of 0.55, RMSE of 3.18, and MAE of 2.44. However, restricting the inputs to MS and thermal data significantly reduced the model performance and resulted in a stark decrease in all metrics including accuracy to 61%, $\overline{CV}$ to 76%, F1-score to 0.51, AUC to 0.51, as well as R^2 to 0.26 while RMSE and MAE increased to 4.11 and 3.15, respectively. While the classification reached an accuracy of 61% the low AUC score of 0.51 highlights the classifier's inability in classification and distinguishing between classes. Using MS features as input, the RF regression and classification models performed poorly thus the results are not included in the analysis.

Regarding the choice of regression versus classification for SWP prediction in the

Table 3.3: Using the Random Forest (RF) model for comparison between various inputs. The units for RMSE and MAE are *bars*.

Model	Orchard	Input	Classification			
			Accuracy	$\overline{CV}$	F1-score	AUC
RF	PO	All	0.88	0.91	0.87	0.86
RF	PO	MS, Thermal	0.78	0.84	0.72	0.78
RF	PO	MS	0.72	0.83	0.68	0.73
RF	AO	All	0.89	0.89	0.86	0.88
RF	AO	MS, Thermal	0.61	0.76	0.51	0.51
Model	Orchard	Input	Regression			
			R^2	RMSE	MAE	
RF	PO	All	0.70	1.13	0.84	
RF	PO	MS, Thermal	0.46	1.54	1.29	
RF	PO	MS	0.33	1.72	1.38	
RF	AO	All	0.55	3.18	2.44	
RF	AO	MS, Thermal	0.26	4.11	3.15	

context of orchard irrigation management, classification models have some advantages over regression models. Irrigation strategies in real-world scenarios often adhere to a threshold-based framework ("irrigate" or "do not irrigate") wherein irrigation is performed once the SWP descends below a certain threshold. This binary decision-making process is intrinsically aligned with classification models, which predict discrete categories. Classifiers focus on categorizing data rather than determining exact values resulting in higher accuracy and more robustness against noise at the expense of less knowledge about the exact output values. They can provide better performance while trained on lower datasets. The deployment of machine learning models, particularly those trained on comprehensive datasets encompassing remote sensing and atmospheric information, could serve as a potential tool in discerning whether the SWP has breached a critical threshold. This could ultimately lead to more precise and timely irrigation decisions. The proposed approach embodies a practical and scalable solution to SWP prediction, enabling more sustainable and efficient water management practices within orchards.

3.4 Conclusions

This study offered a practical approach utilizing machine learning (ML) to evaluate orchard water status on a per-tree basis and enhance water management in orchards. Six ML models were utilized to classify stem water potential (SWP) using weather, thermal, and multispectral (MS) features, in pistachio orchard (PO) and almond orchard (AO). Additionally, random forest (RF) was used for classification and regression with different features. While most of ML classifiers used in this study provided %79 or higher performance in SWP classification, RF showed high performance in both PO and AO with %88 and %89 prediction accuracy, respectively. The feature importance report provided by the RF classifier accentuated the high influence of atmospheric features on SWP. This dependency varied according to the level of water stress and type of crops. Weather features contributed to 48% and 77% of decisions in PO and AO, respectively. Therefore, leveraging such environmental variables that are both influential and easy to obtain, remain a necessity to achieve high performing predictive models. Thermal and MS features can provide valuable insight into water requirements of an orchard on a per-tree basis. Among those features, T_c played a more important role in SWP prediction in both crops. However, this significance was closely followed by OSAVI in pistachios and NDVI in almonds. NDRE exhibited lower importance in both crops. However, the gap between NDRE and NDVI importance was relatively smaller in the water-stressed AO compared to its difference with OSAVI in the non-stressed PO. The findings from this study suggest that the relative importance of features can be influenced by the prevailing water levels in the corresponding orchard. RF regression model predicted SWPs with highest accuracy when all weather, thermal, and MS inputs were involved resulting in $R^2 = 0.70$, $RMSE = 1.13 \text{ bars}$, $MAE = 0.84 \text{ bars}$ in PO, and $R^2 = 0.55$, $RMSE = 3.18 \text{ bars}$, and $MAE = 2.44 \text{ bars}$ in AO.

Future studies can focus on extending the application of the predictive models to other crops. Emphasis should be placed on the development of a model that can be utilized by end-users. This requires the adoption of features that are non-destructive, readily accessible, and reliant on remote sensing for facilitated individualized analysis. In this study, we used point measurements of leaf temperature to estimate average T_c for each tree under treatment. For enhanced scalability and to capture spatial temperature variations across individual trees and the entire orchard, thermal imaging using UAVs or UGVs is recommended. Incorporating machine learning is essential due to its capability in handling complex datasets and deriving meaningful insights. Given the proper quality and quantity of datasets, ML models are capable of capturing the intricate relationships between input features to predict an output. Therefore, input features can be broken down into their foundational components and be integrated with the ML models for training. For example, spectral bands and canopy temperature instead of VIs can directly be used for training the ML models. It is crucial to address the limitations posed by relying on single-season data which may not capture the variability across different growing conditions and locations. Expanding datasets across multiple seasons and regions potentially through collaborative databases or federated learning would enhance model generalizability leading to more reliable predictions. The power of artificial intelligence can be harnessed to unravel the complex relationship between variables that affect tree water status, which leads to better irrigation scheduling and more efficient water management in agriculture.

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Chapter 4

RoMu4o: A Robotic Manipulation Unit For Orchard Operations Automating Proximal Hyperspectral Leaf Sensing

Abstract: *Driven by the need to address labor shortages and meet the demands of a rapidly growing population, robotic automation has become a critical component in precision agriculture. Hyperspectral imaging is shown to be a powerful tool for phenotyping, monitoring crop health, identifying essential nutrients within plants as well as detecting diseases and water stress. This work introduces RoMu4o, a robotic manipulation unit for orchard operations offering an automated solution for proximal hyperspectral leaf sensing. This ground robot is equipped with a 6DOF robotic arm and vision system for real-time deep-learning-based image processing and motion planning. We developed robust perception-manipulation pipelines that enable the robot to successfully grasp target leaves and perform spectroscopy. These frameworks operate synergistically to identify and extract the 3D structure of leaves from an observed batch of foliage, propose 6D poses, and generate collision-free constraint-aware paths for precise leaf manipulation. The end-effector of the arm features a compact design that integrates an independent lighting source with a hyperspectral sensor, enabling*

high-fidelity data acquisition while streamlining the calibration process for accurate measurements. Our ground robot is engineered to operate in unstructured orchard environments. However, the system performance is evaluated on both indoor and outdoor plant models. The results of our field experiments revealed an overall 70% success rate for autonomous leaf grasping and hyperspectral measurement in a pistachio orchard.

4.1 Introduction

Future of agriculture is progressively shaped by the innovation of novel robotic platforms that transform key agricultural practices. Unmanned ground vehicles (UGVs) are an integral component of a smart farm and have been used extensively for research and commercial purposes in agriculture. Agricultural UGVs are developed and used for crop monitoring and physical sampling Kim et al. (2022), harvesting Zhou et al. (2022); Yoshida et al. (2022), seeding and planting Blender et al. (2016), weed detection and removal Albani et al. (2017), precision irrigation and fertilization Thayer et al. (2018); Minßen et al. (2011), phenotyping Gao et al. (2018), and pruning You et al. (2023); Ju et al. (2022). Innovation of new agricultural robots is of great importance globally and especially in countries with severe labor shortages. Consistent performance under harsh conditions, cost reduction, and safety improvement in the long-term have been major reasons for the agricultural industry to develop and deploy autonomous robotic systems in field operations Wang et al. (2021); Rondelli et al. (2022).

