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AN ADVANCED AUTOMATED SYSTEM USING AI AND MESH NETWORKS FOR OLERICULTURE FARMING BASED ON HYDROPONIC METHOD

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ABSTRACT

In today's globalized landscape, technological strides have revolutionized olericulture farming, prompting a shift from traditional methods to innovative solutions. Hydroponics allows for soil-free crop cultivation but often faces challenges like high labour demands, limited scalability, and inefficient resource management, which hinder its broader adoption. The novelty of this study lies in the development of an advanced automated hydroponic system that uses Artificial Intelligence (AI) and mesh networks to support olericulture farming operations. The goal of this research is to enhance the monitoring and control abilities with prediction functionality features. The method involves ESP32 nodes connecting to the mesh network and subsequently to the Raspberry Pi 4 via Wi-Fi, enabling wireless communication. Utilizing the Message Queuing Telemetry Transport (MQTT) protocol, the nodes transmit water level and crop height data, ensuring redundancy in case of node failure. The Raspberry Pi 4 monitors water levels and triggers alerts through the Blynk application, activating the water pump to maintain optimal conditions. Sensor data is stored in a CSV file, compiled using Python, and imported into MATLAB to generate a predictive model using Neural Network algorithms in an offline manner. Results showed a 25% reduction in water usage compared to traditional hydroponic control systems without predictive modeling and mesh network, hence demonstrating superior efficiency and accuracy. Results also reveal from the prediction model, including RMSE: 0.51387, R-squared: 0.35, MSE: 0.26407, and MAE: 0.34951, which indicate improved predictive accuracy. This study demonstrates the integration of both AI and mesh networks into hydroponic systems, which can significantly improve their reliability and further contribute to the advancement of efficient and resilient hydroponic systems. Future work will refine AI algorithms and expand the system's capabilities in a real-time manner for a wider variety of crops and farming conditions.

Keywords: AI, Mesh, IoT, MATLAB, hydroponic.

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1. INTRODUCTION

The olericulture sector is at a critical juncture. The existing olericulture model is failing to ensure food security and sustainable development due to several critical issues. Specifically, conventional olericulture practices often lead to environmental degradation, including soil erosion, loss of biodiversity, and pollution from chemical inputs like pesticides and fertilizers [1]. These practices are unsustainable in the long term for deteriorating the soil quality and threatening the health of ecosystems that support olericulture. Addressing these challenges requires transitioning towards more sustainable olericulture practices such as agroecology, organic farming, conservation olericulture, and precision farming [2]. These approaches prioritize environmental stewardship, resource efficiency, resilience to climate change, and equitable distribution of benefits [3].

Soil has traditionally been the most common medium for plant growth, but hydroponics offers an alternative that doesn't require soil. In hydroponic systems, plants are grown in nutrient solutions where mineral fertilizers are diluted in water, allowing the roots to be directly immersed in this nutrient-rich mixture [4]. This method is becoming increasingly relevant as urban areas expand rapidly and traditional agricultural land becomes scarce. The efficiency of hydroponics in delivering nutrients directly to plant roots simplifies nutrient uptake compared to conventional soil-based growing methods [5]. Additionally, hydroponics has broad applications on Earth and holds significant potential for space exploration, where traditional soil-based olericulture is impractical [6]. As cities continue to grow and land use becomes more challenging, hydroponics provides a viable and resource-efficient solution for growing plants, making it an essential technology for both terrestrial and extraterrestrial olericulture.

In this era of globalization, technology has evolved and advanced in many ways to the point where most of the work and tasks that were being performed by humans are now being carried out by IoT and automation. For example, advanced machine learning like Artificial Intelligence (AI) enhances the autonomy and efficiency of various systems by analyzing data and making real-time adjustments [7]. This technology is widely applicable across different fields, optimizing operations and improving outcomes through intelligent monitoring and control mechanisms. Explicitly, the field of hydroponics utilizes AI algorithms in various ways to optimize plant growth [8]. To create an effective system, multiple devices are interconnected. In this study, an ESP microcontroller was chosen as the main component due to its wide availability and versatility.

