IOT-ENABLED HYDROPONIC FARMING: A SOLUTION FOR HIGH-TEMPERATURE REGIONS

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Electrical and Electronic Engineering with Honours

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"IOT-ENABLED HYDROPONIC FARMING: A SOLUTION FOR HIGH-TEMPERATURE REGIONS"** was prepared by **CHUA SHI JIAN** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Electrical and Electronic Engineering with Honours at Universiti Tunku Abdul Rahman.

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Date	:	15/9/2024

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ABSTRACT

This project focuses on the development of an IoT-enabled hydroponic system designed to mitigate the effects of high ambient temperatures on plant growth and maintain optimal growing conditions, particularly in high temperature regions like Malaysia. By utilizing a Deep Water Culture (DWC) hydroponic method, the system integrates sensors to monitor critical environmental parameters such as temperature, humidity, pH, and Total Dissolved Solids (TDS), ensuring optimal plant growing condition. A fogger system was implemented to reduce temperature stress on plants during peak heat conditions. Experimental results demonstrated that the fogger system significantly improved the growth of lettuce plants, as evidenced by greater plant height and larger leaf area compared to those grown without the fogger cooling mechanism.

Besides real-time environmental monitoring, the system utilizes machine learning models, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), to predict environmental conditions and optimize system performance through adaptive control. The dataset, collected by the hydroponic system over a period of one month, was used to train these models. Comparative analysis showed that the GRU model performed slightly better in predictive accuracy. The integration of IoT and AI technologies into hydroponic farming has the potential to transform agricultural practices by promoting sustainable and efficient crop production. This solution automates environmental control, reduces the need for human intervention, and optimizes resource use, making it a promising approach for the future of modern agriculture.

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LIST OF SYMBOLS / ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Networks
DWC	Deep Water Culture
EC	Electrical Conductivity
GPIO	General Purpose Input/Output
GRU	Gate Recurrent Unit
IoT	Internet of Things
IPCC	Intergovernmental Panel on Climate Change
LSTM	Long Short-Term Memory
MP	Malaysia Plan
NFT	Nutrient Film Technique
NTP	Network Time Protocol
pH	Potential of Hydrogen
RNN	Recurrent Neural Network
SDG	Sustainable Development Goals
TDS	Total Dissolved Solids

CHAPTER 1

INTRODUCTION

1.1 General Introduction

In recent years, the impact of climate change has posed significant challenges to agricultural practices worldwide, particularly in regions with high temperatures. Malaysia is one such region, struggling with the consequences of rising temperatures, where traditional farming methods are increasingly threatened by environmental shifts. Malaysia, located in the equatorial region, has a tropical rainforest climate marked by consistently high temperatures and humidity year-round. However, in recent decades, the nation has witnessed an increase in temperature, largely attributed to anthropogenic activities such as deforestation, urbanization, and industrialization. According to data on climate and temperature development in Malaysia, as shown in Figure 1.1, the average temperature in the country has risen by 0.5 °C over the past 63 years, exacerbating the challenges for traditional farming practices reliant on stable climatic conditions.

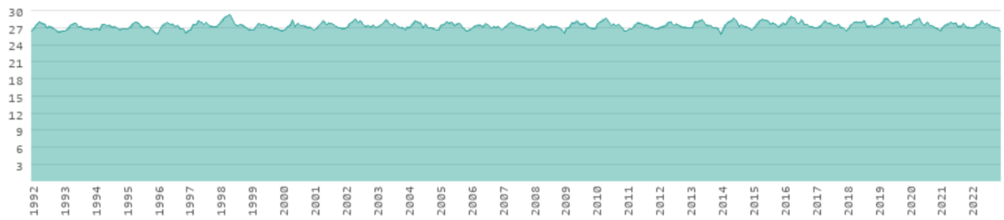


Figure 1.1: Average Annual Temperature in Malaysia from Year 1992 till 2022 (Climate and temperature development in Malaysia, n.d.)

