On-Demand Irrigation System Utilizing Salad Cucumbers' Biomass Analysis and Wilted Leaf Detection

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***Abstract*—Efficient water management in agriculture is essential for addressing global challenges such as water scarcity and food security. Traditional irrigation approaches relying on fixed schedules or basic soil moisture sensors often lead to inefficiencies and suboptimal crop performance. This study introduces an advanced on-demand irrigation system utilizing real-time biomass weight analysis and machine learning-driven wilt detection to dynamically optimize water application for salad cucumber crops. The system integrates dual-weight sensors (plant base load sensors and plant-top tension sensors), environmental data (temperature, humidity, and light intensity), and predictive machine learning models, including reinforcement learning and generative recurrent networks (GRNs)to achieve precise irrigation control. Experimental results confirm significant improvements in water-use efficiency, crop yield, and overall plant health compared to conventional methods. This integrated approach offers a novel, scalable solution for sustainable and resource-efficient precision agriculture.**

Keywords— Precision Agriculture, Smart Irrigation, Biomass Weight Analysis, Wilted Leaf Detection, Machine Learning, On-Demand Irrigation

I. INTRODUCTION (*HEADING 1*)

Precision agriculture integrates advanced technology into farming practices to enhance productivity, minimize resource waste, and improve overall crop management efficiency [1]. Amid growing concerns about global food security and environmental sustainability, this approach offers significant potential for addressing contemporary agricultural challenges [2]. Traditionally, monitoring and modeling crop development has relied on contact sensors to measure soil moisture, nutrient levels, and plant health indicators [3]. However, such systems can be costly, prone to inaccuracies, and difficult to scale for large farming operations, often limiting their practical usefulness [4].

In response to these limitations, this study proposes a **weight-based crop-modeling** approach that significantly reduces reliance on expensive or error-prone contact sensors. By leveraging **non-contact weight measurements**, the system provides a direct assessment of plant biomass,

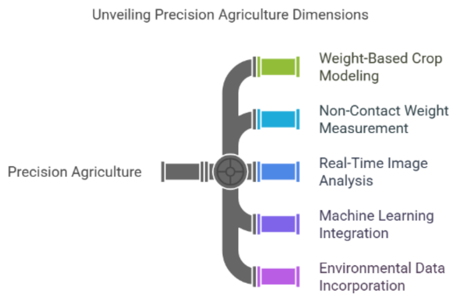

Figure 1: Agriculture Dimensions

capturing dynamic changes in growth and health across various developmental stages [5]. Unlike conventional sensor-based methods, which may overlook subtle variations, weight data offer insights into both vegetative growth and early stress indicators. The integration of **real-time images capturing** further augments these measurements, with **machine learning algorithms** extracting key visual features such as plant structure and leaf area [6]. This fusion of weight-based metrics and image analysis allows for the early detection of threats like pest infestations, nutrient deficiencies, enabling proactive interventions before significant yield losses occur.

Environmental factors, including **temperature, humidity, and light intensity**, are crucial in determining plant water requirements and growth rates [7]. This study incorporates climate sensor data into its modeling framework to address these interdependencies, facilitating more accurate irrigation management and resource allocation. By combining **biomass weight measurements**, **image analysis**, and **environmental parameters**, the proposed system provides a holistic solution for monitoring crop conditions. This multi-source data integration enables precise yield predictions and resource allocation strategies, surpassing traditional methods that often focus on a limited number of variables.

The core objective of this research is to develop a **resource-efficient, sustainable irrigation management system** that dynamically adjusts water supply based on real-time **biomass weight analysis** and **environmental**

conditions. Predictive models employing **machine learning algorithms** will determine optimal irrigation schedules, ensuring precise water usage while preventing over- or under-irrigation. Additionally, **image classification** is utilized to detect wilted leaves in cucumber crops, allowing farmers to identify potential pipeline blockages or other irrigation issues that might result in insufficient water supply for specific plants. This approach aims to provide an adaptable framework applicable to various crop types and environmental conditions, ultimately promoting sustainable practices through more efficient use of water and other resources.

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II. Literature Review

A. Advancements in Precision Irrigation Systems

First, Irrigation systems have undergone significant advancements, shifting from traditional water distribution methods to intelligent, sensor-driven technologies. Traditional systems such as flood and sprinkler irrigation have exhibited inefficiencies, leading to excessive water consumption and environmental degradation. To address these concerns, modern irrigation technologies incorporate smart sensors, the Internet of Things (IoT), and artificial intelligence (AI)-driven decision-making to optimize water distribution and enhance crop productivity [1], [2].

