Intelligent Disease Prediction in Hydroponic Systems Using Machine Learning

Prof.Tom Kurian
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
tomkurian@amaljyothi.ac.in

Ektha P S
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
ekthaps2024@cs.ajce.in

Chethana Raj T
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
chethanarajt2024@cs.ajce.in

Diona Joseph
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
dionajoseph2024@cs.ajce.in

Annu Mary Abraham
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
annumaryabraham2024@cs.ajce.in

***Abstract*—Hydroponics is the soil-less agriculture farming, which consumes less water and other resources as compared to the traditional soil-based agriculture systems. However, mon- itoring hydroponics farming is a challenging task due to the simultaneous supervising of numerous parameters and plant diagnosis system. Therefore, this article focuses on the imple- mentation of web application integrated machine learning-based smart hydroponics expert system. The proposed project with IoT consists of three phases, where the first phase implements hardware environment equipped with real-time sensors such as pH, temperature, water level, and camera module which are con- trolled by Raspberry Pi processor. The second phase implements the CNN Model for plant disease detection and classification and the system includes a chat bot for user interaction, addressing plant-related questions and providing details about any detected diseases. In the third phase, farmers can monitor the real-time sensor data using AWS TwinMaker and plant leaf disease status using an web-based application. In this manner, the farmer can continuously track the status of his field using the mobile app. Through this innovative approach, hydroponic farming can become more efficient, sustainable, and ultimately contribute to addressing global food security challenges.**

***Index Terms*—Digital Twin, CNN, Raspberry Pi**

I. INTRODUCTION

Hydroponics, a technologically advanced method, disrupts the traditional paradigm by replacing soil with a meticu- lously controlled nutrient-infused water solution. This direct nourishment empowers growers with unprecedented precision over environmental variables, leading to accelerated growth, increased yields, and the ability to cultivate in unconventional settings.

The need for hydroponics arises from several pressing issues. Our global population is expanding rapidly, placing immense pressure on food production systems. Water scarcity is a growing concern, and traditional farming practices are often water-intensive. Hydroponics offers a solution by dra- matically reducing water consumption through a re-circulation system. Furthermore, unlike soil-based methods, hydroponics allows for precise control of nutrient concentrations, pro- moting optimal plant health while minimizing reliance on chemical pesticides. Finally, its adaptability allows for year- round cultivation, making it a boon for urban agriculture and regions with limited cultivable land.

This research focuses on creating a smart hydroponics system that integrates automation and the power of the Internet of Things (IoT). Real-time sensor data will provide constant monitoring of crucial parameters, ensuring optimal growth conditions. Use of AWS IoT TwinMaker connects data from a variety of sources such as sensors and creates a knowledge graph to model real-world systems and generate real-time insights from the digital twin. But this system goes beyond mere monitoring - by leveraging a web application with ML-powered disease detection, it empowers farmers to make informed decisions and optimize their hydroponic setups. This innovative approach has the potential to transform hydroponics into a more efficient, sustainable, and accessible method of cultivation, ultimately contributing to addressing global food security challenges.

II. RELATED WORKS

S. V. S. Ramakrishnam Raju et al. [1] introduces an AI-SHES (Artificial Intelligence-based Smart Hydroponics Expert System) integrated with IoT technology. The system, comprising a Raspberry Pi-controlled hardware environment with various real-time sensors, utilizes a convolutional neural network (CNN) model for plant disease detection. The web application, integrated with the IoT setup, provides farmers with a user-friendly interface to monitor and control their hydroponics farm, displaying sensor data and plant disease status. This holistic approach aims to enhance resource efficiency and enable real-time monitoring and control for improved hydroponics farming practices. V. Mamatha et al. [2] utilizes the KNN algorithm for predicting leafy vegetable growth. With a focus on sustainable agriculture, the goal is to automate and optimize greenhouse operations using advanced technologies, ensuring a stable and controlled environment for diverse crop cultivation. The study involves comparing and evaluating various hydroponics forms for commercial crop growth to determine the most suitable technique. Incorporating IoT technology, the system facilitates remote access and efficient monitoring and control of the hydroponics system for maximum yield and resource efficiency.

