Cucumber Fruit Analysis Using Machine Learining techniques For Controlled Environments

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***Abstract*—The integration of advanced image processing and machine learning techniques in agriculture has revolutionized cucumber fruit analysis, particularly in controlled environments. This research aims to develop a real-time monitoring system for cucumber analysis, applying a deep learning algorithm to image processing for defect, size, maturity, and quality detection on cucumber. Traditional monitoring methods rely heavily on manual inspection, which is inefficient and prone to errors and often requires expert's advice and service can be expensive and time-consuming. By leveraging image processing techniques and deep learning algorithms, this system benefits farmers by accurately identifying growth stages and predicting optimal harvesting times. To address these limitations, this study employs deep learning models such as VGG16, ResNet50, and CNN, along with RGB masking and clustering algorithms for quality assessment. A time-series analysis model is also implemented to predict the optimal harvesting period, considering environmental factors such as humidity and temperature. The system will be integrated into a dashboard using Grafana, providing growers with real-time insights into fruit growth stages, quality assessment, and harvesting recommendations. By offering a scalable and data-driven approach, this research enhances decision-making processes in cucumber farming, ultimately improving yield quality, reducing waste, and promoting sustainable agricultural practices.**

Keywords— Cucumber fruit analysis, Machine learning, Instance segmentation, Defect detection, Time-series analysis, Real-time monitoring, Precision agriculture, optimal harvest timing, sustainable farming.

I. INTRODUCTION

Agriculture industry plays a pivotal role in ensuring global food security, and advancements in precision farming have significantly enhanced crop production efficiency. Among the various crops cultivated worldwide, cucumbers (*Cucumis sativus*) hold considerable economic importance due to their high demand in both domestic and international markets. Greenhouse farming has emerged as a preferred method for cucumber cultivation, as it allows for controlled environmental conditions that optimize yield and improve fruit quality [1]. However, despite these advantages, accurate monitoring of cucumber growth, defect detection, and harvest time prediction remain significant challenges in greenhouse farming. Traditional methods, which rely heavily on manual inspection, are labor-intensive, time-consuming, and prone to subjective errors, leading to inefficiencies and economic losses [2].

Traditional monitoring involves farmers visually assessing cucumber plants to determine fruit maturity, detect defects, and evaluate quality. This approach is not only inefficient but also inconsistent, as human judgment can vary significantly. Moreover, environmental factors such as temperature, humidity, and light intensity can greatly influence cucumber growth, making manual monitoring even more complex and unreliable [3]. Without real-time insights, farmers often face difficulties in making timely and accurate harvesting decisions, which can result in lower-quality produce and reduced market value [4]. These challenges highlight the need for more advanced and automated solutions to improve cucumber farming practices.

In response to these limitations, the agricultural industry has begun to adopt smart farming technologies, which integrate machine learning, image processing, and real-time monitoring systems. These technologies offer automated, data-driven solutions for critical tasks such as crop growth analysis, defect detection, quality assessment, and harvest prediction [5]. By leveraging these advancements, farmers can reduce their reliance on manual labor, improve the accuracy of quality assessments, and optimize resource management, ultimately enhancing productivity and sustainability in cucumber cultivation.

Traditional cucumber farming, particularly in greenhouse environments, faces several challenges that hinder efficiency and productivity. One of the primary issues is the labor-intensive nature of manual monitoring. Farmers must regularly inspect cucumber plants to assess growth stages, identify defects, and determine the optimal time for harvesting. This process is not only time-consuming but also impractical for large-scale farming operations [6]. Additionally, manual evaluations are subjective and inconsistent, leading to unreliable classification and grading of cucumbers [7]. Another significant challenge is the delayed detection of defects such as shape deformations, color abnormalities, and disease spots. Without real-time monitoring, farmers may fail to identify these issues early, resulting in significant crop losses and reduced market value [8]. Furthermore, traditional farming methods often lack data-driven decision-making capabilities, making it difficult to optimize critical factors such as irrigation, nutrient supply, and harvesting schedules [9]. These limitations underscore the need for more advanced and automated solutions to improve cucumber farming practices.

Smart farming technologies have emerged as a transformative solution to address the challenges associated with traditional cucumber farming. By integrating machine learning models, image processing techniques, and sensor-based monitoring systems, these technologies enable automated, real-time, and accurate insights into crop conditions [10]. For instance, machine learning algorithms can analyze large datasets to identify patterns and predict crop health, growth stages, and potential issues, enabling proactive decision-making [11].