Persistent crop monitoring is an essential task to mitigate crop loss and maximize yield output Lei et al. (2024). It is crucial to identify plant biotic and abiotic stress at an early stage when severe damage to crops is preventable. Leaf hyperspectral imaging or HSI is proven effective in detection of nutrient deficiencies, diseases, and water stress Xu and Li (2022). Hyperspectral data can be obtained remotely using drones and satellites or at the leaf-level with handheld devices. Aerial hyperspectral imaging can provide data at scale but requires rigorous calibration due to susceptibility to the

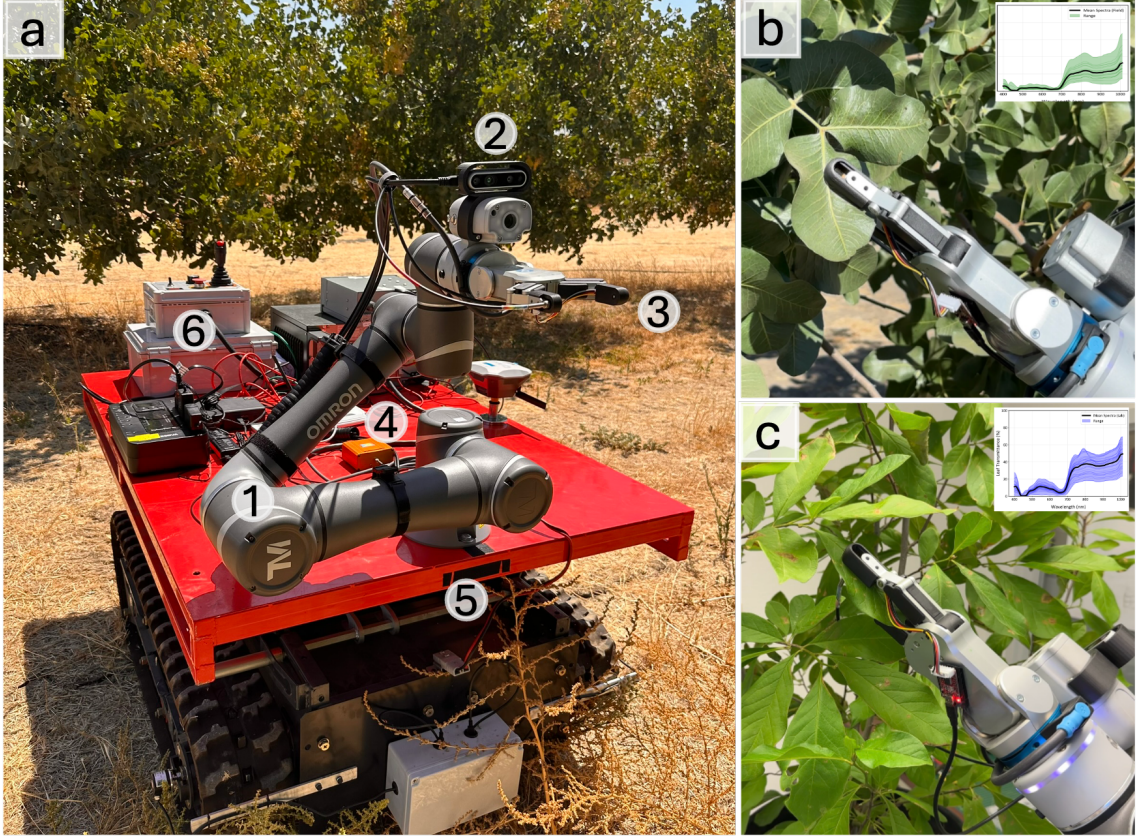


Figure 4.1: (a) RoMu4o, our proposed robotic manipulation unit for orchard operations aimed for autonomous proximal hyperspectral leaf sensing. The system is comprised of 1) 6-DoF robotic manipulator 2) RGBD camera 3) two-finger gripper integrated with a hyperspectral sensing system 4) an independent VIS-NIR light source for referencing and self-calibration 5) crawler-type ground robot 6) electric and control boxes, hardware drivers, portable batteries, processing unit, Ethernet hub, other devices used for the UGV’s navigation. (b) Pistachio leaves used for field experiments (c) and Magnolia for lab experiments.

outdoor lightning conditions. Conversely, portable hyperspectral spectroradiometers benefit from independent lighting source streamlining the calibration process and effectively reducing image sensitivity to outdoor environmental conditions. However, there is a trade-off between high-resolution, reliable data and operational scalability as manual hyperspectral data collection is time- and labor-intensive. This challenge underscores the potential for developing a robotic manipulation system equipped with

a portable hyperspectral sensor capable of delivering consistent and high-quality data while reducing labor demands and bridging the gap between data fidelity and scalability.

In this work, we present RoMu4o, a robotic manipulation unit designed for orchard operations aiming to autonomously collect hyperspectral data from leaf samples (see Figure 4.1). RoMu4o provides an automated solution for crop health monitoring and plant phenotyping in orchard environments. Our sensor integration with the robotic manipulator benefits from a distinctive compact design which enables the robot to operate with high maneuverability free from the limitations that typically hinder the performance of similar systems. We propose a deep-learning based perception framework for leaf detection and segmentation and provide the algorithmic procedure for leaf structure extraction, point cloud processing and 6D pose estimation. Next, the robotic manipulation workflow for leaf grasping and hyperspectral data collection is presented. For system performance evaluation, experiments were conducted both in the lab setting on real magnolia plants and outdoor in a pistachio orchard environment. The flowchart of the leaf manipulation process considering the setup and perception-manipulation pipelines is demonstrated in Figure 4.2.

Another important contribution of this work is the development of a system specifically designed for deployment in real orchard environments which means moving beyond laboratory testing and reliance on structured artificial plants. Field operations pose a range of unique challenges, including varying environmental conditions which introduce external noise resulting in system malfunctioning or reduced performance, unpredictable crop structures, and power and communication limitations that are often absent in controlled lab settings. By addressing these challenges, our system aims to offer a reliable solution for hyperspectral data collection directly in the field to enhance practical utility and pave the way for commercialization and wide access.

4.2 Related Work

Most studies in which a robotic manipulation system is developed to physically interact with crops are associated with fruit harvesting. Other applications among these systems are extended to tasks such as plant phenotyping, disease detection, trait measurements, physical leaf sampling, and pruning.

At the intersection of physical interaction with leaves using robotic manipulators, most studies focused on row crops such as maize and sorghum considering both indoor and outdoor experimental environments. The Robotanist is among earlier ground robots that was used for manipulation of vegetation such as sorghum and corn Mueller-Sim et al. (2017). A plant phenotyping robotic system using a 4DOF robotic arm and a time-of-flight camera combined with VIS-NIR spectroscopy and temperature sensors was proposed by Atefi et al. (2019). These experiments were conducted on indoor plant models with grasping success rate of 78% for maize and 48% for sorghum. A mobile manipulation robot named P-AgBot was developed to perform crop monitoring and physical sampling on corn and sorghum Deb et al. (2023). Image processing techniques was used to extract leaves center points and provide vision-based guidance to a 6DOF robotic manipulator achieving 80% success rate in leaf sampling Kim et al. (2022). A proximal HSI system called LeafSpec was integrated with a 6DOF robotic manipulator and tested on greenhouse in-vivo soybean plants with leaf grasping success rate of 93% Chen et al. (2023). A robotic arm was used to reproduce hand-plucking motion for tea leaf harvesting Motokura et al. (2020). An actuation perception framework was developed to physically cut and retrieve leaf samples in which experiments were performed on avocado trees in both indoor and outdoor environments resulting in 69% success rate in leaf capturing Campbell et al. (2022).