Djakhdjakha Lynda et al. [3] utilizes a novel IoT farming ontology structured with OWL2 and SWRL rules, the system identifies and comprehends agricultural data. Employing a taxonomy, it pinpoints IoT agriculture sensors, and the ontology forms the basis for employing ML classification techniques to accurately classify datasets for IoT agriculture applications. The system prioritizes optimal performance and precision in dataset classification within the IoT agriculture domain. Nahla Sadek et al. [4] To create a smart hydroponics and aeroponics greenhouse in Egypt. The greenhouse is equipped with various sensors to monitor and control the environmental conditions automatically. These sensors measure parameters such as temperature, humidity, luminous intensity, and total dissolved solids. The system is connected to a network of tools that control the weather conditions inside the greenhouse based on the plant type and season. It also incorporates a pesticide spraying tank to control pests within the greenhouse. The IoT platform is used to automate and store system parameters, as well as provide a graphical interface for remote access and monitoring.

Salvi et al. [5] Presents a multi-level hydroponics system that employs IoT and edge computing to enhance agricultural efficiency. Tailored for cost-effective household setups, the system continuously produces fresh green fodder for livestock. The methodology encompasses hydroponics system design, IoT device integration for monitoring and control, edge computing for local data processing, implementation of computer vision for disease analysis, and system testing to measure efficiency. The system is structured into hardware, software, and application layers, utilizing sensors, actuators, and a computer vision system for real-time monitoring, disease detection, and cultivation estimation. With a focus on low-cost maintenance, the hydroponics setup uses nutrient- rich water and trays to cultivate plants without soil, promoting an efficient and productive approach to fodder production.

Vivek Ramakant Pathmudi et al. [6] A logistic regression model aids in classifying seasonal parameters. Cloud computing processes sensor data to identify nutrient deficiencies and calculate plant health scores. Two subsystems, sensor-hub and image-server, collaborate using Azure DataBricks services to consistently report the Healthiness Score. The adaptable and scalable system focuses on water efficiency, minimizing manual intervention for enhanced plant growth. While accommodating different setups, it relies on historical data, with considerations for accuracy in new scenarios and challenges related to hardware constraints. The cloud-based approach enhances flexibility and enables continuous improvement through data analysis.

Margaret S. Gumisiriza et al. [7] The research paper examines the effects of hydroponics on lettuce growth and yield. It found that hydroponics performs similarly to conventional farming in terms of the number of leaves but showed differences in dry matter content, fresh weight, and root length. No significant differences were observed in the edible parts of green and red lettuce between hydroponic and traditional farming. The study highlights the potential of hydroponics for supporting urban food security and suggests further research on seasonal variations and nutritional content for more insights.

III. System Model

The hydroponics system is utilizing Convolutional Neural Networks (CNNs) to achieve real-time disease prediction for tomato plants. CNNs are a specialized type of artificial neural network architecture that excels in image recognition and classification tasks. Unlike traditional methods that rely on manually defined features, CNNs possess the unique ability to automatically extract these features directly from the raw image data itself. This makes them particularly well-suited for our project where disease identification hinges on the subtle visual cues present on the tomato leaves.

The core strength of a CNN lies in its distinct architecture. It comprises multiple convolutional layers that function like filters, meticulously scanning the image for specific patterns and features like edges, shapes, and textures. These layers operate at various resolutions, enabling the CNN to capture a hierarchy of features, ranging from low-level details to more intricate structures within the image. Subsequent pooling layers perform down sampling on the data, effectively reducing its complexity while preserving crucial information. Activation layers introduce non-linearity, empowering the network to model complex relationships between the extracted features. Finally, fully connected layers analyze these features and learn the intricate combinations that differentiate healthy from diseased leaves in our specific context.

Within the hydroponics system, a camera continuously captures images of tomato leaves. These images are then transmitted to a machine-learning model for real-time disease prediction. A Flask application acts as the intermediary between the camera and the model. It utilizes a POST method Image processing API for handling the image from the camera and returning the resulting after prediction.