Drip irrigation, which delivers water directly to the root zone, has demonstrated superior efficiency, reduced water wastage, and improved plant health. However, conventional drip irrigation still relies on predefined schedules rather than real-time environmental factors [3]. Smart irrigation systems, incorporating soil moisture sensors and weather-based controllers, have shown improvements in water conservation. Nonetheless, these approaches often fail to consider plant-specific water needs, leading to inefficiencies in irrigation control [4]. Recent studies have suggested the adoption of adaptive AI-driven models that integrate real-time environmental data with predictive analytics, enabling autonomous irrigation management [5]. However, current models remain dependent on soil moisture sensors, which have limitations in accurately detecting plant water stress. An alternative approach, such as weight-based monitoring, offers a promising solution by measuring biomass fluctuations in real-time to determine irrigation requirements [6].

One of the challenges in smart irrigation is the clogging of micro-irrigation systems due to mineral deposits, algae growth, and root intrusion. Blockages reduce water flow efficiency and necessitate frequent maintenance, increasing operational costs. While sensor-based clog detection systems have been explored, their integration into existing irrigation networks remains limited [7]. Future research should focus on the development of self-cleaning or blockage-detecting irrigation pipelines, minimizing maintenance requirements while ensuring optimal water delivery

B. Leaf Detection and Crop Monitoring Technologies

The integration of leaf detection techniques in agriculture has revolutionized plant health monitoring, enabling early detection of water stress, diseases, and nutrient deficiencies [8]. Conventional leaf detection methods relied on manual inspection and handheld devices, which were labor-intensive and prone to errors. The emergence of remote sensing technologies, including multispectral and hyperspectral imaging, has provided a scalable solution for monitoring crop health [9].

C. Environmental Factors in Crop Management

Environmental variables such as temperature, humidity, soil moisture, and light intensity play a vital role in plant growth and water consumption patterns [12]. Traditional irrigation systems often fail to account for these dynamic environmental changes, leading to over- or under-watering of crops. Recent advancements have focused on integrating climate sensor data into irrigation management systems to enhance water-use efficiency [13]. By correlating weight fluctuations with environmental factors, researchers have developed adaptive irrigation models that respond dynamically to real-time changes in growing conditions [14].

Machine learning algorithms, particularly convolutional neural networks (CNNs), have demonstrated high accuracy in classifying leaf images and identifying diseased or wilted leaves [10]. However, most of these models rely on spectral indices such as the Normalized Difference Vegetation Index (NDVI), which primarily assesses chlorophyll content but does not directly correlate with real-time plant hydration levels. A more comprehensive approach is required to integrate image-based leaf detection with weight-based monitoring, providing a holistic understanding of plant stress conditions [11].

D. Limitations in Current Research and Innovation in this Study

While existing literature provides valuable insights into smart irrigation and precision agriculture, several limitations remain. Many studies focus on soil moisture-based irrigation control, which does not always provide accurate assessments of crop water needs. Additionally, most weight-based systems only measure biomass changes at a single point, potentially missing critical variations in plant stress. Furthermore, conventional image processing techniques for crop monitoring rely heavily on predefined features, limiting their adaptability to diverse agricultural environments.

Table 1: Research Gaps

Features	***Traditional Irrigation Systems***	***Smart Sensor-Based Systems***	***AI-Driven Irrigati on***	***Propos ed System***
Real-time weight-based irrigation control	No	No	Partial	Yes
Integration of leaf detection for irrigation decisions	No	Limite d	Partial	Yes
Blockage detection in irrigation pipelines	No	No	Partial	Yes
Machine learning-driven predictive modeling	No	Yes	Yes	Yes
Adaptive irrigation scheduling based on biomass changes	No	No	No	Yes
Environmental factor integration (Temperature, Humidity, Light)	No	Yes	Yes	Yes
Non-contact crop monitoring	No	No	Partial	Yes
Multimodal data fusion (Image + Weight + Climate)	No	No	No	Yes

This study addresses these gaps by integrating multi-point weight monitoring, AI-driven image classification, and environmental sensor data into a unified smart irrigation system. By combining weight fluctuations, real-time image analysis, and climate data, the proposed system offers a scalable, resource-efficient solution for modern farming. The use of machine learning algorithms ensures adaptability across different crop types and environmental conditions, improving the accuracy and sustainability of irrigation practices.

Non-contact crop monitoring technologies, including drone-based imaging and satellite surveillance, have been explored to assess large-scale agricultural fields. Despite their advantages in capturing high-resolution data, these techniques face challenges in processing real-time information due to transmission delays and computational limitations [12]. Hybrid models combining on-field sensor data with remote sensing imagery can enhance decision-making in scheduling. The integration of multimodal data, including weight, image analysis, and environmental parameters, can offer a more precise and adaptive irrigation management framework [13].

