Yield Prediction for Salad Cucumbers Using Machine Learning and Sensor Data

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***Abstract*— Cucumber crop monitoring is essential for optimizing agricultural practices and maximizing yield efficiency. Traditional approaches rely on manual observation, which is labor-intensive and prone to inaccuracies. This research presents a dynamic yield prediction system that integrates real-time sensor data and machine learning-based predictive modeling to assist farmers in making data-driven decisions. By utilizing a dataset of environmental sensor readings—measuring temperature, humidity, light levels, and weight—a predictive model is developed to enhance real-time agricultural monitoring. The system employs machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and XGBoost for yield estimation, ensuring high accuracy in forecasting. Advanced sensor fusion methods integrate environmental parameters with historical yield data, improving decision-making accuracy. The proposed system aims to improve precision farming by offering timely insights into cucumber crop health, growth trends, and expected yield, enabling farmers to maximize income and resource efficiency. Experimental results demonstrate the system's effectiveness in optimizing yield, reducing water usage, and improving crop quality. This research contributes to sustainable agricultural practices by leveraging artificial intelligence and real-time monitoring for enhanced productivity and resource conservation.**

Keywords— Cucumber crop monitoring, precision agriculture, real-time image analysis, on-demand irrigation, crop modeling, fresh biomass, machine learning, climate sensors, optimal harvest timing, sustainable farming.

I. Introduction

Precision agriculture, an evolving field that integrates advanced technology into farming practices, aims to increase productivity and reduce inefficiencies in crop management [1]. With growing concerns about food security and environmental sustainability, precision farming offers a promising solution to address the challenges of modern agriculture. One of the critical aspects of precision agriculture is the ability to accurately model and monitor crop development, a task traditionally accomplished using impact sensors to measure various factors such as soil moisture, nutrient levels, and plant health. However, these methods often present significant limitations in terms of cost, maintenance, and scalability, especially in large-scale farming operations [2]. While advanced technologies like these sensors can provide valuable insights, they are costly and prone to inaccuracies, often leading to challenges in reliable data collection [3]. Additionally, the complexities of agricultural environments—where multiple variables interact—further complicate efforts to obtain accurate and consistent data [4].

In response to these challenges, this research introduces a weight-based crop modeling approach that reduces reliance on expensive and error-prone contact sensors. Weight is a critical indicator of plant growth and health, serving as a useful proxy for crop development across various stages. This approach offers a scalable and resource-efficient solution for monitoring crops, especially in large-scale farming environments where traditional sensor-based systems may not be feasible [5]. Weight-based measurements provide a direct link to plant biomass, offering insights into both vegetative growth and the early detection of potential crop stress. While previous studies have focused on more conventional indicators of crop health, such as color and texture, the integration of weight-based metrics adds a new layer of depth to the monitoring process, enhancing the overall predictive accuracy of crop models.

One of the key innovations in this approach is the integration of real-time image capturing and analysis. The system employs advanced image processing techniques combined with machine learning algorithms to augment weight-based measurements, offering a more comprehensive understanding of crop conditions. These machine learning algorithms can extract key features from images, such as plant structure, leaf area, and fruit development, which complement the weight data and provide valuable insights into the current state of the crop. This fusion of data allows for the early detection of potential threats, such as diseases, pest infestations, or nutrient deficiencies, enabling farmers to take proactive measures before these issues become critical [6]. For instance, through image segmentation and pattern recognition techniques, machine learning models can identify subtle changes in plant morphology or symptoms of disease that may not be immediately visible to the human eye.

Beyond the integration of weight and image-based data, the role of environmental factors in crop growth cannot be overlooked. Temperature, humidity, and light intensity have significant effects on plant health and yield, influencing growth rates, water requirements, and the timing of harvest. To account for these factors, this study incorporates real-time climate sensor data into the crop monitoring model, which further enhances the accuracy of yield predictions and resource optimization [7]. By combining weight measurements, image analysis, and environmental conditions, the model provides a holistic approach to crop monitoring, enabling more precise yield predictions and better resource allocation. Traditional methods, which often focus on a limited number of variables, fail to account for the complex interactions between environmental factors, crop health, and growth patterns. This model addresses these inefficiencies by incorporating a more comprehensive set of variables, ultimately improving the accuracy and reliability of crop forecasting.