Upon receiving the image data via the POST method, the Flask application performs necessary pre-processing steps like resizing, normalization, or other image manipulation techniques. The pre-processed image is then fed into the pre- trained CNN model.

The CNN meticulously analyzes the image, extracting features through its convolutional layers. These features capture patterns associated with specific tomato leaf diseases. Finally, the network outputs a prediction, classifying the tomato leaf as either healthy or diseased, along with the most likely disease category. This real-time disease detection capability allows for prompt intervention and implementation of disease management strategies, fostering a healthy and productive hydroponic tomato crop. The predicted results obtained from the CNN model are then relayed to the user interface (UI) component, potentially hosted on a separate device or accessible through a web browser. This UI provides a visual representation of the prediction, displaying information such as the health status of the tomato leaves and any identified diseases.

TABLE I: Summary of key performance metrics obtained during the evaluation of the CNN model

	Metrics	Values
1	Accuracy	86.30
2	Precision	96.47
3	Recall	96.45
4	f1 score	96.39
5	Specificity	96.77

The table 1 summarizes the evaluation results of the CNN model. By carefully examining these values, you can gain valuable insights into the model's overall effectiveness and identify areas for potential improvement.

IV. METHODOLOGY

The proposed system integrates a hydroponic IoT setup with a CNN-based disease prediction model, AWS Twinmaker for real-time sensor data visualization, a web application for monitoring and alerting, and a chatbot for user interaction. This comprehensive solution enables early detection of plant diseases through image .Fig 1 shows the architecture of the proposed system.

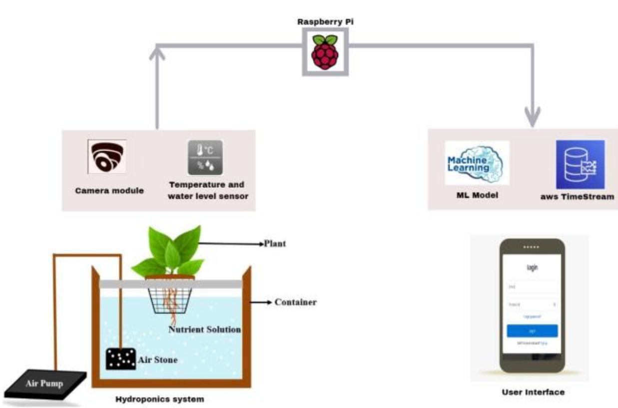

Fig. 1: Architecture of Hydroponics System

The initial step in the proposed methodology is to install various sensor in the hydroponics system. The sensors may include Temperature sensors, pH sensor and Electric conductivity sensor. The system also incorporates a camera module for disease prediction. The sensors will continuously collect data on the plant's growing condition measuring various parameters such as Temperature, Electric conductivity and pH and giving real-time updates in the Dashboard developed using AWS TwinMaker. The IoT devices capture images of plants at regular intervals, enabling the detection of early signs of diseases. The images are then processed using machine learning algorithms deployed on the Raspberry Pi, which analyzes various visual cues indicative of plant health and a chatbot embedded in the user application to improve engagement.

The Raspberry Pi serves as the central processing unit in this system, utilizing pre-trained machine-learning models to classify and diagnose plant diseases based on the analyzed images. Once processed, the data is The web application interface provides users with real-time insights into the health status of their crops, displaying visualizations and alerts generated from the analyzed data. This integrated approach enables proactive management strategies and empowers users with actionable recommendations to optimize yields and ensure the overall well-being of their hydroponic crops.

The system workflow, illustrated in Fig 2, provides an overview of the hydroponics system. As depicted in the figure, the system captures images of the plants using a camera module. These images are then transmitted to the machine learning model for analysis. The model, trained on a comprehensive leaves dataset, classifies the images as healthy or diseased. Finally, the predicted results are displayed on the user interface, enabling real-time disease monitoring and informed decision-making.