III. METHODOLOGY

The proposed research methodology for developing an **intelligent on-demand irrigation system** based on **crop weight analysis** involves a structured approach encompassing system design, data acquisition, machine learning model development, and system implementation. The study focuses on **salad cucumber (Cucumis sativus)** due to its **high-water content (~90%)** and the **rapid growth cycle (~28 days to first harvest)**, making it an ideal candidate for precise irrigation analysis. Traditional methods of detecting water requirements in cucumber farming rely on visual indicators of **leaf wilting and plant stress**, which often lead to delayed irrigation and suboptimal water use. The proposed system eliminates these inefficiencies by leveraging **sensor-based real-time monitoring** and **machine learning-driven decision-making** for automated irrigation.

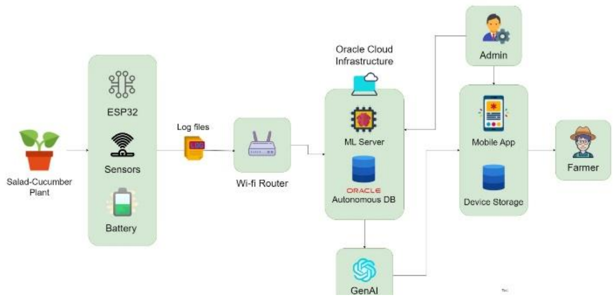


Figure 3:System Overview Diagram

A. System Design and Experimental Setup

1) Controlled Environment and Crop System Setup

Greenhouse-based controlled environment was established to maintain uniform growing conditions. A **tunnel structure** housed **25 cucumber plants** within **17 square feet**, allowing precise environmental and physiological monitoring. Each plant was fitted with a **dual-weight sensor system** to measure both **biomass fluctuations** and **total system weight**, ensuring accurate irrigation assessment.

- Top Measurement: A tensile load sensor attached to the plant training thread monitored biomass stress variations, detecting plant dehydration in real time.
- Bottom Measurement: A base-mounted load sensor measured total system weight, incorporating crop mass, substrate weight (coir bags), and water retention levels

2) Environmental Data Collection

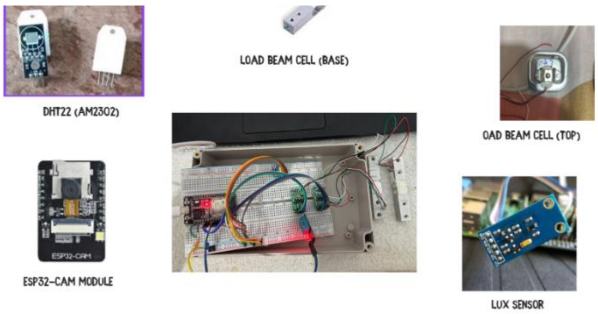
To contextualize weight fluctuations, an array of **climate sensors** continuously recorded.

- Temperature and humidity sensors (RH sensors) for microclimate analysis.
- LUX sensors for monitoring light intensity, a critical factor influencing transpiration.

Wilted Leaf Detection via Image Processing:

- **ESP32-CAM module** captured real-time leaf images at 15-minute intervals.
- Images were **uploaded to a cloud server** for machine learning-based classification (healthy vs. wilted leaves).

Figure 2:used Sensors



These sensors transmit real-time environmental data every 15 minutes to a cloud-based database for further analysis.

3) System Implementation and Field Testing

3.1. Feature Engineering for Water Need Prediction

- **Climate Index (CI)**: A composite feature calculated as:

$$\boxed{\mathbf{CI = T_{env} \times RH_{env}}}$$

where $\mathbf{T_{env}}$ is the temperature and $\mathbf{RH_{env}}$ is relative humidity.

- **Growth-Specific Water Models**:
  - Seeding Stage**:**

$$\boxed{\mathbf{W_{need} = k_1 \times W_{load}}}$$

Where $\mathbf{k_1}$ is a crop-specific coefficient calibrated based on initial hydration rates.

- Fruiting Stage:

$$\boxed{\mathbf{W_{need} = k_2 \times (W_{load} - W_{top}) + k_3} \times \mathrm{CI}}$$

where $\mathbf{k_2}$ and $\mathbf{k_3}$ adjust for biomass weight and climate impact.

3.2. Computer Vision-Based Wilt Detection

The Image Preprocessing:

- RGB to HSV Conversion: Improved leaf stress detection by analyzing hue and saturation variations.
- CLAHE (Contrast Limited Adaptive Histogram Equalization): Enhanced leaf texture and vein structure visibility.