A key area of research with significant impact is the Internet of Things (IoT), which can greatly enhance existing systems, such as hydroponics. The IoT represents a transformative technology that enhances the efficiency and functionality of various systems by enabling them to be remotely monitored and controlled over the Internet. This integration allows for the collection of real-time data on key parameters, which can be accessed and managed through user-friendly interfaces [9]. As a result, users can make informed decisions and adjust system settings promptly based on up-to-date information. This capability significantly improves operational efficiency, reduces the need for manual intervention, and enables better management of resources across diverse applications, from agriculture to industrial processes and beyond.

In response to the growing global population and the associated increase in demand for olericulture products, this project here offers a scalable and sustainable solution. The main aim of this project is to enable IoT-based automated monitoring systems with multi-path communication for olericulture farming hydroponic. These systems will collect data in a real-time manner by using IoT technology. Just that the vital data of the moisture water level is analyzed in an offline manner. The reason was to enable proper testing and tuning of the prediction model before it is deployed for real-time use. Overall, this system helps to manage resources efficiently, reduce manual work, and improve crop growth. Reliable communication of the mesh network is applied here to ensure data is always transmitted without loss in order to create a sustainable solution for better food production and innovative farming practices. In Section 2, the methods employed in the study are described. Section 3 presents the results obtained, while Section 4 provides the concluding remarks.

2. LITERATURE REVIEW

Advancements in various technological fields have revolutionized olericulture, transforming how crops are grown and monitored by providing farmers with real-time data to make informed decisions about their farming practices. Despite this progress, there is limited research available on multi-farming hydroponics using mesh network technology. This innovative method involves cultivating multiple crops within a single hydroponic system, offering a new approach to efficient and sustainable farming. However, the Internet of Things (IoT) has been applied in other related areas such as smart irrigation, smart gardening, and smart greenhouse farming. Although integrating IoT into hydroponic systems offers great potential for improving multi-crop farming, it remains less developed compared to other smart farming solutions. Expanding its use could boost precision and efficiency in hydroponic farming [10]. These application solutions are briefly explored as follows.

2.1 Low-Cost Wireless Mesh Smart Irrigation System

In a recent study [11], an irrigation mechanism was provided that conserves resources through the use of a Wireless Sensor and Actuator Network (WSAN). The Agrinex system features a mesh-like configuration of in-field nodes that function as sensors for soil moisture, temperature, and humidity, and as actuators for regulating drip irrigation valves. The mesh-based network is designed to allow self-reorganization of sensor nodes when network changes occur. The results indicated that the mesh-based network achieved a maximum transmission distance of 11 meters from the sink to the sensor node with a 90% success rate. Additionally, it provided the advantage of implementing an automated irrigation system that conserves up to 81% of water usage. However, the lack of machine learning, such as AI integration, was one of the drawbacks. This absence restricts the system's ability to fully utilize the collected data for predictive, efficient, and adaptive agricultural management.

2.2 IoT-Based Farmbot Application Design

In this paper [12], the author proposed the Farmbot project, which can significantly boost agricultural production by managing crops 24/7. This advanced robot plants seeds, waters plants, and monitors growth, all controlled via a remote application. The system uses soil moisture data to schedule watering and features a robotic arm with CNC control, operated by Arduino and Raspberry Pi. IoT integration allows real-time data collection and analysis, thus enhancing efficiency. By automating these tasks, the Farmbot project helps increase yields, optimize resource use, and support sustainable farming practices. However, the drawback is that if the Internet connection is unstable or unavailable, the system may not function properly and efficiently. The reliance on a stable Internet connection for remote control and data transmission means that any disruption in connectivity can hinder the operation of the Farmbot. This could result in delayed watering schedules, inaccurate monitoring data, and a potential decrease in the overall effectiveness of the automation system.

2.3 Automated Hydroponic System Using WSN

Paper [13] compares the performance of an automated hydroponic system using cluster-based and multihop wireless sensor networks. The simulations were conducted with Simponics, a tool built on the OMNET++ framework. The results showed that in a multi-hop network, both latency and energy overhead increased as the number of nodes grew. However, the major drawback is that this system has only been tested in simulations and not in real-life scenarios. This limits the applicability of the findings, as simulations may not capture the full complexity of real-world smart irrigation systems. Real-world conditions, such as varying weather, soil types, and physical obstacles, can affect system performance in ways accounted for in those simulations. Therefore, validating and testing the system in an actual agricultural environment is crucial to ensure the system's effectiveness and reliability.