Globally, the average temperature is also undergoing a significant rise. Data from the Intergovernmental Panel on Climate Change (IPCC) indicates that the Earth's average surface temperature has increased by approximately 0.99 °C since the pre-industrial era (1850-1900) (IPCC, 2021). This unprecedented warming trend, primarily driven by greenhouse gas emissions, has had significant negative consequences on ecosystems, weather patterns, and agricultural productivity worldwide.

In response to these challenges, innovative agricultural techniques such as hydroponic farming have gained importance. Hydroponics, a soilless farming method that uses nutrient-rich water solutions, offers a viable alternative for crop production, particularly in indoor environments. This technology not only addresses water conservation concerns but also provides the opportunity for year-round crop cultivation, unaffected by external weather conditions. By delivering essential minerals directly to plant roots through nutrient-rich water solutions, hydroponic systems promote optimal growth conditions while minimizing resource usage.

Singapore, for example, imports more than 90 percent of its food. Due to climate change and extreme weather conditions, the supply chain has become increasingly unstable. To address this issue, hydroponic technology has emerged as a promising solution, offering the potential to bolster Singapore's self-sufficiency in food production. ComCrop, a Singaporean company, has demonstrated the success of hydroponic technology in enhancing the nation's food security. Through the implementation of the Nutrient Film Technique (NFT) Hydroponics, ComCrop has successfully cultivated a variety of vegetables, including Japanese Caixin, lettuce, basil, and mint (Godge, 2022). This innovative approach allows for efficient and sustainable year-round production, overcoming challenges such as external weather conditions and land constraints.

By leveraging the power of IoT and AI technology, farmers can overcome the limitations of traditional farming practices, enhance resource efficiency, and cultivate resilience in the face of a changing climate.

1.2 Problem Statement

Over time, traditional farming practices have suffered from extensive misuse and mismanagement of land, leading to issues such as soil degradation, climate variability, and pollution due to chemical substances like fertilizers and pesticides. Continuous monocropping has resulted in the depletion of soil nutrients, decreased organic content, and significant declines in soil fertility (Begum, 2021). In contrast, hydroponic agriculture, whether conducted indoors or outdoors, offers an environmentally friendly alternative for efficient food cultivation.

While hydroponic systems provide benefits in mitigating the effects of extreme temperatures on agriculture, areas for improvement remain, particularly in resource optimization and automation. A critical question arises: Can water from hydroponic systems be repurposed for additional cooling mechanisms, such as scheduled afternoon water showers for plants, using the Network Time Protocol (NTP). NTP, an internet protocol designed for network clock synchronization, could automate this process without human intervention. Additionally, improving the efficiency of hydroponic fogger setups is challenging but essential for maximizing crop production and minimizing the impact of high temperatures.

Integrating IoT sensors in hydroponic farming enables real-time monitoring of critical environmental factors such as temperature, humidity, pH levels, and nutrient levels. However, challenges arise in ensuring seamless integration, accurate data collection, and optimal sensor placement within the system without disrupting plant growth. AI can help in analyzing the collected data, predicting future environmental conditions, and making proactive adjustments to optimize the system. Overcoming these challenges is crucial for maximizing the benefits of IoT-enabled hydroponic farming and achieving sustainable and optimized crop production.

Moreover, hydroponic systems offer significant advantages in water efficiency compared to traditional soil farming. This efficient water use is particularly beneficial in high-temperature regions where water scarcity is a concern. Addressing the optimization of water use in hydroponic systems compared to soil farming will underscore the potential for hydroponics to contribute to sustainable agricultural practices in water-limited, high-temperature environments.

1.3 Aim and Objectives

This project aims to explore innovative solutions to enhance the sustainability and automation of hydroponic farming systems using IoT technology to address high-temperature challenges and increase production. The specific aims and objectives are as follows:

1. To develop and design a fully functional IoT-enabled hydroponic farming system.
2. To investigate the effectiveness of a plant cooling system using fogger setups to help cool plants during peak heat periods and to assess the water efficiency of hydroponic farming through research.
3. To integrate IoT technologies into the hydroponic farming system for real-time environment monitoring, data collection of environmental parameters, and implementation of AI for future prediction.