A review of studies on leaf grasping and manipulation highlights significant challenges of earlier work with leaf detection and pose estimation. This is due to the highly unstructured and cluttered nature of the vegetation that limits the perception capabilities in real agricultural settings. Initial work suffered from two main issues:

lack of reliable or accessible imaging hardware for outdoor agricultural environments and lack of computer vision algorithms for precise detection and pose estimation. As imaging hardware such as depth cameras became more advanced, accurate and accessible, and new convolutional neural network- (CNN) or transformer-based architectures for image processing emerged, perception capabilities for agricultural robotic applications were significantly improved. Such advancements in the past five to ten years paved the way for robust vision-guided robotic systems in precision leaf manipulation.

4.3 System Overview

In this section, we explore various components of the robotic hardware and software, outline the experimental setup, and describe the plant models used for spectral measurements in this study.

4.3.1 Hardware Components

An overview of our integrated hardware is demonstrated in Figure 4.1. RoMu4o is equipped with a 6-degree-of-freedom collaborative robotic arm (TM5M-900, Techman Robot Inc., Taiwan/OMRON Co., Japan), which operates on 22-60V DC input with a maximum payload of $4kg$ and reach of $900mm$, mounted on a non-commercial crawler-type ground robot. The mobile platform has approximate dimension of $1.5m \times 1.0m \times 0.4m$ ($5ft \times 3.3ft \times 1.2ft$) for length, width, and height, and runs on a 24V DC battery with three control degrees of freedom one of which is with regard to vertical displacement of the overhead surface. Our mobile manipulation unit has a complementary advantage for locomotion in unstructured orchard settings due to its high traction and maneuverability. Orchard environments, particularly those featuring pistachio trees, can often reach heights of 6 to 9 meters (20 to 30 feet). To navigate these heights, our platform incorporates an adjustable overhead plate that provides an additional $1-1.5m$ (up to 5ft) of vertical extension. When combined with the reach of the robotic arm, this configuration grants wider access to the entirety of

tree canopy, including regions that are typically beyond the reach of human workers. This capability is critical for comprehensive data collection, precise physical interventions, and ensuring coverage across all areas of a tree structure.

The RealSense D435i RGB-D camera (Intel, USA) is used for capturing color and depth information, with an ideal range of 0.3 to 3m it provides vision-based guidance to the robotic manipulator. A wide-stroke two-finger gripper (RG2, OnRobot, Denmark) is integrated with the a custom-manufactured end-effector designed to encapsulate the optical components. The RealSense depth camera is encapsulated into a lab manufactured encasing and installed on top of the built-in RGB camera of the robotic manipulator. The optical sensing component is comprised of a 350-1010nm VIS-NIR hyperspectral spectrometer (NSP32m W1, NanoLambda, South Korea), and an independent lighting source with 350-2500nm used for self-calibration and consistent data acquisition regardless of environmental conditions. A VIS-NIR fiber optic cable (F600, StellarNet Inc., USA) is used to transmit light from the source to the end-effector finger gripper. An external computational unit (NUC11TNHi7, Intel, USA) with four 11th generation core processors and 64 GB of RAM is provided for computational processing. We utilized robot operating system 2 (ROS2) and MoveIt2 set of libraries and software structure to establish communication between sensors and execute the robotic vision and manipulation processes.

4.3.2 Experimental Setup

The leaf manipulation tests were conducted in both indoor and outdoor environments. We selected pistachio tree crops for the outdoor experiments due to their economic significance. A one year old magnolia shrub with an approximately 2m (5ft) of height is selected as the indoor plant model due to similarities in its leaf structure to pistachios. The test site is an approximately eight-acre pistachio orchard with 11-year-old trees, part of the IoT4Ag experimental testbeds located at UC Merced, California Kagan et al. (2022). We selected a small plot within the orchard containing 24 trees

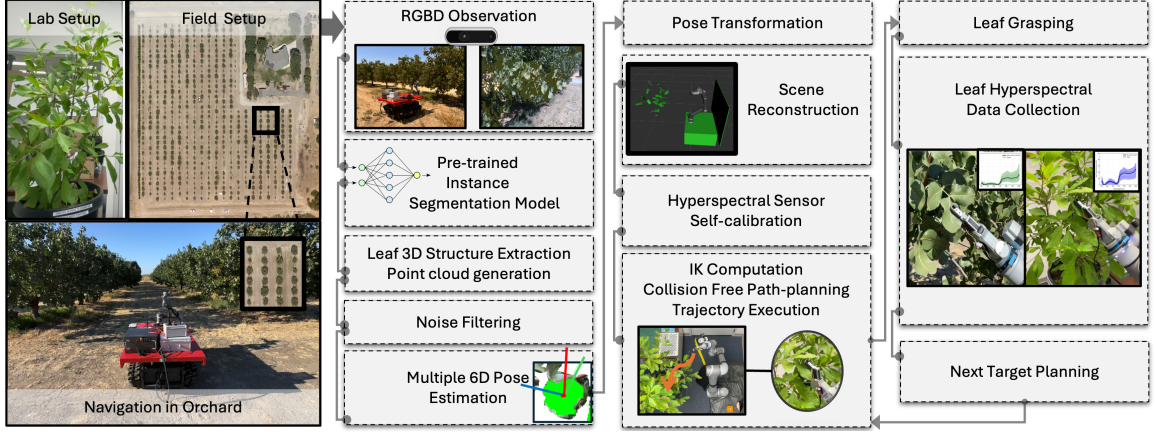
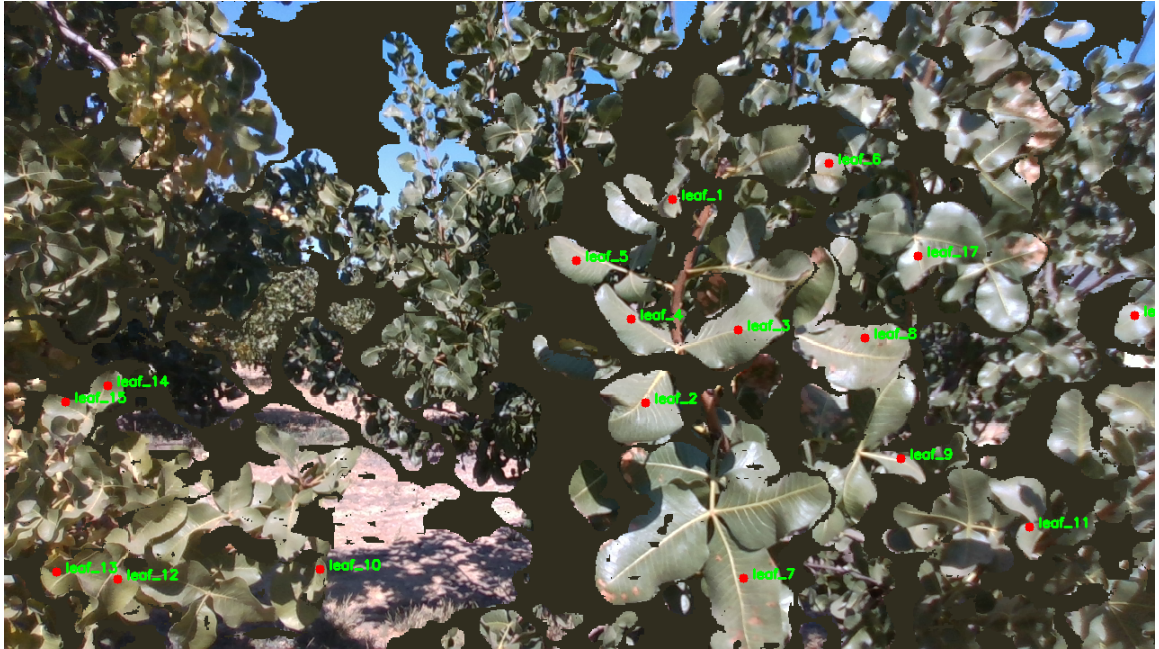