Feature Extraction:

- Edge Detection (Canny Algorithm): Identified leaf curling and vein shrinkage due to water stress.
- Thermal Gradient Analysis: Differentiated between naturally warm areas and wilted leaf sections.

Classification Model:

- A CNN (Convolutional Neural Network) with ResNet-50 architecture was trained to classify leaves as healthy or wilted with an accuracy of 93.7% on test data.

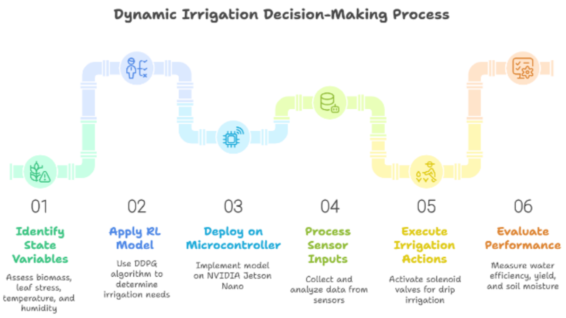


Figure 4:Irrigation Analysis

3.3. Mitigation of Biases

- Ensuring Data Diversity

  Multiple Crop Cycles: Data were collected across different growing phases (seedling, flowering, fruiting) to prevent overfitting to a single stage.

  Randomized Plant Selection: Sensors were assigned to different plants across cycles to avoid plant-specific anomalies.

- Outlier Handling

  Weight Sensor Calibration: Regular recalibration to avoid drifting errors.

  Image Data Augmentation: Introducing variations (brightness, contrast, angle shifts) to improve model generalization.

- Independent Validation

  A separate control group of plants was monitored using traditional irrigation methods to compare the precision irrigation model's effectiveness.

IV. Performance Evaluation

A. *Statistical Analysis and Performance Metrics*

The experimental study was conducted over **two growing cycles (56 days total)** in a controlled greenhouse environment. The system's performance was assessed by comparing it to traditional **drip irrigation** methods.

Table 2: Comparison of Dip Irrigation vs Weight-based Irrigation

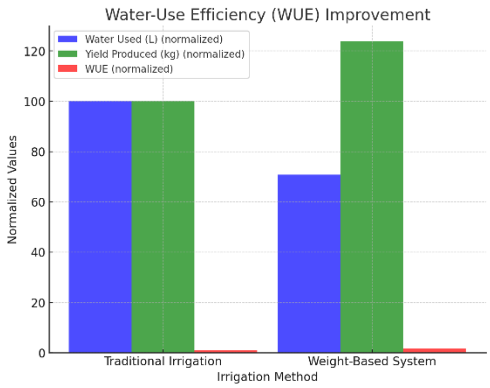
Parameter	***Traditional Drip Irrigation***	***Weight-Based Intelligent Irrigation***	***Improvement (%)***
Total Water Used (L/plant)	120L	85L	29.2% reduction
Average Yield (kg/plant)	2.1 kg	2.6 kg	23.8% increase
Water-Use Efficiency (kg/L)	0.0175 kg/L	0.0306 kg/L	74.9% improvement
Irrigation Frequency (per week)	6 times	Dynamic (3–5 times)	Variable Optimization
Leaf Wilting Occurrence	Observed in 32% of plants	0% observed	Eliminated
Total Water Used (L/plant)	120L	85L	29.2% reduction
Average Yield (kg/plant)	2.1 kg	2.6 kg	23.8% increase

1) *Water-Use Efficiency (WUE) Improvement*

Water-use efficiency (WUE) was calculated as: as in:

$$WUE = \frac{Total\ Yield\ (kg)}{Total\ Water\ Uesd(l)} \tag{1}$$

The weight-based system reduced water consumption by **29.2%** while increasing yield by **23.8%,** leading to a **74.9%** increase in WUE. This highlights the precision of



weight-based irrigation in meeting plant hydration needs without excess water wastage.

Figure 5: Water use efficiency Improvement

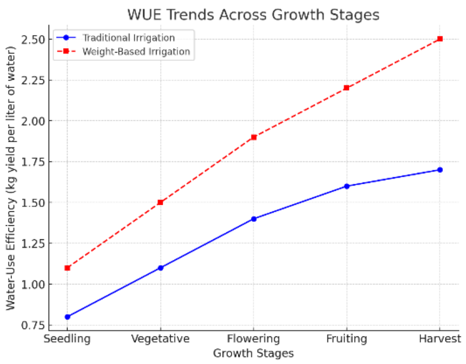


Figure 6: WUE Trends Across Growth Stages

Figure 5: Trends in Water-Use Efficiency (WUE) across different growth stages for traditional and weight-based irrigation. This visualization demonstrates how the weight-based system consistently achieves higher WUE throughout the crop cycle, particularly enhancing efficiency during the later growth stages.