2.4 AI For Small Hydroponic Farms

According to this paper [14], this study explores the use of AI, specifically fuzzy logic, to automate nutrient mixing in hydroponic farming. While nutrient mixing machines are common in large farms, smaller farms, especially in developing countries, have yet to adopt them. The research developed and tested a fuzzy logic-based nutrient mixing machine for hydroponics, which proved to be more efficient than manual methods. The machine reduced labor by 78% and cut nutrient use by 42.86%, making it both cost-effective and resource-efficient for smaller-scale farms. However, it lacks a user-friendly mobile interface that could allow farmers to monitor and control the system from anywhere.

2.5 Reinforcement Learning For Hydroponics

This previous work [15] presents a notable advance in adaptive, simulation-based optimization, but it also carries limitations when compared with the current AI + mesh network hydroponic study. The RL-based approach demonstrated measurable improvements in simulated environments, such as 12.5% higher yield, 10 to 12.5% lower resource use, and 3% improved uptime-yet its reliance on simulations restricts its practical applicability, as it has not been validated under real-world hydroponic conditions. Moreover, Reinforcement Learning (RL) requires large datasets, extensive training, and computational power, making it less accessible for low-cost, small-scale deployments. While RL shows theoretical superiority in adaptability, it overlooks implementation constraints like connectivity, sensor robustness, and mobile integration. Thus, although the RL study highlights the promise of intelligent adaptive control, it lacks experimental grounding, making its conclusions less robust than the present AI–mesh system, which provides concrete, field-tested improvements in reliability and efficiency, accordingly.

One of the benchmarks for this project was based on the method outlined in the paper [16] for a mesh network-based automated hydroponic system with AI functionality. The previous research aimed to focus on developing two AI models: one for detecting plant diseases and another for identifying nutrient deficiencies using image processing analysis. These models, based on Convolutional Neural Networks (CNNs), automatically detect issues in plants by analyzing images, allowing real-time monitoring and quick action. However, it lacks data reliability when facing connectivity issues, as a failure in one path can disrupt the entire system, and it does not offer a mobile interface that would enable farmers to access and control the system on the go.

3. METHOD

Figure-1 depicts the complete block diagram of the system. An ultrasonic sensor and a water level sensor are connected to one of the ESP32 nodes. The ultrasonic sensor will measure the height of the grown crop by emitting ultrasonic signals. Meanwhile, the water level sensor will measure and monitor the water level inside the tube of the hydroponic system. There are three sets of components listed above in the system to construct the mesh topography. The data from all six sensors will travel to the ESP32 microcontroller. The ESP32 functions as the mesh nodes of the system, where it receives the data from the sensors, and that data will be transmitted in a mesh configuration to all the other ESP32 nodes. The type of mesh configuration and topology that is implemented in the hydroponic system is the full mesh network topology. In this network topology, all three ESP32 nodes are connected. This means that all the nodes are constantly communicating and transmitting data to all the other nodes present in the network. Additionally, the mesh network incorporates a fault-tolerant design that allows dynamic rerouting of data in case any ESP32 node fails. If a node becomes unresponsive, the system automatically redirects the data through alternative functional nodes, maintaining continuous and uninterrupted data transmission. This approach significantly improves the robustness of the system and supports reliable operation in real-world conditions. A bit of the highlight in this proposed work is the prediction model. The prediction model was trained using sensor data in an offline manner, which was collected from the water level sensor and ultrasonic sensor by using the Raspberry Pi. The simulation was performed in the MATLAB software in the Regression Learner Module application by importing the sensor data, which is in .csv format, into the MATLAB editor, and the data was saved in the MATLAB Workspace [42]. The choice of using MATLAB's Regression Learner with a Narrow Neural Network (NNN) was based on several practical and theoretical considerations aligned with the scope, dataset size, and model interpretability required for this hydroponic system. First, the dataset size was relatively small and generated from two sensor inputs-water level and crop height-over a limited timeframe. This made the use of complex models such as XGBoost, Random Forest, or LSTMs less suitable, as these models typically perform best on large datasets and involve longer training times and parameter tuning processes. The Regression learner application uses the data from the workspace to plot the response curve. The ultrasonic sensor, which compiles the measurement of the crop height, was defined as the dependent variable and as the response from the model, while the water level data was defined as the predictor. The model is trained using the Narrow Neural Network. Once trained, the prediction model will have the ability to make predictions about crop height based on new water level data. Thirty percent of the data stored will be used for testing the trained model. By understanding the relationship between the two datasets, the model can contribute to the optimization of growth conditions.