1.4 Scope and Limitations of the Study

Scope of the Study

This study focuses on the design and development, and evaluation of an IoT-enabled hydroponic farming system specifically adapted to high-temperature regions such as Malaysia. The primary scope of the project includes:

1. **Hydroponic System Development**: The project involves the design and construction of a Deep Water Culture (DWC) hydroponic system, incorporating IoT sensors to monitor crucial environmental factors like temperature, humidity, pH levels, and Total Dissolved Solids (TDS). The system is built to provide real-time tracking and automated regulation of these environmental conditions.
2. **Fogger Cooling System**: The study examines the effectiveness of a fogger cooling system in reducing the impact of high ambient temperatures on plant growth, particularly focusing on lettuce plant growth.
3. **Data Collection and Analysis**: The research includes a one-month data collection phase, during which environmental data from the IoT sensors was logged, and plant growth measurements, such as height and leaf area, were measured and recorded. This data was analyzed to evaluate the system's overall performance and the effectiveness of the fogger in enhancing plant growth.
4. **Machine Learning AI Integration**: Implementing and comparing two AI models, Long Short-Term Memory (LSTM) and Gated Recurrent

Units (GRU), to predict future environmental conditions and optimize system performance through proactive adjustments.

Limitations of the Study

Several limitations could potentially affect the outcomes of this study:

1. **Budget Limit and Sensor Accuracy**: The RM500 budget cap for this project meant that most electrical components, including sensors, were chosen for their affordability rather than precision. Inexpensive sensors, while functional for basic monitoring, often lack the sensitivity and accuracy of professional-grade equipment. As a result, the data obtained from these sensors may be less reliable due to measurement errors or delayed detection of changes in environmental conditions. This limitation impacts the overall reliability of the system, particularly for applications where precise real-time data is critical for decision-making.
2. **Duration of the Study**: The data collection period was limited to one month, which constrains the study's ability to account for long-term environmental changes and plant growth patterns. Given the short timeframe, the dataset may not capture seasonal variations or extreme weather conditions that could significantly influence the performance of the hydroponic system. This limitation also affects the machine learning models, as they are trained on a relatively small dataset, reducing their ability to generalize to broader scenarios or predict outcomes over longer periods.
3. **Limited Crop Variety**: The study focused on lettuce cultivation under controlled condition, which limits the system's adaptability to other types of crops. Different crops, such as tomatoes or herbs, have varying nutrient requirements, growth patterns, and environmental sensitivities. The system's configuration, including its IoT sensors and AI models, is adapted to lettuce, meaning it may not perform as effectively when applied to other crops without additional modifications. To extend the system's utility, future studies should include data from a broader range of crops to improve its versatility.

4. **Geographical and Climate Specificity**: The system was designed for use in Malaysia, a region characterized by high temperatures and humidity. This geographic and climate-specific setup may not be directly applicable in other regions with different environmental conditions. For example, areas with cooler climates or drier conditions would likely require adjustments to the fogger cooling system or different sensor calibrations. The AI models, trained on data from a specific climate, might also perform poorly in regions with contrasting weather patterns. Expanding the study to include diverse climatic data would enhance the system's adaptability for broader use.
5. **Limited AI Training Data**: Due to the short study duration, the machine learning models were trained on a limited dataset, which affects the accuracy and generalization capabilities of the AI predictions. Machine learning models typically perform better with larger datasets that capture a wide range of conditions, including extreme or unusual environmental scenarios. In this case, the limited data size reduces the model's ability to predict rare events or long-term trends, which may affect the system's effectiveness in optimizing plant growth. Future studies should focus on collecting larger datasets over more extended periods to enhance the robustness and accuracy of the AI models.

1.5 Contribution of the Study

This study makes several significant contributions to the fields of smart agriculture, IoT, and AI-based automation for sustainable farming. The primary contribution is the development of a fully functional IoT-enabled Deep Water Culture (DWC) hydroponic system that provides real-time monitoring and automated control of critical environmental parameters such as temperature, pH, humidity, and TDS.

The integration of AI, specifically through Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, allows for predictive control of the hydroponic environment, enhancing the system's ability to make proactive adjustments based on future predictions. This not only improves plant growth but also minimizes the need for human intervention.