The Fig 3 shows the high level architecture of AWS TwinMaker. The data generated from the sensor connected to Raspberry Pi device is sent via Python Script to AWS IoT Core, that easily and securely connects devices through MQTT and HTTPs protocols. Using AWS IoT Core rules, data is streamed to an Amazon Timestream database, On the AWS TwinMaker side, created the workspace environment where a virtual entity is defined together with its 3D Model representation. A component is created which used Lambda Function to read data from Amazon Timestream to syc digital twin with data arriving from sensor. For the visualization part, used AWS IoT Twinmaker Grafana dashboard Integration to create dashboard which present data together with 3D model. The dashboard is accessible in SSO via AWS IAM Identity Center. Finally created the AWS IoT TwinMaker rules to be able to easily see changes in dashoard whenver the temperature or pH goes below or above the thresholds defined.

V. RESULTS AND DISCUSSIONS

Traditional methods for disease detection can be time-consuming or subjective. Our system leverages the power of CNN to achieve rapid and accurate disease identification. By analyzing high-resolution images captured within the hydroponic system, the CNN model can effectively distinguish healthy leaves from those infected with diseases relevant to tomatoes. This early detection capability empowers users

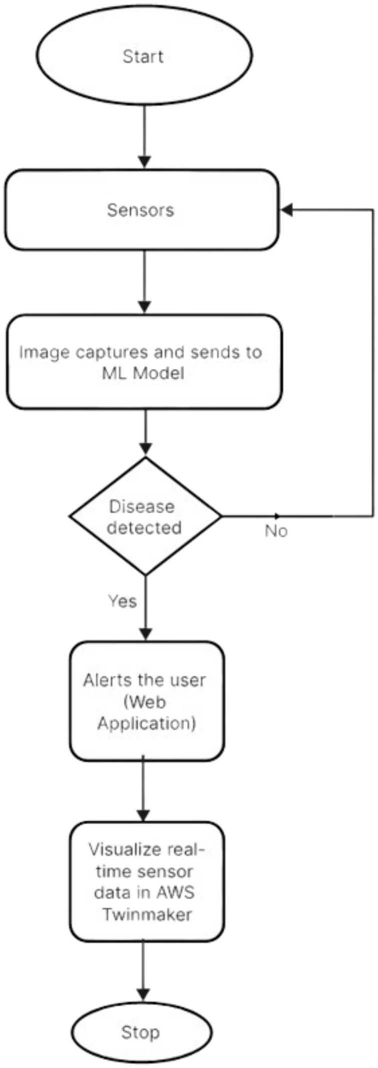

Fig. 2: Working Flow of System

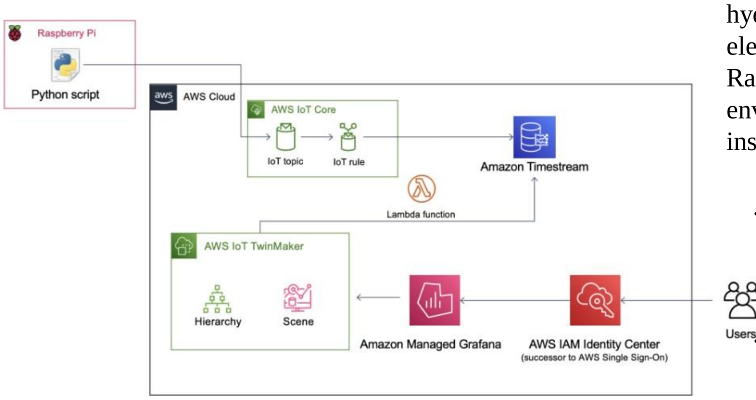

Fig. 3: Architecture of AWS TwinMaker

to take timely actions, such as targeted treatment or plant removal, to prevent the spread of disease and maintain a healthy crop.

Fig. 4: Tomato leaves Dataset

The foundation of our disease prediction system lies in a well-curated leaves dataset specifically designed for tomatoes. Fig 3 dataset comprises high-resolution images meticulously labeled by experts. The images encompass a variety of leaf conditions, including healthy leaves and leaves infected with different tomato diseases. Focusing on a specific plant species allows the model to train on highly relevant data, potentially leading to superior accuracy compared to using generic plant disease datasets.

Fig 4 depicts the training and validation accuracy of our CNN model during the training process. The training accuracy curve represents the model's performance and how well the model can correctly classify images in the training dataset it was trained on. Ideally, this curve should steadily increase as the model learns from the data. The validation accuracy curve reflects the model's performance on a separate validation dataset that the model was not exposed during training.