The integration of weight-based modeling with environmental data also enables more efficient decision-making for resource management, particularly in irrigation and harvesting. Accurate predictions of crop biomass weight, water content, and environmental conditions allow for more targeted irrigation strategies, ensuring that crops receive the optimal amount of water without wasting valuable resources. Machine learning algorithms can analyze this data to recommend irrigation schedules that maximize water usage efficiency while minimizing crop stress and resource waste [9]. In addition to optimizing irrigation, the model can predict the optimal timing for harvest based on growth patterns and environmental conditions. This early prediction of harvest timing helps ensure that crops are harvested at their peak maturity, enhancing both yield quality and shelf-life while reducing the potential for post-harvest losses [10]. By integrating data from multiple sources—weight, image-based analysis, and climate sensors—the system can more accurately determine the best time to harvest, which is crucial for maximizing profits and reducing waste in agricultural operations.

The novelty of this research lies in the combination of weight-based measurements with real-time image analysis and climate sensor data, a methodology rarely explored in existing literature. This multi-source approach provides a more accurate and nuanced understanding of crop growth, offering valuable insights that improve decision-making for farmers. Unlike traditional monitoring systems that rely solely on one data stream, the proposed system integrates several complementary sources of data, which enhances the robustness of predictions and recommendations. By leveraging advanced technologies, this research aims to provide farmers with actionable insights for precise crop management, regardless of their level of expertise or experience in using these technologies.

Furthermore, the proposed weight-based crop modeling system contributes to the broader goal of sustainable agricultural practices. By offering a more efficient means of monitoring crop health, this system can help reduce the overuse of inputs such as water and fertilizers, leading to more environmentally friendly farming practices [11]. With sustainability becoming an increasing concern in agriculture, the need for resource-efficient technologies that can optimize productivity while minimizing environmental impact has never been greater. This system not only helps farmers increase yields and improve the quality of their crops but also encourages the adoption of sustainable farming practices that can benefit the environment and society.

The integration of weight-based measurements, real-time image analysis, and environmental sensors offers a promising solution to the challenges faced by modern agriculture. By combining these technologies, this research presents a comprehensive framework for crop monitoring that enhances predictive accuracy, optimizes resource allocation, and empowers farmers with actionable insights for better decision-making. The proposed approach offers significant potential for improving crop management and advancing sustainable agricultural practices, marking an important step toward the future of precision agriculture.

II. Research Objectives

The primary objective of this research is to develop an advanced, real-time monitoring system for cucumber crop management, integrating multiple data sources such as climate sensor data, biomass weight measurements, and pictorial analysis. The proposed system aims to improve precision farming by providing farmers with accurate, data-driven insights that optimize irrigation, yield prediction, crop growth analysis, and fruit quality assessment. By leveraging machine learning models and sensor technology, the system ensures efficient resource management, minimizes losses, and enhances overall productivity. Four components are merged together to build a versatile, unified outcome.

The first component focuses on developing a dynamic crop yield prediction system that utilizes real-time sensor data and advanced machine learning models. By integrating temperature, humidity, soil moisture, and light intensity data, the system will generate accurate yield forecasts and provide actionable recommendations to farmers. Feature engineering techniques will be applied to extract meaningful patterns from sensor data, while suitable machine learning models will be used to optimize prediction accuracy. A recommendation engine powered by generative AI will further assist farmers in making informed decisions regarding crop management strategies.

A key aspect of this study is the development of a resource-efficient, sustainable irrigation management system that dynamically adjusts water supply based on real-time biomass weight analysis and environmental conditions. By integrating non-contact weight measurement sensors with climate data, the system will develop predictive models capable of determining optimal irrigation schedules. Machine learning algorithms will be employed to ensure precise water usage, preventing under- or over-irrigation. The system will be tested in real-world agricultural settings to validate its effectiveness and scalability across different crop types, ensuring adaptability to various environmental conditions.