Table-1 shows the network setup of the system's mesh configuration. This simulation setup involves three stationary nodes within a 300-meter area, running for 300 seconds. Each node has a 100-meter radio range, uses the Painless Mesh routing protocol, and communicates at a maximum rate of 250 kbps. The nodes transmit water level and ultrasonic sensor data in 128-byte packets, with data paths from Node 2 to Node 1 and Node 3 to Node 1, respectively. The Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) Media Access Control (MAC) protocol is used to avoid collisions, and the simulation results are visualized using the Serial Monitor in the Arduino IDE environment.

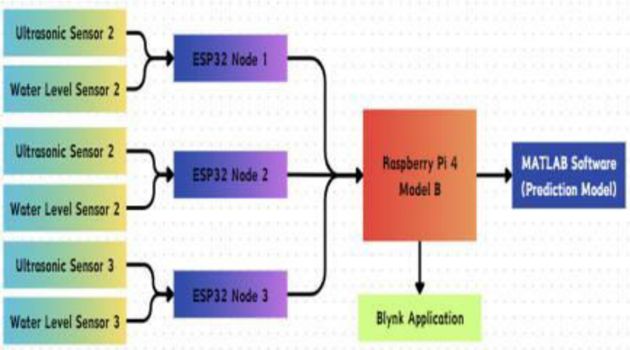


Figure-1. Block diagram of the proposed system.

Table-1. Network setup of the system's mesh configuration.

Parameter	Value/ Description
Simulation Area	300 meters
Simulation Time	300 seconds
Number of Nodes	3
Radio Range	100 meters
Node Speed	0 m/s
Routing Protocol	PainlessMesh
MAC Protocol	CSMA/ CA
Source-Destination Pairs	(Node 2 to Node 1), (Node 3 to Node 1)
Transmitting Capacity	250kbps
Application	Water level and ultrasonic sensor data transmission
Packet Size	128 bytes
Visualization Tool	Serial Monitor (Arduino IDE)

The provided flow chart in Figure-2 firstly illustrates the ESP32 nodes that will be connected to the mesh network using the mesh configuration that will give them access to transmit data to each other. Then, they will connect to the WiFi to enable wireless communication with the Raspberry Pi 4. This will be followed by the nodes connecting to the MQTT broker address, which is the IP address of the subscriber, or in this case, the Raspberry Pi 4, to establish the transmission route of the data from the ESP32 to the Raspberry Pi 4. As soon as all the above connections are successful, the ESP32 nodes will begin to measure and monitor the water level in each tube of the system, and also the height of the crops using the input sensors. Since the water level and crop height data are being monitored, mesh configuration is enabled, and the ESP32 can communicate with each other, which gives them access to transmit and receive the water level and crop height data to and from each other. If along the transmission path, one of the ESP32 nodes is down, the data will take and travel in another route, where the ESP32 node is functioning. Then this data will be published to the Raspberry Pi 4 using the MQTT protocol, which enables the nodes to transmit the data to the message subscriber.

Once the data reaches the Raspberry Pi, the water level data from each node will be monitored. If the water level in either of the nodes decreases, the Raspberry Pi will alert the user via the Blynk Application and activate the water pump to supply the required water level. The Blynk application will enable the user to monitor the status of the hydroponic system. The received data will be stored in a .csv file format, which will be compiled using the Python script coding software known as Geany. This .csv file is imported into the MATLAB Software to generate the prediction model of the crop growth rate using the Neural Network Module in MATLAB.