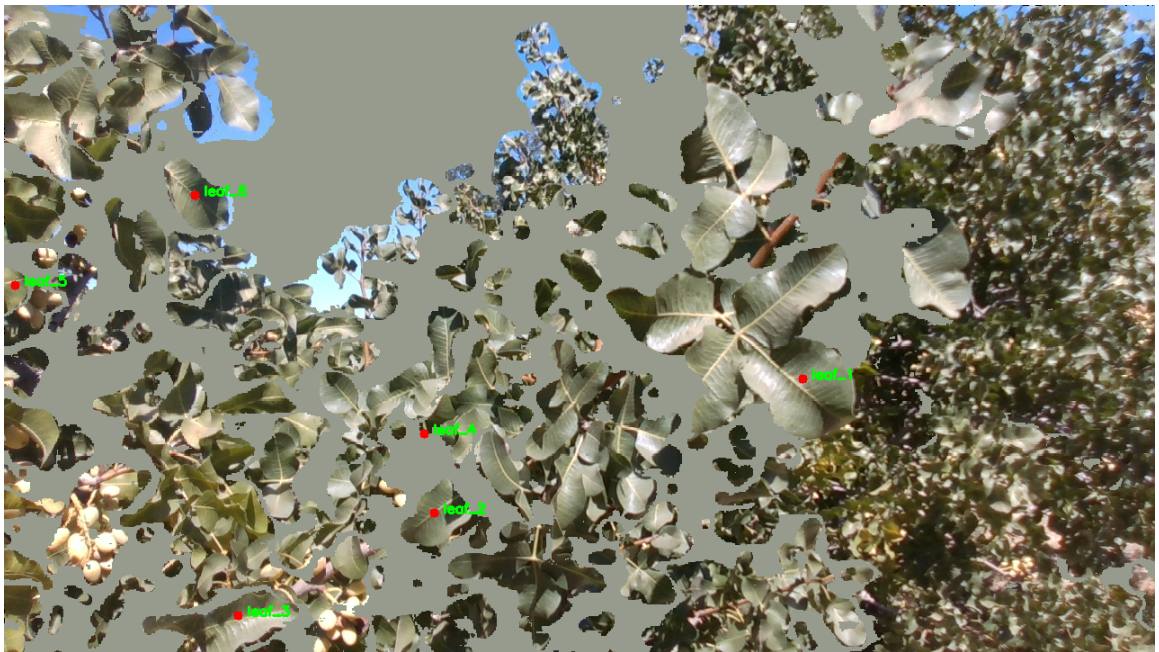
Figure 4.2: Flowchart for the autonomous proximal hyperspectral leaf sensing process. The workflow consists of a perception pipeline for image processing and 6D pose estimation followed by a robotic manipulation pipeline for precise leaf grasping and hyperspectral data collection.

to conduct the experiments for autonomous hyperspectral data collection from leaf samples.

The orchard tests were conducted during August 2024, between 8:00-11:30 AM. This timeframe offered optimal sunlight intensity and angle for leaf detection. As the day approached noon, the depth camera performance significantly deteriorated due to overexposure resulting in more missing depth values especially at the leaf boundaries. The difficulty with depth saturation and leaf segmentation at different times of day can be seen in Figure 4.3.



(a) Early morning



(b) Close to noon

Figure 4.3: Difficulty with leaf candidate identification, segmentation, and depth matching in field trials as outdoor light intensity increased.

To mitigate the impact of missing signals and improve the signal-to-noise ratio, we configured the RealSense camera to operate on a medium depth density preset. This preset was found to be an appropriate balance between depth signal density and accuracy in our experimental environments. Additionally, the depth camera was calibrated using a ground truth reference to ensure accurate depth measurements. To prepare the robotic unit for experiments, we tested the system in advance, to identify and address any potential biases that could arise from misaligned camera installation and reference frame discrepancies. By carefully adjusting for these biases, we ensured that the transformations between the camera’s coordinate frame and the robot’s base frame were accurately aligned so that the gripper can reach exact target locations for leaf grasping with accuracy within one centimeter.

4.4 Leaf Grasping Pipeline

A successful grasp in an unstructured environment is the result of a proper perception of the scene complemented by robust motion planning and dexterous grasping. The main goal of the perception pipeline is to estimate at least one 6D pose for each target leaf within an observed image and identify the collision obstacles occupying the working space of the manipulator that need to be avoided. The systematic procedure demonstrating the perception pipeline is given by Figure 4.4. The pose information is then processed by the manipulation pipeline resulting in joint-space trajectories that are executed and controlled by the actuators of the robotic arm. In this section, we provide a mathematical framework to explain the details of these two pipelines. A summary of the perception and robotic manipulation pipelines can be seen through algorithm 1 and algorithm 2, respectively.

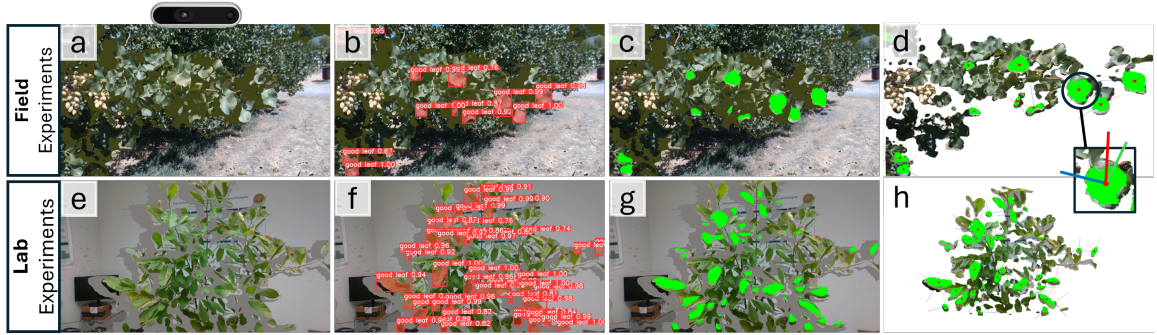


Figure 4.4: Perception pipeline for leaf manipulation. (a,e) the RGB image as seen by the RealSense depth camera. (b,f) leaf detection and segmentation using pre-trained instance segmentation deep-learning networks (c,g) extracting the 3d structure of identified target leaves by aligning the ordered depth channel to RGB pixels (d,h) noise elimination and 6D pose estimation for each target.

4.4.1 Perception

Instance segmentation

This pre-processing step leverages a deep learning model not only to distinguish leaves from the background and non-leaf objects but also to identify optimal leaf candidates for robotic manipulation. This dual focus significantly enhances the decision-making process. By training the model on a single category, we detect leaves that are minimally occluded and exhibit ideal visibility and accessibility for robotic grasping. This approach streamlines the leaf selection process within dense foliage, ultimately increasing the chance of successful grasps for spectral sampling. Two YOLOv8-x instance segmentation models are trained to process captured images for indoor plant model magnolia and the outdoor tree crop pistachio. As a result this model provides the region of interest (ROI) within an input image, which are then used to generate 3D point clouds for leaf targets.

Leaf structure extraction

Let $\mathcal{O}$ represent an observation by the RGB-D camera, where each observation $\mathcal{O} \in \mathbb{R}^{H \times W \times 4}$ consists of an image $\mathcal{I} \in \mathbb{R}^{H \times W \times 3}$ and a depth map $\mathcal{D} \in \mathbb{R}^{H \times W}$ with H and W denoting the image height and width, respectively. An instance segmentation model $\mathcal{S} : \mathbb{R}^{H \times W \times 3} \rightarrow \mathbb{B}^{H \times W \times N}$ with $\mathbb{B} = \{0, 1\}$, processes the RGB image $\mathcal{I}$ to produce N binary masks $\mathcal{M} = \{M_j \mid M_j \in \mathbb{B}^{H \times W}, j = 1, \dots, N\}$, where M_j corresponds to individual leaf masks detected in the image $\mathcal{I}$. For each mask M_j , we extract the corresponding depth values from $\mathcal{D}$ to form masked depth maps $D_j = \mathcal{D} \odot M_j$ containing the depth values of each identified leaf in $\mathcal{O}$ considering $D \in \mathbb{R}^{H \times W}$.