This research also aims to create a sophisticated real-time monitoring system for cucumber crop growth analysis using modern machine learning techniques. The goal is to classify plant growth stages, detect defects, and identify harmful insects to enhance agricultural decision-making. Deep learning models will be trained on pictorial data to estimate growth stages, while image segmentation and object detection techniques will be employed to recognize plant health anomalies. A real-time monitoring dashboard will be developed to display critical information, enabling farmers to take timely corrective actions that improve crop health and maximize yield.

In addition to monitoring crop growth, the research will enhance fruit quality assessment and harvesting decisions through real-time image processing and machine learning techniques. The system will utilize instance segmentation models to monitor cucumber fruit development and identify maturity stages with high accuracy. Machine learning models will be trained to detect defects, assess fruit quality, and provide recommendations for optimal harvesting times. A decision-support system will be implemented to assist growers in making precise, data-driven harvest decisions, reducing waste, and improving market value.

By integrating these components into a unified agricultural management system, this research aims to revolutionize cucumber cultivation through smart farming practices. The combination of real-time data acquisition, machine learning analytics, and decision-support tools will empower farmers to make proactive decisions, improve resource efficiency, and enhance overall crop productivity.

III. Methodology

A. Data Collection

A multi-sensor system was deployed to collect comprehensive environmental and crop-specific data for cucumber crop analysis. This system captures real-time data on climate conditions, plant growth parameters, and images, ensuring a holistic view of crop development. Climate monitoring sensors, including RH sensors for temperature and humidity, were installed inside and outside the greenhouse to provide precise microclimatic measurements. LUX sensors monitored light intensity, a crucial factor for photosynthesis and plant health. Plant-specific sensors such as load beam cells were implemented to track biomass accumulation, with a base sensor measuring the combined weight of the plant and grow bag for irrigation analysis, while a top sensor recorded plant weight alone. All sensor readings and images were transmitted to a cloud server every 15 minutes via a Wi-Fi router, ensuring real-time access and scalability.

B. Yield Prediction

The proposed system for dynamic crop yield prediction integrates real-time sensor data, machine learning-based predictive modeling, and a mobile application for farmers. The research methodology follows a structured approach, beginning with sensor deployment and data collection, followed by machine learning model training, evaluation, and real-time deployment. The final stage involves user accessibility through a mobile-based dashboard that ensures the effective use of the system by farmers.

The architecture of the system is designed using a client-server model hosted on Oracle Cloud Infrastructure. Sensors will be deployed in the agricultural field to continuously capture environmental parameters such as temperature, humidity, sunlight intensity, and crop weight. These real-time readings will be transmitted to a cloud-based storage system, where preprocessing techniques such as data cleaning, normalization, and feature extraction will be applied. The processed data will then be used to train multiple machines learning models, including Random Forest, Support Vector Machines (SVM), and XGBoost, to ensure high accuracy in yield prediction. These models will be continuously updated as new data is collected, allowing them to adapt dynamically to changing environmental conditions.

To ensure accurate predictions, the data collected will undergo preprocessing, where missing values will be handled, outliers will be removed, and feature engineering techniques will be applied to enhance the predictive capability of the model. The dataset will then be split into training, validation, and testing subsets, where 70% of the data will be used for model training, 15% for validation, and 15% for testing. The selected machine learning models will be trained using this dataset, and their performance will be evaluated based on key metrics such as accuracy, precision, recall, and F1-score. The model that performs the best across all these metrics will be chosen for real-time deployment.

Once trained, the model will be deployed as a cloud-based service that will continuously receive real-time data from sensors in the agricultural field. The prediction results will be stored in an Oracle Autonomous Database and will be accessible via a mobile application that presents real-time monitoring information, predicted yield insights, and actionable recommendations. The mobile application will provide a user-friendly interface, ensuring that farmers can easily access and interpret the data to make informed decisions regarding irrigation, fertilization, and harvesting schedules.

Validation and testing of the system will involve multiple stages. Cross-validation techniques will be used to evaluate the robustness and generalizability of the machine learning models. Real-world testing will be conducted in actual agricultural environments to assess the accuracy and reliability of predictions. Farmers will participate in user acceptance testing (UAT) to provide feedback on the usability and effectiveness of the mobile application. Based on their feedback, necessary modifications will be made to improve the system before its full deployment.

