

Poster Abstract: Low-Cost Soil Sensing and Two-Level Classification for Early Stress Detection in Avocado Plants

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Abstract

We present a systematic evaluation of low-cost soil sensors for early stress and disease detection in avocado plants. Our monitoring system was deployed across 72 plants divided into four treatment categories within a controlled greenhouse environment collecting data over six months. We developed a two-level hierarchical classifier leveraging soil electrical conductivity (EC) and moisture data to improve classification accuracy. The proposed classifier achieved 75-86% accuracy across different avocado genotypes, outperforming conventional machine learning approaches by over 20%. Our findings demonstrate that while low-cost sensors exhibit certain limitations in field conditions, strategic classification techniques can significantly enhance their utility for precision agriculture.

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1 Introduction

Plant diseases and environmental stressors pose significant challenges to agricultural productivity, particularly for high-value crops like avocados. Early detection of these issues is crucial for preventing widespread damage and optimizing management strategies.

Traditional methods for assessing plant health involve in-lab analysis of soil and leaf samples, requiring expensive benchtop equipment and expert knowledge.

Advances in wireless sensor networks have enabled the use of low-cost commercial sensors for agricultural monitoring due to their affordability and ease of integration with embedded systems. These sensors can measure soil parameters like moisture and electrical conductivity (EC) at a fraction of the cost of traditional benchtop equipment. However, despite their potential, there remains a critical gap in understanding their real-world performance and limitations when deployed in field conditions.

Our study investigates the viability of low-cost soil sensors for stress detection in avocado plants, focusing on salinity stress and Phytophthora root rot (PRR). We propose a novel approach that integrates soil sensor data with a two-level hierarchical classifier to overcome the inherent low sensitivity of these sensors and improve classification accuracy, thereby enabling early stress detection.

2 Proposed Work

Our system monitors 72 avocado plants using low-cost soil sensors to collect soil electrical conductivity (EC) and moisture data, key indicators of plant stress. The plants represent two rootstocks, Thomas (susceptible to salinity and PRR) and PP40 (resistant to PRR and tolerant to salinity), and are divided into four treatment categories: (i) control, (ii) salinity stress, (iii) PRR, and (iv) combined salinity and PRR. The collected sensor data is labeled according to these categories, with the objective of classifying these plants into treatment types for early stress detection.

We used commercially available soil sensors costing \$25 per unit. These sensors measure moisture using a high-precision sensor strip and EC via four stainless steel electrodes. Data is transmitted wirelessly to a Raspberry Pi via Bluetooth 4.1, and the sensors are powered by CR2032 batteries with a three-month lifespan.

To understand the limitations of conventional classification methods, we analyzed the features extracted from the last layer of a trained ResNet model using Principal Component Analysis (PCA).

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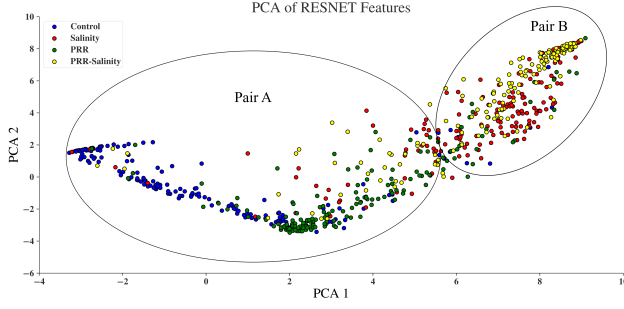


Figure 1: PCA of the features of a trained ResNet model

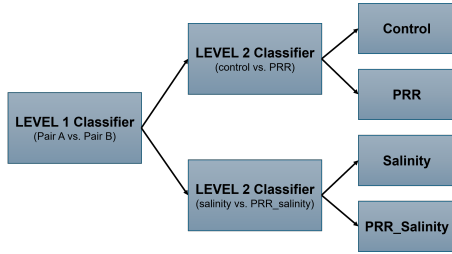


Figure 2: Proposed two-level hierarchical classifier

As shown in Fig. 1, certain treatment group pairs overlap significantly leading to poor detecting accuracy on baseline classification methods. However, there exists a separation between two pairs of groups: Pair A (control and PRR), and Pair B (salinity and salinity-PRR). This observation motivated us to design a two-level hierarchical classifier that first distinguishes between these pairs, then classifies the specific treatment within each pair.