Additionally, the study demonstrates the water efficiency of hydroponic farming compared to traditional soil-based methods, highlighting its potential as a sustainable agricultural solution, especially in water-scarce regions like Malaysia. Another key contribution is the evaluation of a fogger-based cooling system, which effectively reduces high-temperature stress on plants, promoting better growth in tropical climates.

Overall, this project supports climate-resilient agriculture by leveraging IoT and AI technologies to enhance the scalability, automation, and sustainability of hydroponic farming, aligning with Malaysia's push for smart and sustainable agricultural practices. This study has made significant contributions to the fields of agriculture and technology, serving as a foundation for future research in this domain.

1.6 Outline of the Report

The report begins with an Introduction, discussing the challenges that climate change poses to traditional farming, especially in tropical regions like Malaysia. It introduces hydroponic farming as an innovative solution, enhanced by IoT and AI technologies to optimize plant growth and resource usage. The Problem Statement outlines the limitations of traditional farming, such as soil degradation and inefficient resource use, and identifies the need for automation in hydroponic systems. The Aim and Objectives focus on developing an IoT-enabled hydroponic system, assessing the effectiveness of a fogger-based cooling system, and integrating AI for predictive environmental monitoring.

The Literature Review explores existing research on hydroponic farming, IoT platforms, environmental factors affecting plant growth, and AI models, providing justification for system design choices. The Methodology outlines the steps taken to construct the system, integrate IoT sensors, experiment with the fogger system, and train AI models, ensuring accurate environmental predictions.

The Results and Discussion present findings on the fogger system's positive impact on plant growth, water efficient benefits of hydroponics, and a comparison of LSTM and GRU models in managing environmental conditions. The Conclusions and Recommendations summarize the project's success in meeting its objectives, suggesting improvements in sensor accuracy, data expansion, and AI model refinement for future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Hydroponic farming is a technique of growing plants without soil, where nutrient-rich water solutions to supply essential minerals directly to the plant roots. This method allows for precise control over the growing environemental parameters. Hydroponic systems can be set up indoors or outdoors and often use inert growing media like perlite, vermiculite, or rock wool to support the plants.

In contrast, soil farming involves growing plants in soil, which serves as both a support medium and a reservoir of nutrients and water. Soil provides a natural environment for plant roots, allowing them to access nutrients, water, and oxygen. Traditional soil farming relies on the natural composition of soil, which varies widely in nutrient content, structure, and drainage capabilities.

For hydroponic farming, several important environmental parameters affect plant growth and health such as the pH level of the nutrient solution, electrical conductivity (EC) value or Total Dissolved Solids (TDS) value of the nutrient solution, the temperature of the nutrient solution, the light intensity, the surrounding temperature and humidity are discussed. The plant growth parameters including plant height, fresh weight, dry weight and total leaf area, are the main parameters to evaluate the plant development (Lou et al., 2022).

From research, 6 types of hydroponic systems are discovered, there are nutrient film technique (NFT), deep water culture, wick, Ebb and flow, drip and aeroponic. The advantages and disadvantages of each farming method are studied and discussed. The operation of the fogger to cool down the plant is discussed.

Next, the microcontroller such as Arduino and ESP32 are compared and discussed. There IoT platforms, Blynk are discussed. After that the most suitable hydroponic farming system, mircocontroller and IoT platform for this FYP project are being selected. The considerations are based on the ease of construction, the construction cost and the ease of implementation of parameters. Lastly, the machine learning models are chosen for hydroponic farming monitoring and detection is discussed.

2.2 Environmental Parameters

The environmental parameters are greatly affecting the growth of the plant. Table 2.1 shows the list of the environmental parameters.