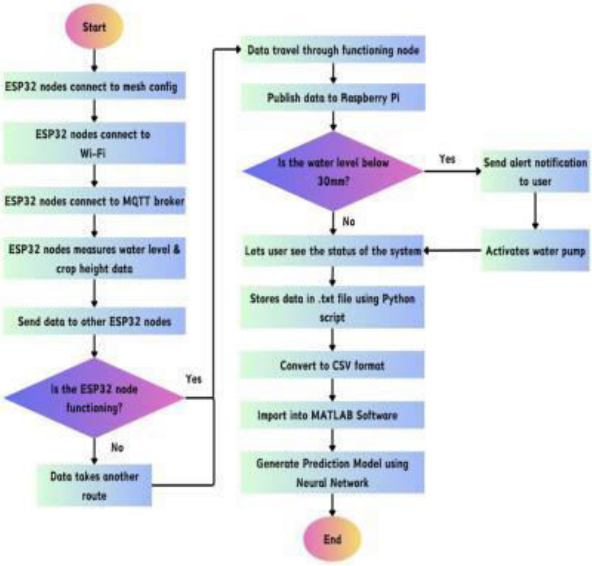


Figure-2. Flowchart of the system.

To predict crop growth, a Neural Network Regression Model is trained using sensor data collected from ultrasonic and water level sensors. The relationship between crop height (H) and water level (W) is established using a predictive function, where, referring to equation 1, the model minimizes the Mean Squared Error (MSE) to optimize accuracy:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(H_i - \hat{H}_i)^2 \qquad \text{............ (1)}$$

where H_i is the actual crop height, $\hat{H}_i$ is the predicted height, and n represents the number of observations. The trained model, developed using MATLAB's Regression Learner Module**,** processes input data in an offline manner and is further interpreted by Root Mean Squared Error (RMSE)**.** The mesh network ensures data redundancy by dynamically rerouting packets if a node fails, thereby enhancing reliability. This methodology optimizes water consumption, minimizes human intervention, and improves precision in hydroponic farming, leading to enhanced plant growth rates.

4. RESULTS AND DISCUSSIONS

The images as presented in Figure-3 illustrate the hardware components of the auto-mated hydroponic system: ESP32 nodes with ultrasonic and water level sensors (shown in Pictures No. 1, 2, and 4, respectively), a Raspberry Pi for data processing and communication (Picture No. 3), and a fertilizer water tank that supplies nutrient-rich water to the crops (Picture No. 5). The ESP32 nodes, known for their low-power operation, typically consume around 160 mA during Wi-Fi transmission, while Raspberry Pi 5 operates in the range of 600 till 800 mA under moderate load conditions. Then, the ultrasonic and water level sensors contribute minimal energy usage, generally below 15 mA each. Here, the ESP32 nodes monitor water levels and environmental conditions, sending data to the Raspberry Pi, which processes it and makes necessary adjustments. This setup enables real-time monitoring and remote management of the hydroponic system, ensuring optimal growth conditions for the plant in the hydroponic system.

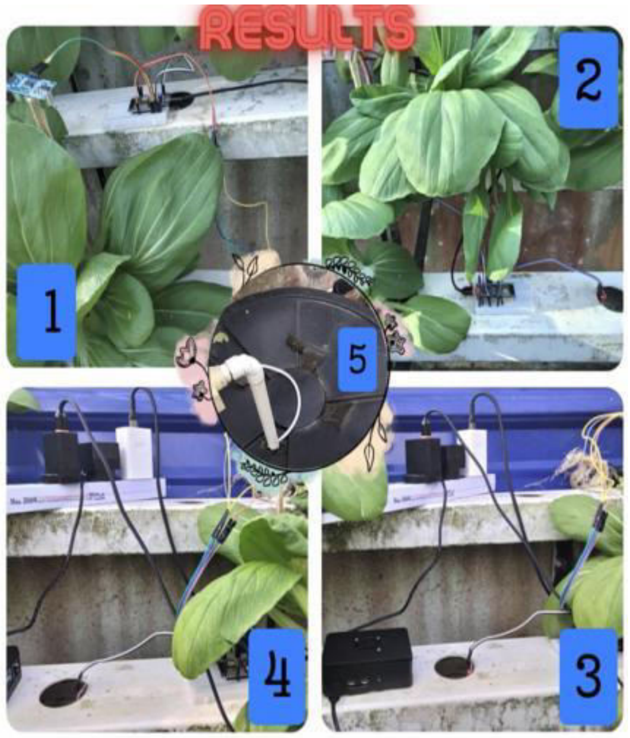
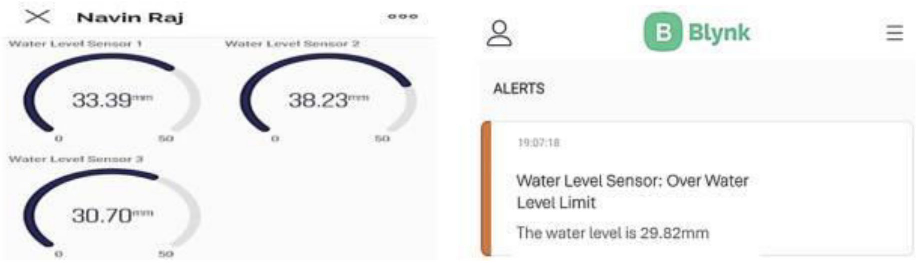