Image processing techniques, such as RGB masking and clustering algorithms, have been developed to detect damaged, discolored, or underdeveloped cucumbers in real time. These methods eliminate the subjectivity associated with manual evaluations, ensuring consistent and reliable quality assessments [12]. Additionally, advanced deep learning models, including Convolutional Neural Networks (CNNs) and instance segmentation models like Mask R-CNN, have been employed to accurately identify and classify cucumbers based on their growth stages and defects [13].

Sensor-based monitoring systems play a crucial role in smart farming by continuously tracking environmental conditions such as temperature, humidity, soil moisture, and light intensity. This real-time data is analyzed using machine learning models to optimize irrigation, nutrient delivery, and other critical factors.

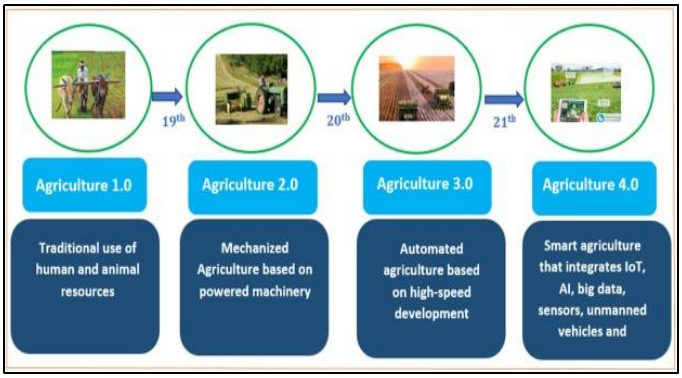

Figure 1.1 Farming Methods

II. Research Objectives

The key objective is to develop a cutting-edge, real-time cucumber monitoring system that integrates machine learning, image processing, and environmental sensing technologies to enhance fruit growth classification, defect detection, and harvest prediction using visual data. To address these challenges, the proposed system leverages advanced deep learning algorithms, real-time image analysis, and predictive modeling to enable data-driven decision-making, thereby improving crop quality, yield, and sustainability.

The research focuses on several key objectives to achieve this goal. First, it aims to develop machine learning models to identify the cucumber fruits at various growth stages in real time. This will reduce the errors and inefficiencies associated with manual observations, enabling farmers to track fruit development with greater precision. Implement a deep learning model to identify common defects and fruit quality such as color abnormalities, shape deformations, and disease symptoms. Integrated maturity classification and quality assessment to get more valuable insights, ensuring consistent and reliable evaluations. Another key objective is to incorporate environmental parameters such as temperature, humidity, and soil moisture into the monitoring system. By integrating real-time sensor data, the model will improve the accuracy of growth predictions and optimize cultivation practices, accounting for environmental variability and providing actionable insights to enhance crop health and productivity. Furthermore, the research will develop a time-series forecasting model using Long Short-Term Memory (LSTM) networks and Gradient Boosting Machines (GBM) to predict the optimal harvesting time based on real-time and historical growth data. This predictive capability will assist farmers in planning harvesting schedules more efficiently, minimizing losses caused by premature or delayed harvesting.

Finally, the study will design a user-friendly, real-time monitoring dashboard using Grafana to visualize critical data, including growth stages, defect detection reports, environmental parameters, and harvest recommendations. This dashboard will provide an accessible interface, empowering farmers to monitor cucumber crops effectively and make informed decisions in real time. By addressing these objectives, this research contributes to the field of precision agriculture by enhancing the accuracy and efficiency of cucumber monitoring, enabling farmers to optimize cultivation practices, reduce post-harvest losses, and improve overall productivity.

III. METHODOLOGY

A. Data Collection

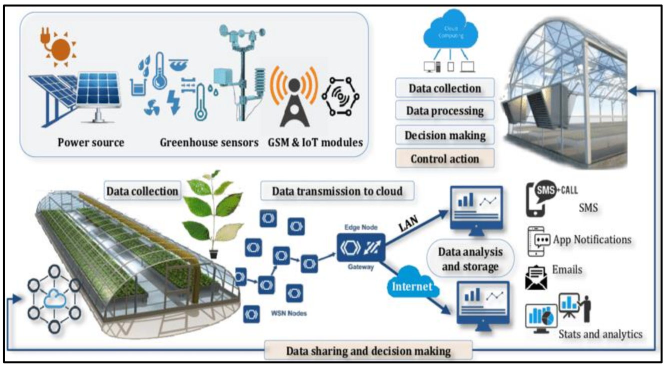

Figure 2 Data Collection

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. Image data was captured using an ESP32-CAM module, which documented plant growth stages from flowering to fruiting. 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. Conceptual Framework