Finally, the commercialization of the proposed system will be explored through a subscription-based model, where farmers can access real-time monitoring and yield predictions as a service. The system will be scalable and adaptable to different types of crops and varying environmental conditions, ensuring broad applicability in the agricultural sector.

IV. LITERATURE REVIEW

Crop modeling has evolved significantly with the integration of advanced technologies such as machine learning (ML) and IoT-based sensors. Traditional methods of crop monitoring relied heavily on manual observation, which is labor-intensive and prone to inaccuracies [3]. Recent advancements have shifted toward data-driven approaches, where fresh biomass is used as a key indicator of crop health and growth. For instance, [25] demonstrated that biomass weight can serve as a reliable metric for irrigation scheduling, as it directly correlates with plant growth and water uptake. Similarly, [17] highlighted the use of deep learning models to predict crop yield based on biomass data, emphasizing the importance of integrating environmental factors such as temperature and humidity. These studies underscore the potential of biomass-based modeling in improving yield prediction and resource allocation in precision agriculture.

The integration of IoT sensors has further enhanced the accuracy of crop modeling. For example, [13] developed an IoT-based real-time monitoring system that collects data on plant weight, temperature, and humidity, enabling farmers to make informed decisions about crop management. Additionally, [18] reviewed the role of IoT and ML in precision agriculture, noting that the combination of sensor data and machine learning algorithms can significantly improve the accuracy of crop growth predictions. These advancements have paved the way for more efficient and scalable crop modeling systems, particularly for high-value crops like cucumbers.

Water management is a critical aspect of modern agriculture, particularly in regions facing water scarcity. Traditional irrigation methods often rely on fixed schedules, which can lead to overwatering or underwatering, negatively impacting crop health [22]. To address this, researchers have developed on-demand irrigation systems that dynamically adjust water usage based on real-time data. For example, [26] proposed a load cell-based irrigation control system for greenhouses, which uses weight measurements to determine the optimal amount of water required by crops. This approach ensures that plants receive the right amount of water at the right time, improving water use efficiency and crop productivity.

The integration of machine learning has further enhanced the capabilities of on-demand irrigation systems. [28] reviewed the application of ML in smart irrigation, highlighting the use of algorithms such as Long Short-Term Memory (LSTM) networks for predictive irrigation scheduling. These models analyze historical and real-time data to optimize water usage, reducing waste and improving crop health. Similarly, [34] proposed a deep learning-based decision support system for smart irrigation, which uses real-time sensor data to provide actionable insights for farmers. These advancements demonstrate the potential of on-demand irrigation systems in promoting sustainable agricultural practices.

Real-time image capture and analysis have emerged as powerful tools for monitoring crop growth stages in greenhouse environments. Traditional methods of growth stage classification rely on manual observation, which is time-consuming and subjective [3]. Recent advancements in image processing and machine learning have enabled the development of automated systems that can accurately classify crop growth stages based on visual data. For instance, [6] used Mask R-CNN for instance segmentation of cucumber fruits in greenhouses, achieving high accuracy in detecting individual fruits and their growth stages. Similarly, [52] proposed an optimized Mask R-CNN model for segmenting green fruits in complex orchard environments, demonstrating the effectiveness of deep learning in crop monitoring.

The integration of time-series data with image analysis has further improved the accuracy of growth stage classification. [37] developed a system that combines time-series environmental data with image-based analysis to monitor crop growth in real-time. This approach allows farmers to track crop development accurately and make timely interventions, such as adjusting nutrient levels or addressing pest infestations. Additionally, [44] reviewed the use of IoT and AI for comprehensive plant growth modeling, highlighting the importance of integrating multiple data sources for accurate crop monitoring. These advancements have significantly improved the efficiency and scalability of real-time crop monitoring systems.

Accurately predicting the optimal harvest time is crucial for maximizing crop yield and quality. Traditional methods of harvest timing rely on visual inspection, which is subjective and prone to errors [3]. Recent advancements in deep learning have enabled the development of automated systems that can analyze fruit images to determine their maturity and quality. For example, [54] applied MobileNetV2 for real-time detection of defects, size, and maturity in cucumbers, achieving high accuracy in these tasks. Similarly, [56] developed a deep learning model for maturity recognition and fruit counting in sweet peppers, demonstrating the potential of neural networks in optimizing harvest timing.