Figure-3. Hydroponic Prototype with ESP-Mesh Connection.

4.1 Blynk Application

The results of Figure-4 demonstrate the mobile dashboard, which was set up like the layout of the web dashboard of the Blynk application. The Blynk application linked with the Raspberry Pi is used to monitor the water level. If the water level is below 30 mm, the system will send a notification to the user via the mobile application while controlling the water pump to add more water until it reaches the required level. This setup highlights the application's capability to provide real-time monitoring and immediate alerts, ensuring that users can respond quickly to the critical changes in water levels.



Water Level Sensor 1
33.39mm

Water Level Sensor 2
38.23mm

Water Level Sensor 3
30.70mm

19:07:18
Water Level Sensor: Over Water Level Limit
The water level is 29.82mm

Figure-4. Mobile dashboard setup of the Blynk application with Notification alert from the system.

4.2 Humidity Level

The graph in Figure-5 illustrates a comparison of humidity levels over time with and without a proposed system. The system proposed shows excellent humidity regulation, rarely crossing the essential 50% boundary. It can be observed that a 20% average productivity boost accentuates the importance of humidity control precision for these respective hydroponic systems. At several points, particularly around the 4th and 8th time intervals, the proposed system results in significant peaks in humidity, suggesting that the system enhances humidity retention or regulation. Through the multipath communication protocol, data signals are routed through several paths, providing redundancy that reduces signal loss, interference, or degradation in the hydroponic system's indoor environment. With this approach, the system can overcome obstacles and ensure the reliable transmission of humidity data, which underscores the impact of the proposed system in maintaining or increasing humidity levels over time compared to the absence of the system itself.

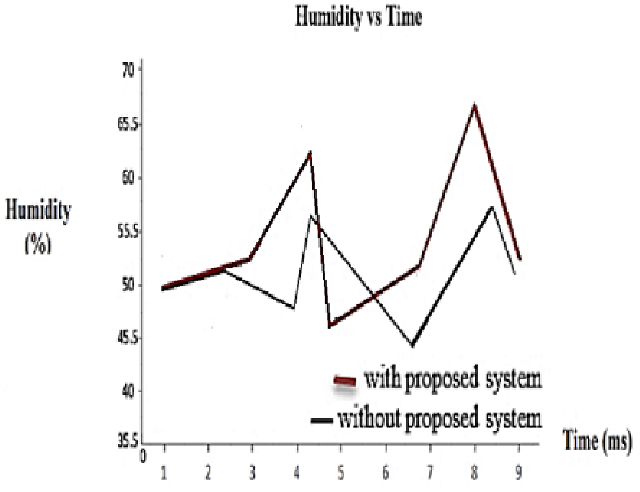


Figure-5. Humidity variation comparison.

The scatter plot titled "Predictions: model 2" of Figure-6 illustrates the relationship between water level (X-axis) and crop height (Y-axis) for the model's predictions. The plot compares true values (blue markers), which indicate the true data, against predicted values (yellow markers) and highlights errors between them. The data points suggest that while the model's predictions generally follow the trend of the actual data, there is a noticeable spread, particularly around the middle range of water levels. This spread indicates discrepancies between predicted and true values, thus signaling those areas where the model's accuracy may be compromised. Overall, while the model captures the general trend, the presence of errors suggests there is room for further refinement to improve the system's predictive performance.