Point cloud reconstruction

Using the intrinsic parameters of the camera and the operator $\mathcal{T}(D_j(u, v), f_x, f_y, c_x, c_y)$ where $\mathcal{T} : \mathbb{R}^{H \times W} \rightarrow \mathbb{R}^{H \times W \times 3}$, we transform the extracted depth maps $D_j(u, v)$ into $P_j(u, v)$ to represent the individual 3D point clouds for each identified leaf while u and v show the pixel locations. Note that P_j contains non-zero values for masked pixels where a leaf is identified and zero values anywhere else. Let $\mathcal{P}_j \in \mathbb{R}^{m_j \times 3}$ represent a new set that contains only the 3D point clouds of each leaf with m denoting the number of available points for the j^{th} leaf instance.

We filter out potential noise from each individual point cloud $\mathcal{P}_j$ to ensure only valid points are retained for subsequent analysis. The noise filtering process aims to remove erroneous points and outliers that misrepresent the surface of the desired leaf. These unwanted clusters can arise from several factors such as segmentation errors containing background pixels or occlusions from overlapping leaves. We adopted a Gaussian filter to address the potential anomaly in the initial extracted point cloud. Consider $\mathcal{P}_j^k \sim \mathcal{N}(\mu_j^k, \sigma_j^{2k})$ with $k = 1, 2, 3$ and μ_j^k and σ_j^{2k} denoting the mean and standard deviation across each of the three-dimensional axes. The z-scores for each point in $\mathcal{P}_j^k$ are then calculated. For each dimension k , the z-score for points in $\mathcal{P}_j^k$ is calculated by $Z_j^k = (\mathcal{P}_j^k - \mu_j^k) / \sigma_j^k$ such that $\mathcal{P}_j^k, Z_j^k \in \mathbb{R}^{m_j}$ and $\mu_j^k, \sigma_j^k \in \mathbb{R}$. To filter

out noise, we establish a threshold of $Z_{th} = 2.33$ which corresponds to a confidence interval of 98%. Thus, any points with a z-score greater than Z_{th} in any dimension are considered outliers and removed. The filtered point cloud $\hat{\mathcal{P}}_j$ is then constructed by retaining the points that satisfy $|Z_{j,i}^k| \leq Z_{th} \forall i = 1, 2, \dots, m_j$.

Pose estimation

We estimate the central point for each filtered point cloud $\hat{\mathcal{P}}_j$ to localize the target leaves with respect to the camera reference frame. Let $\hat{\mathcal{P}}_j = \{\hat{\mathbf{p}}_{j,1}, \dots, \hat{\mathbf{p}}_{j,m_j}\}$ such that $\hat{\mathbf{p}}_{j,i} \in \mathbb{R}^3$ and define the central point $\bar{\mathbf{p}}_j \in \hat{\mathcal{P}}_j$ which will be found by computing the closest point to the medians shown by the *med* operator. Therefore, the central point $\bar{\mathbf{p}}_j$ can be written by:

$$\bar{\mathbf{p}}_j = \arg \min_{\mathbf{x} \in \hat{\mathcal{P}}_j} \left\| \mathbf{x} - \text{med}(\hat{\mathcal{P}}_j) \right\| \quad (4.1)$$

To determine the orientation of each leaf, we perform principal component analysis (PCA) on each point cloud. Using PCA, we find the three principal axes of variance in $\hat{\mathcal{P}}_j$. A singular value decomposition technique is used to decompose the covariance matrix of points and provide eigenvalues and eigenvectors associated with the three orthogonal vectors that best explain the variance through the data. The eigenvalues $\lambda_1, \lambda_2, \lambda_3$ represent the magnitude of variance along the eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$. The eigenvector corresponding to the smallest eigenvalue aligns with the direction of least variance in the point cloud. This unique eigenvector is perpendicular to the plane that best fits the surface of the leaf. We denote this unit vector as $\mathbf{n}_j$ representing the normal vector to the surface of leaf j . The normal vectors are adjusted to ensure they are oriented toward the viewpoint, with their direction reversed if initially oriented away from the viewpoint.

To establish an orthogonal local coordinate system on each leaf with unit vectors $(\mathbf{t}_j, \mathbf{b}_j, \mathbf{n}_j)$, we need to determine $\mathbf{t}_j$ and $\mathbf{b}_j$ such that they lie within the leaf surface plane. To determine $\mathbf{t}_j$ we first select a reference point on the edge of the point cloud that represents the uppermost point along the vertical axis of the camera. This point

Algorithm 1 Perception Pipeline

Input: RGBD observation: $\mathcal{O} = \{\mathcal{I}, \mathcal{D}\}$

Output: Leaf pose estimates: $\mathcal{L}_j^{\{C\}}$

```
1:  $\mathcal{M} \leftarrow \mathcal{S}(\mathcal{I})$ 
2: for number of masks  $j = 1$  to  $N$  do
3:    $D_j \leftarrow \mathcal{D} \odot M_j$ 
4:    $\mathcal{P}_j \leftarrow \mathcal{T}(D_j(u, v), f_x, f_y, c_x, c_y)$ 
5:   for  $k = 1, 2, 3$  do
6:      $\mu_j^k, \sigma_j^{2k} \leftarrow (\mathcal{P}_j^k)$ 
7:      $Z_j^k \leftarrow \mathcal{N}(\mu_j^k, \sigma_j^{2k})$ 
8:     for number of points  $i = 1$  to  $m_j$  do
9:        $\hat{\mathcal{P}}_j \leftarrow \{\mathbf{p} \in \mathcal{P}_j \text{ if } |Z_{j,i}^k| \leq 2.33\}$ 
10:    end for
11:  end for
12:   $\bar{\mathbf{p}}_j \leftarrow \arg \min_{\mathbf{x} \in \hat{\mathcal{P}}_j} \|\mathbf{x} - \text{med}(\hat{\mathcal{P}}_j)\|$ 
13:   $\{\lambda_k, \mathbf{v}_k\}_{k=1}^3 \leftarrow \text{PCA}(\hat{\mathcal{P}}_j)$ 
14:   $\mathbf{n}_j \leftarrow \arg \min_{\mathbf{v}_k} \lambda_k$ 
15:   $\mathbf{t}_j \leftarrow \mathbf{p}_j^* - \bar{\mathbf{p}}_j$ 
16:   $\mathbf{b}_j \leftarrow \mathbf{n}_j \times \mathbf{t}_j$ 
17:   $(\bar{\mathbf{p}}_j, \mathbf{q}_{j,1}) \leftarrow (\bar{\mathbf{p}}_j, \mathbf{t}_j, \mathbf{b}_j, \mathbf{n}_j) \in SE(3)$ 
18:   $\mathcal{L}_j^{\{C\}} \leftarrow (\bar{\mathbf{p}}_j, \mathbf{q}_{j,1}, \alpha)$ 
19: end for
```

provides an initial guess close to the stem attachment point. Let $\mathbf{v}_j^* = \mathbf{p}_j^* - \bar{\mathbf{p}}_j$ serve as a vector that connects this point to the center of the leaf. To ensure $\mathbf{v}_j^*$ lies within the surface plane, we project it onto the plane defined by $\mathbf{n}_j$. This projection can be written as $\mathbf{v}_j = \mathbf{v}_j^* - (\mathbf{v}_j^* \cdot \mathbf{n}_j)\mathbf{n}_j$ so that we arrive at $\mathbf{t}_j = \mathbf{v}_j / \|\mathbf{v}_j\|$. With $\mathbf{t}_j$ and $\mathbf{n}_j$ available we compute their cross product to obtain $\mathbf{b}_j = \mathbf{n}_j \times \mathbf{t}_j$. Therefore, we obtain a 6D pose for each leaf by establishing an orthogonal coordinate system centered at $\bar{\mathbf{p}}_j$ with orientations given by unit vectors $\mathbf{t}_j$, $\mathbf{b}_j$, and $\mathbf{n}_j$.