VI. Implementation

Hardware setup: The project involved setting up a hydroponic system with various sensors, including pH sensors, electric conductivity sensors, temperature sensor, and Raspberry pi, to collect data about the nutrient levels and environmental conditions of the system. A camera module also installed to capture images of the plants.

- Data collection. Data was collected from the sensors and camera module and stored in a database. The data included pH levels, turbidity levels, temperature, humidity, and plant images.
- Data pre-processing: The collected data was pre-processed by cleaning and normalizing it to remove any noise or outliers.
- Feature extraction: The convolutional neural network was used to extract features from the plant images. The

features were then combined with the sensor data to create a comprehensive dataset.

- Model training: The model was trained on the dataset to predict the nutrient levels required for optimal plant growth and detect any diseases present in the plants.
- Model evaluation: The trained model was evaluated on a test dataset to measure its performance in predicting.
- AWS Digital Twin Integration : To create digital Twin of a Raspberry Pi device connected to sensor that col- lects Temperature and Humidity data integrating with an Amazon Managed Grafana dashboard to visualize
- System implementation. The final step involved integrating the hardware and software components to create a complete system that could provide real-time information about the hydroponic system's nutrient levels and plant health.

The system has potential applications in improving crop yields and reducing the use of pesticides and fertilizers and results in greater efficiency.

VII. CONCLUSION

In this research, we performed a comprehensive analysis of developing an Intelligent Disease Prediction in Hydroponic Systems Using Machine Learning. According to our analysis, our system stands as a complete solution to concerns related to the hydroponic system. With the integration of a wide range of features like AWS Digital Twin for real-time visualisation of Raspberry Pi, integration of Chat bot for customer interaction, and continuous monitoring of the plants for disease prediction satisfies the needs of users.

Overall, this research presents an innovative approach to hydroponic crop management, offering users a powerful tool to optimize yields, minimize risks associated with plant diseases, and ensure sustainable agricultural practices. With further refinement and implementation, this methodology has the potential to revolutionize the way we cultivate crops and contribute to food security in a rapidly changing world.

REFERENCES

[1] S. V. S. Ramakrishnam Raju, B. Dappuri, P. Ravi Kiran Varma, M. Yachamaneni, D. M. G. Verghese, and M. K. Mishra, "Design and implementation of smart hydroponics farming using iot-based ai controller with mobile application system," *Journal of Nanomaterials*, vol. 2022, Jul 2022.

[2] V. Mamatha and J. Kavitha, "Machine learning based crop growth management in greenhouse environment using hydroponics farming techniques," *Measurement: Sensors*, vol. 25, p. 100665, 2023.

[3] D. Lynda, F. Brahim, S. Hamid, and C. Hamadoun, "Towards a semantic structure for classifying iot agriculture sensor datasets : An approach based on machine learning and web semantic technologies," *Journal of King Saud University - Computer and Information Sciences*, vol. 35, no. 8, p. 101700, 2023.

[4] N. Sadek, N. kamal, and D. Shehata, "Internet of things based smart automated indoor hydroponics and aeroponics greenhouse in egypt," *Ain Shams Engineering Journal*, vol. 15, no. 2, p. 102341, 2024.

[5] S. Salvi, S. Savitha, S. Sawargaonkar, V. Bhaktavatsala, H. T K, and S. Jain, "Hydroiot: An iot and edge computing based multi-level hydroponics system," pp. 1–6, 12 2021.

[6] V. R. Pathmudi, N. Khatri, S. Kumar, A. S. H. Abdul-Qawy, and A. K. Vyas, "A systematic review of iot technologies and their constituents for smart and sustainable agriculture applications," *Scientific African*, vol. 19, p. e01577, 2023.

[7] M. S. Gumisiriza, P. A. Ndakidemi, Z. Nampijja, and E. R. Mbega, "Soilless urban gardening as a post covid-19 food security salvage technology: A study on the physiognomic response of lettuce to hydroponics in uganda," *Scientific African*, vol. 20, p. e01643, 2023.