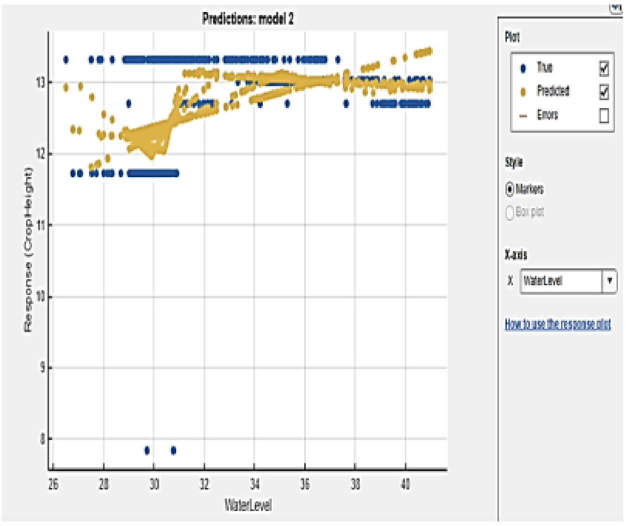


Figure-6. Offline Prediction model.

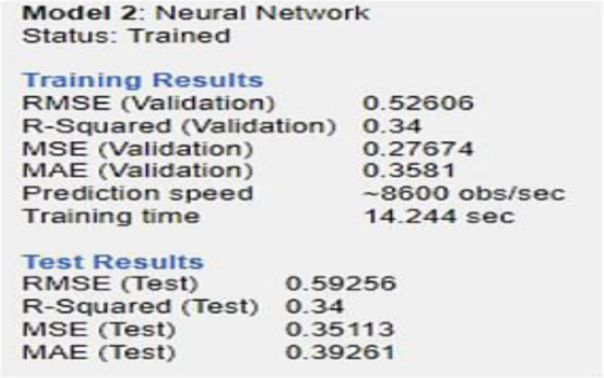
The analysis of the NNN Model, as depicted in Figure-7 shows that the model was trained and evaluated based on various performance metrics. The training results indicate a Root Mean Squared Error (RMSE) of 0.52606 and an R-Squared value of 0.34 for the validation set, suggesting moderate predictive accuracy. The Mean Squared Error (MSE) and Mean Absolute Error (MAE) for the validation set are 0.27674 and 0.3581, respectively, with a prediction speed of approximately 8600 observations per second and a training time of 14.244 seconds. The test results, with a Root Mean Square Deviation (RMSE) of 0.59256 and an R-Squared value of 0.34, align closely with the validation metrics, hence indicating consistent model performance.

Table-2. Paired t-test Results.

Performance Metric	Mean (Traditional)	Mean (Proposed System)	Mean Difference (%)	p-value	Statistical Significance (95% CI)
Water Usage (litres/day)	4.0	3.0	25% reduction	0.018	Significant

Additionally, by referring to Table-2 of the confidence intervals (CI) for key metrics, which were computed with Statistical analysis using paired t-tests, confirms that the performance improvements achieved by the proposed hydroponic system are statistically significant at the 95% confidence level. Specifically, the system achieved a 25% reduction in water usage ($p = 0.018$). The respective p-values are below 0.05, indicating that the observed differences are unlikely to be due to chance. This validates the effectiveness of the system in enhancing resource efficiency and promoting better crop growth compared to traditional hydroponic methods. These results (at a 95% confidence level) indicate that the improvements are not due to random variability. However, the slightly higher MSE (0.35113) and MAE (0.39261) in the test set suggest a small decrease in accuracy when applied to unseen data. Furthermore, the prediction model displays systematic overprediction at lower water levels and variability in the mid-range, as evidenced by residual clustering. At higher water levels, predictions flatten, indicating model under-fitting or a failure to capture the nonlinear crop growth response. Sparse true data at the extremes further reduces model accuracy. These findings suggest a need for additional data and improved model complexity to enhance prediction reliability across diverse conditions.