Given the fact that our ultimate goal is to collect leaf hyperspectral data, we are not limited to a unique 6D pose. Rather we aim to propose a solution that increases the chance of successful leaf grasping by the robotic manipulator. Thus, we propose a total of five 6D poses for each target leaf. The additional four poses are derived from

the initial guess with four counter clock wise $\alpha = \{-\pi/4, -\pi/2, -3\pi/4, \pi\}$ intrinsic rotations along the normal vector $\mathbf{n}_j$. Lastly, these rotations will be computed and the resulting 6D poses for each leaf are obtained. Let $\mathcal{L}_j^{\{C\}} = \{(\bar{\mathbf{p}}_j, \mathbf{q}_{j,1}), \dots, (\bar{\mathbf{p}}_j, \mathbf{q}_{j,5})\}$ where $\mathbf{q}$ denote the rotation quaternions and $\{C\}$ represent the camera reference frame.

4.4.2 Robotic Manipulation

Given the obtained pose information, we construct a robotic manipulation workflow for effective leaf grasping and hyperspectral data sampling using the integrated optical sensor. This workflow establishes a collision-aware motion planing framework that accounts for both the kinematic and task-specific constraints. Leaf 6D poses are transformed from the camera reference frame $\mathcal{L}_j^{\{C\}}$ into the robot base frame $\mathcal{L}_j^{\{B\}}$.

The planning scene is populated with geometrically simplified representations of each leaf to prevent unintended collisions as a contact may result in missed targets or compromised spectral data. The objective is then to align the gripper reference frame $G^{\{B\}}$ with the identified target poses $\mathcal{L}_j^{\{B\}}$ while adhering to kinematic constraints and minimizing collision risk. This alignment relies on an inverse kinematics (IK) solver. We use a numerical, Jacobian-based solver to compute valid joint configurations for the robotic arm to reach the desired end-effector poses. Once a feasible joint-space solution is obtained through the IK solver, a rapidly-exploring random tree connect (RRTC) path planner is employed to generate a collision-free path from the current state to the target state of the robotic arm. The RRTC path planner operates by concurrently building two rapidly exploring random trees, one rooted at the start state and the other at the goal state within the configuration space. The trees expand by iteratively sampling random states, steering toward the sampled points and connecting them through feasible joint space while avoiding collisions with both the robot itself as well as the predefined objects. Once a connection between the trees is established, a collision-free path is generated. Our planner leverages parallel exploration of the configuration space to find optimized paths. Based on the obtained paths, the

Algorithm 2 Robotic Manipulation Workflow

Input: $\mathcal{L}_j^{\{C\}}$ **Output:** Leaf hyperspectral data

- 1: $\mathcal{L}_j^{\{B\}} \leftarrow \mathcal{L}_j^{\{C\}}$
 - 2: Add collision objects to scene
 - 3: self-calibrate hyperspectral sensor
 - 4: **for** number of leaf targets: $j = 1$ to N **do**
 - 5: **for** each pose in $\mathcal{L}_j^{\{B\}} : n = 1$ to 5 **do**
 - 6: Run IK Solver and RRTC | $\mathcal{G}^{\{B\}} := \mathcal{L}_j^{\{B\}}$
 - 7: **if** solution exists **then**
 - 8: Compute and execute trajectory
 - 9: Control actuation and verify goal reached
 - 10: Trigger gripper to capture leaf
 - 11: Acquire hyperspectral data
 - 12: Break; proceed to leaf $j + 1$
 - 13: **else**
 - 14: Continue to pose $n + 1$
 - 15: **end if**
 - 16: **end for**
 - 17: **end for**
 - 18: Save collected data
 - 19: Return gripper to initial state
 - 20: Go to next batch with new observation: $\mathcal{O}^{new} = \{\mathcal{I}, \mathcal{D}\}$
 - 21: Run perception and manipulation pipelines
-

manipulation workflow first generates and executes a trajectory to the initial target, then sequentially transitions into processing solutions to the subsequent targets as each task is completed. During trajectory execution, motor controllers continuously monitor the joint states and compare their real-time poses with the target state. Adjustments to the actuation are made as needed to maintain precise alignment with the planned trajectory. Upon reaching each target, the gripper captures the target leaf and allows the built-in optical sensor system to acquire the hyperspectral data.

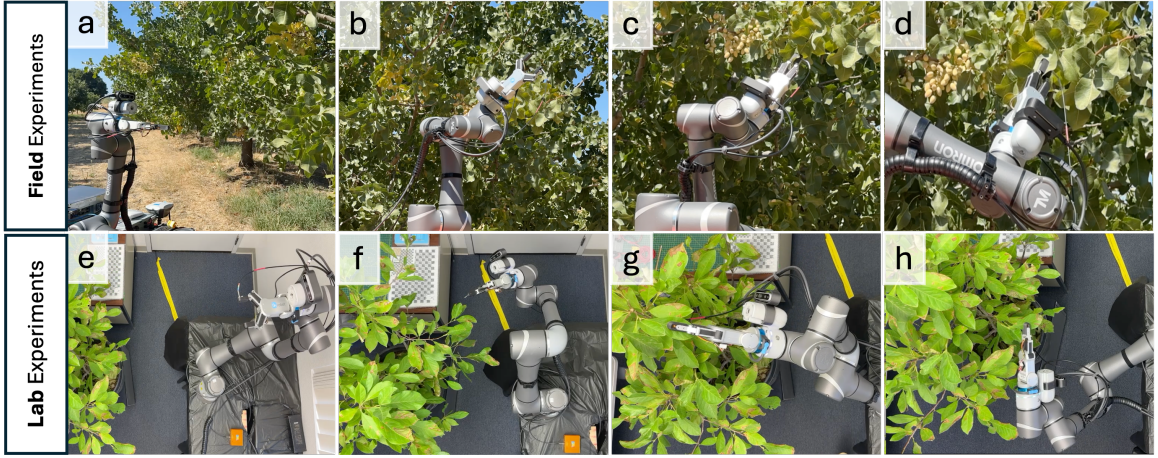


Figure 4.5: Leaf manipulation process in action. Pistachio trees representing field experiments on the *top row*, and magnolia shrub representing lab experiments on the *bottom row*. **(a,e)** a batch of foliage is observed by the camera for the perception pipeline to generate 6D poses for leaf targets **(b,f)** pose estimates are processed through the robotic manipulation workflow for path planning and trajectory execution while hyperspectral sensor is calibrated **(c,g)** first target is approached and grasped with hyperspectral data collected and stored **(d,h)** planning to the next target for leaf grasping and spectroscopy.

4.5 Results and Analysis

This robotic unit is designed to operate in orchards and autonomously collect hyperspectral data from leaf samples. High fidelity hyperspectral data can be used for phenotyping purposes, early detection of biotic or abiotic stress, and nutrient deficiencies. In this work, our design was primarily focused on pistachio trees. However, to facilitate system development and refinement, we initially conducted experiments indoors using magnolia plant models due to the similarity in leaf structure between magnolia and pistachio. This approach allowed us to iteratively test and enhance the robotic system in a controlled environment before transitioning to outdoor field trials.