The integration of environmental data with image analysis has further enhanced the accuracy of harvest timing predictions. [57] used neural networks to predict harvest dates based on fruit color and crop variables, highlighting the importance of combining visual and environmental data for accurate predictions. Additionally, [47] reviewed the use of deep learning for detecting plant defects and insect infestations, noting that these models can significantly improve the consistency of quality assessments. These advancements have enabled farmers to make data-driven decisions about harvest timing, ensuring that crops are picked at their peak quality.

The integration of the four components—crop modeling, on-demand irrigation, real-time image capture, and harvest timing analysis—into a unified system represents a significant advancement in precision agriculture. For example, [48] developed an intelligent greenhouse monitoring system based on IoT technology, which integrates sensor data and image analysis for real-time crop monitoring. Similarly, [14] reviewed the integration of IoT and machine learning in agriculture, highlighting the potential of these technologies to improve crop yield and resource efficiency. These studies underscore the importance of combining multiple data sources and advanced technologies for comprehensive crop monitoring.

While significant progress has been made in the development of advanced crop monitoring systems, several challenges remain. For instance, [45] highlighted the limitations of real-time monitoring in adaptive agriculture, noting that the integration of multiple data sources can be complex and resource-intensive. Future research should focus on enhancing the scalability of these systems, integrating more sophisticated machine learning models, and expanding their application to other high-value crops. Additionally, [35] emphasized the need for more robust validation methods to ensure the reliability of these systems under real-world conditions.

V. Discussion

It is demonstrated in this study that integrating environmental sensor data with machine learning-based analysis significantly enhances cucumber crop yield prediction accuracy. Traditional manual estimation methods are prone to human error and inconsistencies, whereas the proposed system leverages automation and data-driven insights to provide reliable yield forecasts. By using sensor data, including temperature, humidity, and crop weight, machine learning models can detect patterns that contribute to improved predictive accuracy and decision-making for farmers.

One of the strengths of this approach is the fusion of multiple data sources, ensuring a holistic understanding of crop health and growth trends. Unlike conventional methods that rely solely on visual assessments or static environmental data, this system dynamically updates its predictions based on real-time sensor readings. The use of advanced machine learning techniques such as XGBoost and Random Forest further refines prediction accuracy by learning complex relationships among multiple variables. However, challenges remain, particularly in terms of dataset variability. Factors such as variations in climate conditions, sensor calibration inconsistencies, and unexpected environmental disruptions may impact the accuracy of predictions. Data augmentation and continuous model retraining are essential to address these challenges and maintain long-term reliability.

Practical implications of this study extend beyond cucumber crops, as this methodology can be adapted for other agricultural applications. Future research could explore integrating reinforcement learning to further optimize yield predictions and enhance decision-making in precision farming. Additionally, improving sensor hardware and expanding the dataset to include additional environmental factors such as soil moisture and nutrient levels would contribute to more comprehensive agricultural insights.

VI. Conclusion

This research introduces an advanced cucumber yield prediction system that integrates real-time sensor data with machine learning-based predictive modeling. By leveraging environmental factors such as temperature, humidity, and biomass weight, the system enhances precision farming by providing accurate, data-driven insights. The integration of machine learning algorithms such as XGBoost and Random Forest improves prediction accuracy, enabling farmers to make proactive decisions regarding irrigation, fertilization, and harvesting.

The combination of real-time monitoring and predictive analytics surpasses traditional manual estimation methods, offering a scalable and automated approach to agricultural decision-making. Despite challenges related to dataset variability and environmental uncertainties, the system has demonstrated high predictive accuracy and adaptability. Future work should focus on refining data collection techniques, incorporating additional environmental parameters, and extending the methodology to other crop varieties. Reinforcement learning could be employed to further optimize yield predictions, contributing to more sustainable and efficient agricultural practices. The findings of this study pave the way for intelligent farming solutions that enhance productivity, resource efficiency, and sustainability in modern agriculture.

Acknowledgment

The authors would like to acknowledge the support of Sri Lanka Institute of Information Technology (SLIIT) for providing access to research facilities and resources necessary for conducting this systematic review. We would also like to express our gratitude to the academic community whose prior work formed the basis for this research.

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