Table 2.1: List for Environmental Parameters

No	Environmental Parameters
1	pH level of the nutrient solution
2	electrical conductivity (EC) value or Total Dissolved Solids (TSD) value of the nutrient solution
3	temperature of the nutrient solution
4	light intensity
5	surrounding temperature
6	surrounding humidity

2.2.1 pH level of Nutrient Solution

The pH value which stands for potential hydrogen, is considered to be one of the fundamental parameters affecting plant health, pH level in hydroponics determines the level of acidity or alkalinity of the nutrient solution. The pH scale ranges from 0 to 14, 0 being the most acidic, 7 is the pH-neutral point and 14 being the most alkaline. According to (Henry et al., 2018), hydroponic lettuce should be grown with a pH range of 5.5 to 6.0, with an optimal value of 5.8. The pH level higher or lower than the optimum range will affect the availability of corresponding nutrient absorption of plants. For example, nutrients such as iron, zinc, and copper tend to form insoluble compounds in alkaline environments, making them inaccessible to plants. On the other hand, nutrients like calcium, potassium, and magnesium become less available in an acidic environment. The lack of any nutrients will affect the growth and the health of the plant (Horticulture, 2023). Hence, in hydroponics, it is essential to maintain the optimum pH range in order to guarantee that plants absorb as much nutrition as they need.

When the pH level of the solution is too low, add substances such as sodium bicarbonate or potassium hydroxide to the nutrient solution whereas When the pH level of the solution is too high, add substances such as citric acid or phosphoric acid to the nutrient solution (Horticulture, 2023). The pH value of the solution is affect by the temperature of the solution, normally the higher the solution temperature, the lower the pH value.

2.2.2 Electrical Conductivity (EC) Value and Total Dissolved Solids (TSD) Value of the Nutrient Solution

EC value and TSD value are the measure of the ability of a solution to conduct electricity, it indicate the amount of nutrients dissolved in the hydroponic solution (Horticulture, 2023). EC value is measured in milli Siemen (mS) whereas TDS value is measured in Part Per Million (PPM). Maintaining the right EC value of the solution is crucial in ensuring optimal plant growth and health, which EC value varies depending on the stage of growth, plant species and external factors. Figure 2.1 shows the recommended EC value for different stages of growth of the plant. A high EC value of the solution can lead to nutrient toxicities, due to an increase in osmotic pressure at the root zone, making it more difficult for plants to absorb water, causing plants to dehydration and stunted growth. On the other hand, a low EC value of the solution can affect plant growth and health caused by nutrient deficiency (Dubaniewicz, 2021). Hence, maintaining the suitable EC value of the solution is crucial for plant growth and health. According to (Cooper, 2023), the preferred EC value of solution for planting lettuce is 1.2 to 1.8.

When the EC value of the solution is too low, add more nutrients or salts to the solution whereas when the EC value of the solution is too high, dilute the solution by adding fresh water into the solution (Horticulture, 2023). The EC value of the solution is affect by the temperature of the solution, normally the higher the solution temperature, the higher the EC value.

EC level (mS/cm)	Plant growth
0.2-0.5	Seedlings and young plants
0.5-0.8	Vegetative growth and leafy greens
0.8-1.0	Flowering and fruiting stages

Figure 2.1: Recommended EC Value for Different Stage of Growth (Horticulture, 2023)

2.2.3 Temperature of Nutrient Solution

The temperature of the nutrient solution directly affects the plant roots' temperature. For example, the respiration rate of the roots will increase when the nutrient solution temperature increases. Additionally, higher temperature solutions have lower dissolved oxygen levels, hence with the increase in respiration rate of the roots and the low dissolved oxygen level in the solution, this will often inhibit plant growth due to respiration exhaustion (Lee et al., 2020).

At lower temperatures, the majority of plant species experience a decrease in root nutrients uptake, leading to a lower growth rate. Therefore, to allow plants to achieve a balance between the rate at which they absorb nutrients and the amount of oxygen in the solution, the water temperature should be kept within an optimum range. In a study made for lettuce hydroponic farming, the ideal solution temperature is 24°C (Thompson et al., 1998).

2.2.4 Light Intensity

Plant growth and development are greatly influenced by light intensity. The light intensity in measured in lux (lumens per square meter). Photosynthesis process of plant requires a specific range of light intensity for optimal performance. For most plant species, this range is between 2000 and 100,000 lux. This allows for healthy growth, efficient energy production, and a healthy metabolism. At lower light intensities, it will cause slowing down in the rate of photosynthesis, which causes them to grow more slowly and have extended stems as they seek for the light. On the other hand, extreme light levels more than 100,000 lux can cause photodamage and photoinhibition, which stresses out cells and reduces the effectiveness of photosynthetic processes.