Input	⇨	**Process**	⇨	**Output**
Captured images of Cucumber Fruits		Generated algorithms to train the model		Maturity and Quality Assessment

C. Cucumber Fruit Analysis

The dataset includes 4125 images undergo preprocessing to enhance their quality and prepare them for analysis. This includes contrast enhancement to improve clarity and image segmentation to isolate cucumber fruits from the background. For precise object detection, instance segmentation techniques such as U-Net are employed. These techniques enable the accurate identification and separation of individual cucumber fruits, even in complex scenes with overlapping foliage or fruits. Once the images are preprocessed, feature extraction is performed to identify critical characteristics of the cucumbers, including morphological features (size, shape, and boundary contours), color features (RGB and HSV color space analysis), and texture features (surface patterns and defects). These features are essential for tasks such as defect detection and quality assessment.

A unified model was developed to integrate both image data and environmental data for accurate crop monitoring. The image classification component of the model utilizes convolutional neural networks (CNNs), including custom CNN architectures, VGG16, and ResNet50, to identify the maturity of the fruit and detect the quality of the cucumber fruit based on texture, color, shape, and size. For defect detection and quality assessment, deep learning models such as ResNet and EfficientNet are employed to analyze texture and color features, enabling the identification of defects (e.g., spots, cracks) and the assignment of quality scores. Additionally, regression models such as Gradient Boosting Machines (GBM) and Long Short-Term Memory (LSTM) networks are used to predict optimal harvest timing by analyzing growth patterns, environmental data, and historical yield data.

To ensure the reliability of the trained models, model validation is conducted using techniques such as cross-validation and performance metrics like accuracy, precision, recall, F1-score, and mean absolute error (MAE). These validation steps ensure that the models are robust and capable of delivering accurate predictions under real-world conditions.

The proposed methodology represents a holistic and innovative approach to precision agriculture, combining advanced image processing, machine learning, and real-time monitoring to address key challenges in salad cucumber cultivation. By integrating these components, the system provides a scalable and cost-effective solution for improving crop yield, quality, and resource management in greenhouse environments.

IV. LITERATURE REVIEW

The adoption of advanced technologies in agricultural monitoring has become increasingly vital for enhancing the efficiency, yield, and sustainability of high-value crops. With the growing global demand for fresh, high-quality produce, the agricultural sector has transitioned from traditional manual inspection methods to automated systems that incorporate image processing, machine learning (ML), and real-time data analysis. These smart farming technologies are designed to improve crop monitoring, defect detection, and optimal harvest predictions, ensuring that crops meet market standards for quality and freshness [2].

High-value vegetable crops requires consistent monitoring and rigorous quality assessment before produce can enter the market. Ensuring uniformity in size, proper maturity, and the absence of defects is critical for both economic profitability and consumer satisfaction. Recent studies have explored the use of advanced deep learning models, such as MobileNetV2, for detecting defects, assessing maturity, and enhancing grading systems for cucumbers and other greenhouse-grown crops [5]. This literature review examines the current state of research in cucumber analysis, with a focus on real-time monitoring, defect detection, quality assessment, and harvest prediction using image processing and machine learning models.

Real-time monitoring systems have emerged as a cornerstone of modern precision agriculture, particularly in controlled environments where environmental factors such as temperature, humidity, and light levels can be precisely controlled to optimize plant growth. Research has demonstrated the effectiveness of integrating sensor networks and image capture technologies to continuously monitor crop growth stages [9]. These systems enable the immediate detection of anomalies, allowing farmers to intervene promptly to maintain crop health and maximize yield.

For example, a study by Jadhav et al. [6] developed a real-time image processing system for monitoring tomato growth stages in a greenhouse setting. The system successfully detected changes in fruit color and size, providing farmers with automated insights into the optimal harvesting time. Similar methodologies have been applied to cucumber cultivation, where continuous image-based monitoring helps identify growth abnormalities caused by environmental fluctuations.

The integration of Internet of Things (IoT)-enabled systems with computer vision technologies has further enhanced the accuracy of real-time monitoring. By integrating high-resolution cameras with AI-driven analytics, researchers have developed early-warning systems capable of preventing diseases, predicting yield, and optimizing irrigation schedules for greenhouse-grown cucumbers [10]. Despite these advancements, most existing studies lack a fully integrated system that combines real-time monitoring with predictive analytics, highlighting a critical gap in the current research landscape.