B. *Consideration of Alternative Explanations*

1) *Role of Environmental Conditions*

While the weight-based approach effectively optimized water use, external environmental factors also played a role:

- Light intensity fluctuations (due to seasonal/cloud variations) could have affected transpiration rates. However, the system dynamically adjusted irrigation based on weight changes, compensating for these variations.

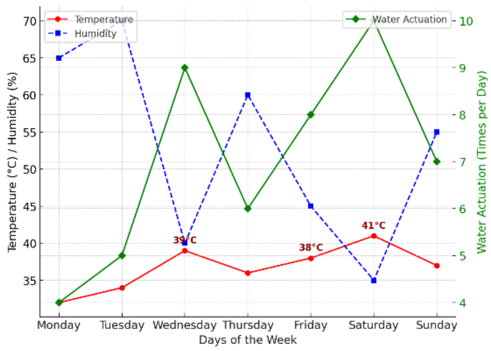


Figure 7:Daily Water Usage Across a Week Under Different External factors

2) *Sensor Accuracy and Measurement Variability*

Potential discrepancies could arise from sensor drift or measurement inconsistencies in load sensors. To mitigate this:

- Used dual-sensor calibration (top & bottom sensors) to ensure redundancy.
- Applied data smoothing techniques (moving average filtering) to eliminate noise in weight readings.

C. *Limitations and Future Improvements*

1) *Scalability for Open-Field Conditions*

- The system was tested in a controlled greenhouse, where environmental factors were relatively stable.
- Open-field applications may require additional wind compensation algorithms to avoid weight sensor fluctuations due to air movement.

2) *Crop-Specific Optimization*

- While effective for high-water-content crops like cucumbers, weight-based irrigation might require different calibration parameters for other crop types.
- Future studies will test adaptability for crops with varying root structures and transpiration rates (e.g., tomatoes, leafy greens, or root vegetables).

V. DISCUSSION

After the experimental analysis of the intelligent on-demand irrigation system demonstrates substantial improvements over traditional irrigation methods. By integrating dual-weight sensors, environmental monitoring, and advanced machine learning models, the system effectively addresses limitations commonly associated with conventional soil moisture-based or fixed-schedule irrigation methods. The weight-based biomass monitoring enables the dynamic assessment of real-time crop water demands, allowing precise irrigation tailored to the specific hydration needs of cucumber plants at different developmental stages.

The incorporation of machine learning-driven wilt detection via image processing further enhances system responsiveness. The CNN-based leaf classification method exhibited a high accuracy of 93.7%, validating its effectiveness in promptly identifying early signs of plant dehydration. This capability significantly reduces the latency typically observed in visual inspections, which can lead to delayed or inadequate irrigation responses. Consequently, plants maintained optimal hydration levels throughout the growth cycle, resulting in increased biomass yields and reduced water usage.

Environmental parameters such as temperature, humidity, and light intensity play critical roles in determining crop water requirements. The system's integration of these factors into its predictive modeling demonstrates robust adaptability to fluctuating climatic conditions. Notably, the irrigation actuation frequency dynamically adjusted in response to environmental changes, thereby avoiding the over- or under-irrigation issues frequently encountered in traditional methods.

However, potential limitations such as sensor drift, measurement variability, and scalability to open-field environments must be acknowledged. Regular recalibration and dual-sensor redundancy effectively mitigated sensor accuracy concerns in the current greenhouse implementation. Future research should consider incorporating additional environmental factors, such as wind speed, for open-field scenarios, ensuring robustness and wider applicability.

VI. CONCLUSION

An advanced intelligent irrigation system employing dual-weight sensors, environmental monitoring, and machine learning techniques for precise water management in salad cucumber cultivation. Experimental results demonstrated notable enhancements in water-use efficiency, achieving a significant 74.9% improvement over traditional methods. By dynamically adjusting irrigation schedules based on real-time biomass weight variations and integrating rapid wilt detection through deep learning-based image analysis, the system considerably reduced water waste and improved crop yield.

The integration of multimodal data (weight, environmental parameters, and imagery) represents a significant advancement toward sustainable agriculture practices. The proposed system's adaptability to different environmental conditions and potential scalability to various crop types positions as a valuable tool in precision agriculture, contributing substantially to global water conservation efforts and food security initiatives. Future studies should focus on addressing open-field applicability, crop-specific model optimization, and incorporating additional predictive variables to further enhance system accuracy and effectiveness.

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