A perception-manipulation pipeline is run sequentially to identify and grasp leaf targets. To begin each experiment the robotic arm is positioned approximately 50cm away from a target *batch* of the foliage. A demonstration of the leaf manipulation

process in action is given in Figure 4.5. The perception pipeline is then activated to analyze the scene, identify leaf samples that are suitable for manipulation, extract their 3D structure, and propose 6D poses that are positioned at the center of leaf surfaces. These 6D poses are then organized with respect to their distance to the camera reference frame and leveraged into the robotic manipulation workflow for grasping and hyperspectral data sampling. While multiple 6D poses are identified within each batch, the manipulation pipeline may not always execute a trajectory for the robotic arm to approach all targets. This can be due to certain poses being highly clustered or out of reach resulting in an unavailable path or IK solution or no approach. An *approach* is considered when the manipulation pipeline is able to plan and execute a trajectory for the robotic arm to approach a target leaf, regardless of the outcome. If an approach results in successful leaf grasping and hyperspectral data collection, this is considered a *successful approach*. Considering a note on terminology, let leaf per batch (LPB) demonstrate number of approached leaves per selected batch. Note that each batch contains one or more approaches. For instance, 22 batches with 2-LPB means that there were 22 batches in which at least two leaves are approached by the robotic manipulator. Moreover, 1-LPB also demonstrates total number of batches since there is at least one approach in any batch.

4.5.1 Leaf Manipulation Performance

A summary on the statistics of the experiments can be found in Table 4.1. In total, there were 131 approaches by the robotic arm resulting in leaf grasping and data sampling. Of these, 75 approaches were performed on magnolia the indoor plant model, while 56 approaches were conducted on pistachio leaves representing outdoor field experiments.

Indoor tests were comprised of 22 total batches all of which contained at least 2-leaves approached per batch, and 17 of which contained 3-LPB. Field experiments resulted in a total of 24 batches, with 17 and 10 of them containing 2-LPB and 3-LPB, respectively. In lab experiments, a 0% and 23% reduction in 2- and 3-LPB was

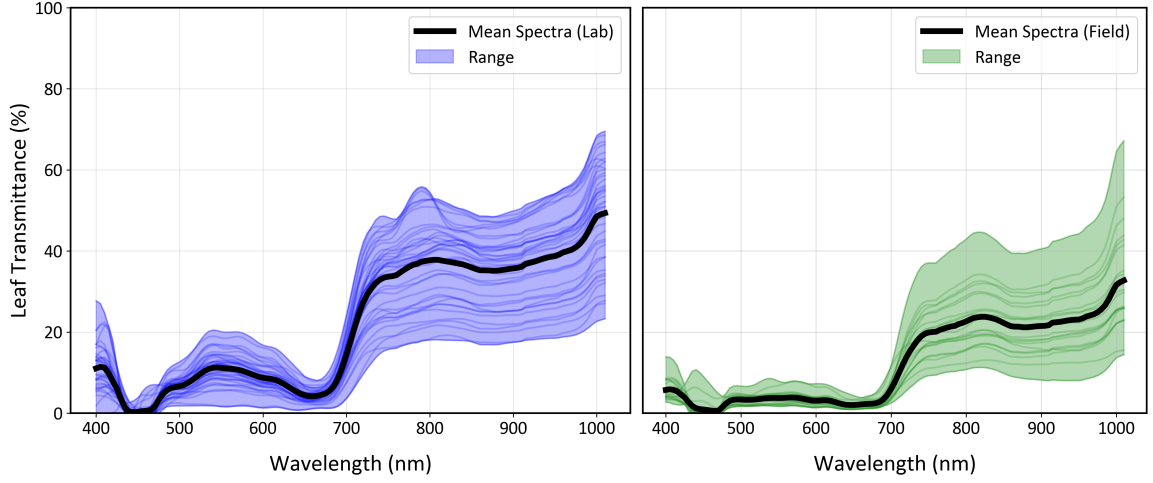


Figure 4.6: Leaf hyperspectral data collected using our proposed robotic system. **(left)** spectral transmittance of magnolia leaves used as a plant model for indoor lab experiments **(right)** spectral transmittance of pistachio leaves representing our outdoor field experiments.

Table 4.1: Number of available tests.

	Total approaches (%)	1-LPB (%)	2-LPB (%)	3-LPB (%)
In-Field	56	24	17	10
In-Lab	75	22	22	17
Combined	131	46	39	27

observed compared to 1-LPB, while field trials exhibited 29% and 58% reductions for the same comparisons. In both indoor and outdoor experiments combined, there were 46, 39, and 27 batches with 1-, 2-, and 3-LPB, respectively. These numbers represent 15% and 41% reduction in 2- and 3-LPB compared to 1-LPB, respectively.

A quantitative analysis on leaf grasping performance is presented in Table 4.2 and Figure 4.7, where success rates are reported across different experimental settings. For in-field trials, the overall success rate considering total approaches was 70%. The

Table 4.2: Success rate of leaf grasping using the robotic manipulator in different experimental settings.

	Total approaches (%)	1-LPB (%)	2-LPB (%)	3-LPB (%)
In-Field	70	79	70	60
In-Lab	63	95	77	41
Combined	66	87	74	48

success rate for the 1-LPB group was 79% following by 70% and 60% for 2- and 3-LPB, respectively. Leaf manipulation on indoor tests yielded a 63% overall success rate, with 95% for 1-LPB, dropping to 77% for 2-LPB and 41% for 3-LPB. Combined results from both settings show a total success rate of 66%. This means that on average 2 out of 3 leaves are successfully grasped and their data are acquired. For these successful grasps leaf transmittance on a 400-1010 nm range is collected and the results are demonstrated in Figure 4.6. LPB analysis on both indoor and outdoor results combined reflects a 87% success rate for 1-LPB, with a gradual decrease to 74% for 2-LPB followed by 48% for 3-LPB.

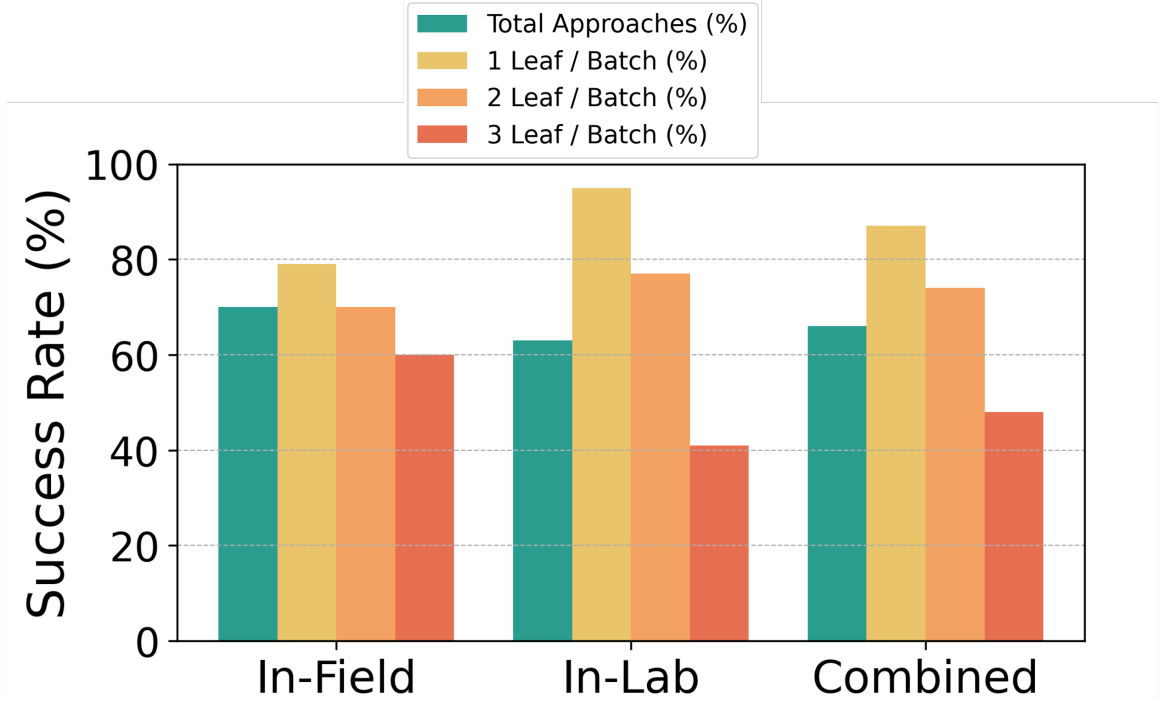


Figure 4.7: Success rate of leaf grasping using the robotic manipulator in different experimental settings.