According to (Zhou et al., 2022), the optimal light intensity for lettuce is 500 to 600 $\mu mol \cdot m^{-2} \cdot s^{-1}$ which is 21739 lux to 26087 lux.

2.2.5 Surrounding Temperature and Humidity

The surrounding temperature and humidity greatly affect the plant's growth as these parameters will affect the photosynthesis process in the leaves of plants. The photosynthesis process needs carbon dioxide gas from the air and photosynthesis enzymes to undergo carbon fixation to produce glucose. Hence, the surrounding temperature and humidity will affect the enzyme activity and the amount of stomata open on the leaves, open stomata will allow the exchange of air inside and outside the leaves.

When the temperature is too high, the enzymes for photosynthesis will denature, slowing down the rate of photosynthesis. When the temperature is too low, the enzymes for photosynthesis will become inactive, slowing down the rate of photosynthesis.

When the humidity is too high or too low, the stomata will close to prevent water loss to the surrounding, slowing down the rate of photosynthesis due to the lack of carbon dioxide gas (McDonald, 2023).

Figure 2.2 shows that, for each plant species, only the optimum surrounding temperature will have the highest growth response which means the highest growth rate.

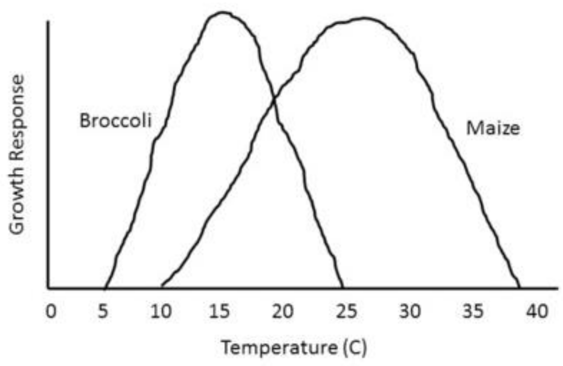


Figure 2.2: Growth Response of Plant Varies by Surrounding Temperature (Hatfield & Prueger, 2015)

According to (Ahmed et al., 2020), a research base on lettuce plant growth, the optimal surrounding temperature for carbon dioxide gas uptake for lettuce is 22 – 25 ˚C. According to (Mattson, 2018), the surrounding humidity for lettuce growth is 50 – 70 %.

2.3 Plant Growth Parameters

The plant growth parameters a important parameters as shown in Table 2.2 for the evaluation of the plant development and the plant growth is needed to examine the suitability of the environmental factors. Plant height is the length of the plant stem without including plant roots. The total leaf area is the summation of the approximation area of all the leaves of the plant. Fresh weight is the weight of all the organism parts of the plant including water whereas dry weight is the weight of all the organism parts of the plant after all water has been removed out. Technically, the dry weight is more reliable in evaluating the plant growth compared to fresh weight.

Table 2.2: List for Plant Growth Parameters

No	Plant Growth Parameters
1	plant height
2	fresh weight
3	dry weight
4	total leaf area

2.4 Types of Hydroponic Farming

2.4.1 Nutrient Film Technique (NFT) System

NFT hydroponic systems refering to (Michael, 2023) shown in Figure 2.3 utilize a water pump to continuously circulate a shallow stream of nutrient solution over the roots of crops. This ensures that the roots receive a constant supply of nutrients, while any unused solution is efficiently recycled back into a container or tank within the closed system. The one of the main characteristics of the NFT system is slightly sloped growing channels, it facilitate the flow of the nutrient solution down due to gravity (Adelmann, 2023).

Besides, the shallow stream of the nutrient solution makes sure the plant roots can absorb the nutrient solution while the unsoaked roots can absorb air from the surroundings. Because often only little growth medium is used, without sufficient support, NFT is more suitable for small and light plants such as lettuce. Table 2.3 discusses the advantages and disadvantages of the NFT system.