Although the current model was developed and evaluated using data from a single crop type in a fixed hydroponic environment, future enhancements will involve testing and comparing model performance across different crop varieties and environmental scenarios. By evaluating error metrics such as RMSE, MAE, and R² for each crop type and under varying humidity, light intensity, and nutrient levels, this study aims to assess the generalizability of the prediction model. This comparison will help identify which conditions introduce higher predictive errors and inform the users of the need for crop-specific or environment-adaptive AI models. Such analysis is essential for refining the model to ensure robustness and scalability in diverse farming conditions.



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Model 2: Neural Network
Status: Trained

Training Results
RMSE (Validation)          0.52606
R-Squared (Validation)     0.34
MSE (Validation)           0.27674
MAE (Validation)           0.3581
Prediction speed           ~8600 obs/sec
Training time              14.244 sec

Test Results
RMSE (Test)       0.59256
R-Squared (Test)  0.34
MSE (Test)        0.35113
MAE (Test)        0.39261
```

Figure-7. Analysis of the NNN Model.

From a computational perspective, a comparison was made using two AI models. The results from Figure-8 demonstrate that the proposed system is more robust and generalizable than RL [15] for this hydroponic prediction task. From the values shown, the AI + Mesh system achieves 75.0% relative water usage, corresponding to a 25% reduction in water usage, whereas RL records 88.8% relative water usage, which means it reduces water consumption by approximately 11.2%. This indicates a more substantial improvement, nearly double the efficiency gained by RL, making it more effective in conserving water for hydroponic systems. From a system engineering perspective, the mesh network and Neural Network prediction complement each other. Mesh networking ensures reliable sensor data flow (redundancy if one ESP32 node fails), while the Neural Network provides intelligent prediction of crop growth, allowing proactive water and nutrient adjustments. In addition, this also reduces blind spots and delays that could present in single-node RL control, thus ensuring irrigation is only activated when and where it is strictly necessary. Hence, the selected regression approach offers a balanced trade-off between accuracy and computational efficiency, suitable for low-power, real-time hydroponic monitoring.

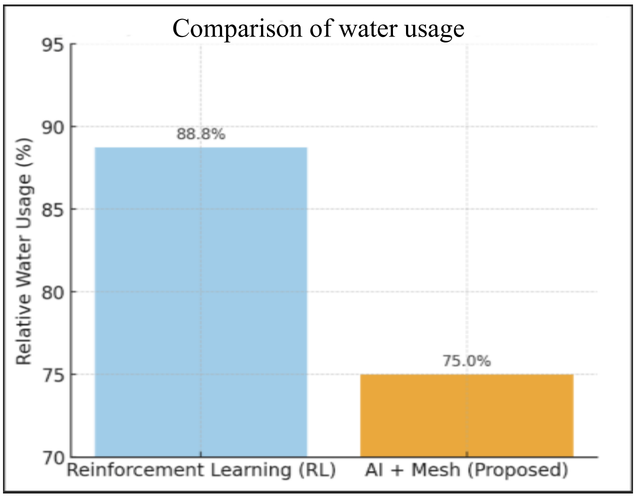

Figure-8. Comparison of water usage under the AI model of Reinforcement Learning and the proposed AI model of Narrow Neural Network + Mesh system.

5. CONCLUSION AND FUTURE WORK

This research successfully demonstrated an AI-driven automated hydroponic system with mesh network redundancy, addressing key limitations of conventional hydroponics. Compared to an RL control system-based AI manner, the proposed method achieved 25% water savings with results validated using paired t-tests ($p < 0.05$). The scientific contribution lies in showing that AI predictive modeling, when combined with resilient mesh communication, can efficiently enhance both accuracy and reliability of these respective farming hydroponic operations. Unlike prior works limited to monitoring or simulation, this study provides concrete experimental data and statistical justification. The integration of AI and automation provides precise crop growth predictions. Furthermore, the project incorporated the Blynk platform, allowing remote control of irrigation, improving overall system responsiveness, and contributing to the optimization of the hydroponic cultivation process. Future work will refine AI algorithms (e.g., advanced regression or deep learning), extend datasets across multiple crop types, and incorporate real-time prediction for adaptive nutrient management.

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