Fig. 2 illustrates our two-level classification approach. Level-1 classification is trained directly on the time-series data and uses a ResNet model, which showed the best performance among the baseline methods in distinguishing between Pair A and Pair B. For level-2 classification within each pair, we first extracted time-series features capturing both temporal trends and statistical variations using skewness and kurtosis, enabling a more reliable classification of stress conditions. These features were computed for each day (window), allowing a time-sensitive analysis of plant responses. The level-2 classifier was then trained on these extracted features using Random Forest, chosen for its effectiveness in binary classification and low computational cost.

3 Evaluation

For evaluation, we compared our system against: (i) traditional methods including Random Forest, KNN, and SVM; (ii) more advanced models such as RNN with LSTM cells, ResNet, and Multivariate Unsupervised Symbols and Derivatives (MUSE) [4]; and (iii) state-of-the-art classifiers like MR-HYDRA [1], HIVE-COTE 2.0 [3], and QUANT [2], which leverage dictionary-based and ensemble learning techniques.

Table 1 compares the classification accuracy results. We trained these models using a dataset from December 2023 to mid-March 2024, a period when no visible symptoms such as tip burns were present on the leaves. We then tested them on a dataset from mid-March to late April 2024, during which significant tip burns were observed. As shown in the table, our approach achieved significantly

Table 1: Comparison of classification accuracy

Category	Method	Accuracy	
		Thomas	PP40
Traditional Machine Learning	Random Forest	58.6%	44.5%
	KNN	45.6%	36.1%
	SVM	44.1%	39.5%
Time Series Classification	MUSE	60.1%	42.5%
Neural Networks	RNN (LSTM)	46.4%	37.5%
	RESNET	61.4%	45.5%
State-of-the-Art	HIVE-COTE 2.0	38.4%	37.7%
	HYDRA	43.9%	39.1%
	QUANT	59.4%	43.6%
Our Approach		86.5%	75%

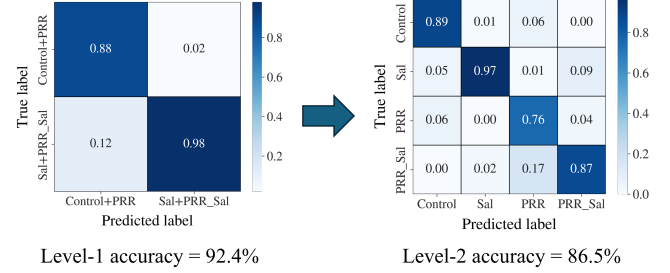


Figure 3: Confusion matrices for Level-1 and 2 of our proposed classifier for Thomas rootstocks

higher accuracy than other methods: 25.1-48.1% point higher for Thomas and 29.5-38.9% point higher for PP40.

To better understand the performance of our approach, Fig. 3 shows confusion matrices for our level-1 and 2 classifiers. Level-1 accurately differentiated Pair A (Control and PRR) and Pair B (Salinity and Salinity-PRR). In level-2, classification accuracy declined slightly, reflecting the accumulated degradation from level-1.

4 Conclusion

This work presents a low-cost soil sensing system with a two-level classifier for early stress and disease detection in avocado plants. Our results show that while low-cost sensors have inherent limitations, strategic classification techniques significantly improve their effectiveness. Future work includes: comparing our approach against conventional lab-based analysis for detection accuracy and cost-effectiveness; testing under outdoor conditions with fluctuating humidity and heterogeneous soil composition; and addressing generalizability beyond the experimental setup for broader applicability to precision agriculture.

Acknowledgments

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