One of the key considerations in agriculture is the automated detection of fruit defects and fruit quality. Ensuring the quality of cucumbers before they reach the market is critical for economic viability and consumer satisfaction. Traditional methods rely on manual visual inspections, which are often inconsistent and prone to human error. Advanced AI models, particularly Convolutional Neural Networks (CNNs), VGG16, and ResNet50, have demonstrated significant accuracy in automating this process. [14]

For instance, a study by Quang Uoc et al. [8] applied CNNs to classify cucumber fruit defects, achieving high precision in distinguishing between healthy and defective cucumbers. These models analyzed image datasets of cucumbers at various growth stages, identifying defects such as discoloration, deformation, and disease symptoms. Additionally, Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) algorithms have been explored for similar applications, with varying degrees of success depending on dataset quality and environmental factors [11].

Instance segmentation, a subfield of machine learning, has proven particularly valuable for distinguishing individual cucumbers in densely packed greenhouse environments. Traditional image processing techniques often struggle with overlapping fruits and background noise, whereas deep learning models like Mask R-CNN offer precise fruit segmentation and growth stage classification [15]. For example, Jia et al. [12] developed an accurate segmentation model using Mask R-CNN for green fruit, which successfully identified different ripening stages and provided farmers with detailed harvest insights. [16]

Moreover, MobileNetV2-based quality assessment has been applied to multiple vegetable crops, including ladies' fingers, bitter gourds, and cucumbers. Valiente et al. [5] utilized MobileNetV2 to classify defects, size, and maturity levels in vegetables, demonstrating the feasibility of using lightweight deep learning models for real-time agricultural applications. The ability of MobileNetV2 to operate efficiently in resource-constrained environments makes it highly suitable for small-scale farmers and mobile-based applications.

Accurately predicting the optimal harvest time is essential for maximizing yield, minimizing waste, and ensuring peak crop quality. Traditionally, farmers estimate harvest time based on visual cues, which are prone to inconsistencies. Machine learning models have been employed to enhance prediction accuracy by analyzing historical growth patterns and real-time environmental data.

For instance, Escamilla et al. [17] developed a deep learning model for maturity recognition and fruit counting in greenhouse-grown sweet peppers, using temperature and light exposure data to determine the optimal harvest window. Similarly, Lin and Hill [4] applied neural network modeling to predict harvest dates for greenhouse-grown peppers, demonstrating that AI-based predictions outperform traditional estimation methods.

In cucumber farming, time-series forecasting models such as Long Short-Term Memory (LSTM) networks and Gradient Boosting Machines (GBM) have been utilized to analyze growth trends and environmental influences. These models process large datasets collected from sensor-equipped greenhouses, allowing farmers to optimize irrigation schedules and anticipate yield fluctuations [18]. However, despite these advancements, few studies have combined real-time monitoring with predictive analytics in a fully automated system.

The integration of real-time monitoring systems, machine learning models, and predictive analytics has significantly advanced precision agriculture. However, critical research gaps remain, including the lack of fully integrated systems, limited consideration of environmental factors, and the absence of real-time visualization tools [19], [20], [21].To address these challenges, this research aims to develop an integrated, real-time cucumber analysis system that combines image segmentation, defect detection, and time-series-based harvest prediction while incorporating environmental monitoring into an interactive dashboard for farmers [13]. This system will bridge existing gaps, enabling farmers to make data-driven decisions and optimize crop management practices effectively.

V. Discussion

The implementation of machine learning models for cucumber analysis was centered on three critical domains such as maturity classification, quality assessment, and harvest time prediction. The overarching objective was to develop a robust system capable of delivering real-time insights into cucumber growth dynamics, thereby ensuring optimal harvesting conditions and minimizing losses attributable to premature or delayed harvesting. A comprehensive evaluation of various models was conducted, with performance metrics such as accuracy, precision, recall, and error rates being employed to assess their efficacy in predicting cucumber maturity, quality, and harvest timing.

In the context of maturity classification, three deep learning architectures VGG16, ResNet50, and a Convolutional Neural Network (CNN) were trained utilizing a dataset partitioned into 80% for training and 20% for testing. The preprocessing pipeline encompassed image augmentation, resizing, normalization, and noise reduction to enhance model performance. Post-training evaluation revealed that the CNN model outperformed both VGG16 and ResNet50, achieving an accuracy of 68%. The superior performance of CNN can be attributed to its streamlined architecture, its proficiency in extracting salient image features, and its suitability for binary classification tasks. Nevertheless, the moderate accuracy level indicates potential areas for improvement, including dataset expansion, refinement of image preprocessing techniques, and the incorporation of more advanced feature extraction methodologies.