4.6 Conclusions

We presented RoMu4o, a robotic manipulation unit for orchard operations, effectively addressing the need for continuous and automated orchard monitoring solutions. RoMu4o is engineered for proximal hyperspectral leaf sensing and leverages the compact integration of a hyperspectral spectrometer and an independent lighting source with the end-effector of a 6-DOF robotic arm. We proposed an algorithmic procedure for image processing and 6D pose estimation. Our computer vision method relies on a deep-learning instance segmentation model trained to identify minimally occluded leaf candidates deemed suitable for robotic manipulation. Furthermore, we created a collision-aware motion planning workflow for robust robotic manipulation and leaf grasping. To evaluate system performance, experiments were initially conducted on real magnolia plants in controlled lab setting, followed by field trials in a pistachio orchard with unstructured and previously unseen batches of foliage. The

system demonstrated reliable performance for 1-LPB hyperspectral sampling under both controlled and uncontrolled conditions, achieving a 95% success rate in lab trials and a 79% in field trials. Overall, the field experiments yielded a grasping success rate of 70%, which highlights the system ability and performance in unstructured orchard environments.

4.7 Acknowledgment

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Chapter 5

Conclusion

5.1 Contributions

The contributions of the research projects of this dissertation are discussed below.

- In Chapter 1, we discussed the pressing need for enabling technologies that contribute to the next agricultural revolution. In Chapter 2, we introduced the research projects explored in this dissertation and showcased the innovative engineering solutions proposed to automate, enhance, or transform a range of agricultural practices.
- We established IoT infrastructure in two model orchards to enable seamless connectivity between sensors and robots while facilitating real-time orchard monitoring. These testbeds provided a robust platform for extensive research and robotic deployments, as described below.
- In Chapter 3, we demonstrated the potential of data-driven models to enhance water management in orchards. With a focus on practical utility for end-users, the objective was to develop a predictive model for SWP using non-destructive and accessible data sources. Six machine learning models were employed to classify SWP using weather, thermal, and UAV-based MS features in pistachio (PO) and almond orchards (AO). While most classifiers achieved 79% or higher

accuracy, the Random Forest (RF) model excelled with 88% and 89% accuracy in PO and AO, respectively. RF regression model provided the highest accuracy when combining weather, thermal, and MS inputs, yielding $R^2 = 0.70$ in PO and $R^2 = 0.55$ in AO. These results underscore the potential of data-driven models in optimizing water management and irrigation scheduling. However, as robust models rely on extensive datasets, the establishment of unified databases is essential for reliable and scalable predictions.

- In addition to the approach discussed above, we implemented a new ML model to improve performance for SWP prediction. We introduced a stochastic decision tree (SDT) model to enhance the precision of water stress detection in pistachio and almond orchards. The SDT model outperformed established methods such as SVM, KNN, and RF, owing to its ability to handle complex datasets without requiring feature selection. This approach preserved data integrity, reduced computational costs, and ensured adaptability to diverse agricultural conditions.
- Chapter 4 highlights the transformative potential of robotic automation in orchard operations by addressing the critical need for continuous, scalable, and persistent crop monitoring solutions. We introduced RoMu4o, a robotic manipulation unit designed for operation in orchards tailored for proximal hyperspectral leaf sensing. The system features a compact end-effector design integrating a hyperspectral spectrometer and an independent lighting source, enabling high-fidelity data acquisition while streamlining the calibration process for consistent and reliable measurements. We presented a perception algorithm capable of identifying target leaves from dense foliage for precise robotic manipulation. The robotic manipulation pipeline integrates the perception algorithm with a collision-aware motion planning framework to enable precise and reliable leaf grasping for hyperspectral data acquisition. The system underwent extensive testing beyond laboratory settings in a pistachio orchard to ensure reliability under unstructured and dynamic conditions. To promote accessibil-

ity and further innovation, we open-sourced our software packages to empower researchers to adapt the system with diverse agricultural applications.

- In a collaborative work between UCM and UPenn within the IoT4Ag ERC, we introduced a 4D metric-semantic mapping approach for persistent orchard monitoring. This method integrates various sources of information including 3D LiDAR, RGB camera, and IMU data to track and analyze fruit growth over time. This system integrates an advanced data fusion algorithm to accurately track fruits. It enables detailed spatiotemporal insights into the fruit count, size, and development. Tested in real orchard conditions, the proposed method demonstrates high precision in estimating fruit characteristics while addressing challenges of dynamic agricultural environments. Field tests conducted in a real orchard environment achieved only 3.1% error in total fruit count estimation across 60 apple trees and a mean size estimation error of 1.1 cm. The datasets are made available to public for further use and extensive research.

5.2 Challenges and future work

While this dissertation highlights the significant advancements made in agricultural automation and data-driven water management, several challenges encountered during the research point to potential directions for future work:

- **Federated Learning Framework for Water Stress Detection:** A federated learning framework is needed to provide a robust database that allows growers to input their local data and receive real-time insights into the water status of their orchards. Such a system would enable growers to make informed decisions regarding irrigation scheduling resulting in water use efficiency. This decentralized approach is beneficial because it leverages the impact of collective data while preserving privacy and facilitating technological adoption.
- **Transition to Transformer-Based Models:** Future efforts could explore the replacement of CNN-based models with transformer-based architectures.

Transformers, with their ability to handle varying light intensities, shadows, and other complex environmental conditions, offer a promising alternative for outdoor agricultural tasks.

- **Integration of Multiple Leaf Sensors:** Our current crop monitoring prototype, RoMu4o, leverages a single hyperspectral sensor for leaf sensing; however, integrating additional sensors such as temperature or leaf moisture sensors could enhance the accuracy of stress detection. Multi-modal sensor data can provide a more holistic approach to orchard monitoring which paves the way for more precise and actionable insights.
- **Time Optimization:** First prototype of RoMu4o, focused on demonstrating feasibility rather than optimizing the time required for hyperspectral leaf sampling. Future work could prioritize developing strategies to accelerate data collection without compromising measurement accuracy. For example, light-weight deep learning models can be used instead of heavy-weight models. This would indeed require more data for training the models but can decrease the image processing time by an order of magnitude.
- **Hybrid Robotic Manipulation Workflows:** The current leaf manipulation pipeline operates sequentially. Developing a dynamic hybrid workflow that integrates parallelized or more adaptive robotic manipulation could significantly improve the system performance.
- **Working With Real Plants:** Working with real plants posed unique challenges. Limited growing seasons provided only short time-frame for experiments. Lab plants required careful attention and their structure drastically changed through time. These factors necessitated retraining the deep learning models multiple times, which increased the operational difficulties. Future work could leverage robust, pre-trained fine-tuned segmentation tools such as SAM1 or SAM2 to enhance efficiency and reduce the need for frequent model retraining.

- **Field Experiments vs Lab Experiments:** Field conditions differ vastly from controlled laboratory settings, with challenges such as intense sunlight, high temperatures, unexpected environmental events, limited network and power sources. Future research should aim to create solutions specifically designed for these unstructured environments, moving beyond lab testing to robust field-ready implementations.
- **Extending to Other Crops:** Adapting the system to other crops presents an exciting opportunity but requires crop-specific fine-tuning of models and workflows. Investigating how the framework generalizes across diverse crop types could open new avenues for broader adoption in agriculture.
- **Practical Grower Applications and Commercialization:** Ensuring that the system is user-friendly and applicable to growers practical needs is critical for its adoption. Future work should focus on developing software tools that are accessible, easy to use, and aligned with growers need. This will be essential for commercialization and widespread deployment.