For quality assessment, critical parameters such as texture, defect detection, size, and color were analyzed. Two machine learning models, the Random Forest Classifier and Gradient Boosting Algorithm were implemented to classify cucumber quality. Among these, the Random Forest Classifier demonstrated superior performance, achieving an accuracy of 83%, thereby establishing itself as the most reliable model for quality assessment. The robustness of the Random Forest model stems from its capacity to handle multiple features, mitigate overfitting, and classify data effectively in a non-linear manner. The model successfully identified cucumbers exhibiting surface defects, size variations, and color inconsistencies, thereby facilitating improved grading and quality control. However, the inherent variability in cucumber textures and color intensities presented challenges, occasionally resulting in misclassification. Future enhancements could involve the integration of advanced deep learning models such as EfficientNet to improve classification accuracy, as well as the adoption of multi-spectral imaging techniques to detect internal defects that may not be discernible through conventional RGB image processing.

For harvest time prediction, a Random Forest Regression model was implemented to estimate the optimal harvestable age of cucumbers. The workflow encompassed data preparation, feature selection, model training, and evaluation, with performance metrics including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The model achieved an accuracy of 73%, indicating moderate effectiveness in predicting the optimal harvesting time. While the model demonstrated satisfactory predictive capabilities, the observed error rate highlights the need for further refinement. Specifically, incorporating real-time environmental factors such as temperature, humidity, and soil conditions could significantly enhance prediction accuracy.

The performance of all implemented models, the Convolutional Neural Network (CNN) achieved the highest accuracy in maturity classification (68%), the Random Forest Classifier excelled in quality assessment (83%), and the Random Forest Regressor demonstrated moderate success in harvest time prediction (73%). These results underscore the potential of machine learning models to enhance real-time cucumber monitoring, enabling farmers to make data-driven decisions that improve crop quality and optimize harvesting processes.

Despite these promising outcomes, several limitations must be addressed to further advance the system. First, the dataset size was constrained and expanding it with more diverse images captured under varying environmental and growth conditions could improve model generalization. Second, integrating real-time environmental data is crucial for enhancing the accuracy of harvest time predictions, as factors such as temperature and humidity significantly influence cucumber growth. Third, exploring advanced deep learning architectures, such as Vision Transformers (ViTs) or EfficientNet, could improve the performance of maturity classification tasks. Additionally, deploying edge computing solutions using AI-powered hardware like Raspberry Pi or Jetson Nano could enable real-time processing in on-field environments, eliminating the reliance on cloud-based servers.

Future research should focus on developing a scalable and automated system that integrates multi-sensor fusion, combining image analysis with sensor-based environmental data for a more comprehensive monitoring approach. Furthermore, designing a user-friendly mobile application could provide farmers with real-time insights into cucumber maturity, quality assessment, and harvest recommendations. Enhancing data augmentation techniques, such as leveraging Generative Adversarial Networks (GANs) to generate synthetic training images, could also improve model robustness and performance.

However, further optimizations, integration of environmental factors, and deployment strategies are necessary to enhance real-world applicability. The proposed AI-powered monitoring system holds significant potential to advance precision agriculture, reduce manual labor, and ensure optimal yield quality, ultimately benefiting farmers and the broader agricultural industry.

VI. Conclusion

The integration of machine learning, image processing, and real-time monitoring technologies has significantly transformed precision agriculture, particularly in greenhouse cucumber farming. Traditional methods of manual fruit inspection are time-consuming, inconsistent, and inefficient, often leading to quality inconsistencies and economic losses. This research aims to address these challenges by developing an automated, real-time cucumber monitoring system that leverages advanced deep learning techniques, instance segmentation, and time-series forecasting for accurate growth stage classification, defect detection, and harvest time prediction.

The literature review highlights the significant advancements in agricultural automation, demonstrating the effectiveness of models such as CNNs, VGG16, ResNet50, and MobileNetV2 for defect detection and quality assessment. Additionally, instance segmentation models like Mask R-CNN and U-Net have proven highly effective in fruit segmentation, even in complex greenhouse environments. Furthermore, predictive models such as Long Short-Term

Memory (LSTM) networks and Gradient Boosting Machines (GBM) have shown great potential in forecasting optimal harvest times based on sensor-based environmental data. However, existing studies often lack an integrated approach that combines all these elements into a single, cohesive real-time system, representing a significant research gap.

This research proposes a comprehensive cucumber analysis system that not only automates fruit classification and defect detection but also integrates real-time environmental data to enhance harvest planning and yield optimization. By implementing a Grafana-based dashboard, the system will provide farmers with user-friendly, real-time insights, enabling data-driven decision-making and reducing reliance on manual assessments. This integrated approach addresses the limitations of traditional methods and offers a scalable solution for modern precision agriculture.

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