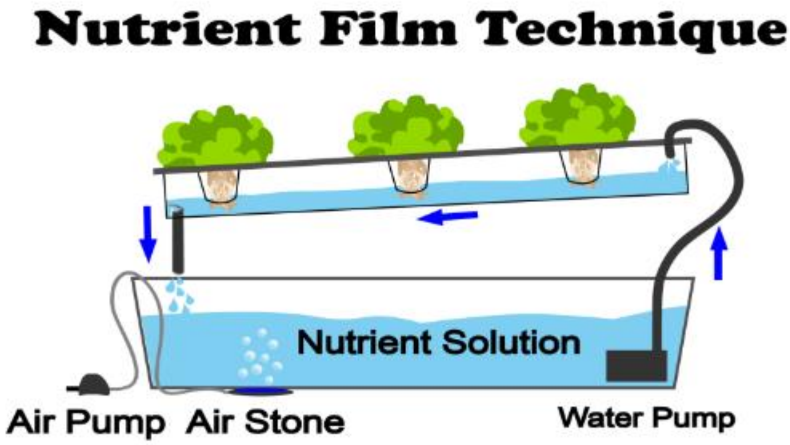


Figure 2.3: Nutrient-Film-Technique (NFT) System (Michael, 2023)

Table 2.3: Advantages and Disadvantages of the NFT System (Adelmann, 2023)

Advantages	**Disadvantages**
Low water and nutrient consumption	Nutrient solution need to flow permanently
Easy and simple setup	Not suitable for large and heavy plants due to insufficient support
Easy to check the health of the plants as the roots and the plants can be accessible easily	The stream can be blocked by roots
Less salt deposits as water is in motion	

2.4.2 Deep Water Culture (DWC) System

DWC hydroponic systems refering to (Michael, 2023) shown in Figure 2.4 submerge the plant's roots in a well-oxygenated solution full of nutrients. The reservoir that contains the plants must able to hold a good amount of water that can submerge the plant's roots (Michael, 2023). Since roots are constantly submerged in solution, an air pump and air stone is needed to balance the oxygen levels in the water and offer additional aeration to the root systems. Table 2.4 discusses the advantages and disadvantages of the DWC system.

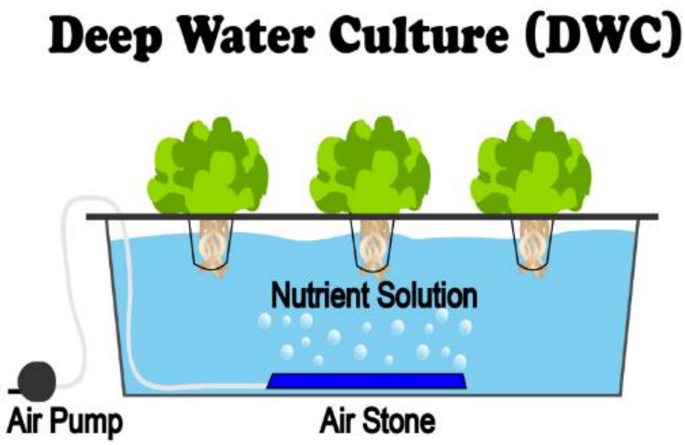


Figure 2.4: Deep Water Culture (DWC) System (Michael, 2023)

Table 2.4: Advantages and Disadvantages of the DWC System (Adelmann, 2023)

Advantages	**Disadvantages**
Accelerated growth	Not suitable for small system
Once set up, only requires little maintenance	The solution needs to aerate constantly
Easy setup	Difficult to maintain consistent water temperature

2.4.3 Wick System

The wick hydroponic system refering to (Michael, 2023) shown in Figure 2.5 is one of the simplest forms of hydroponic systems. In this setup, plants are grown in an inert growing medium coconut coir. A wick, typically a soft fabric like cotton, extends from the nutrient solution reservoir to the growing medium where the plant roots are growing. Based on capillary action, the wicks will draw up the nutrient solution until the growing mediums are moist. Without the need for pumps or electricity, this passive process ensures that the roots have access to water and nutrients as needed (McCandless, 2024). While the wick system is easy to set up and requires minimal maintenance, it may not be suitable for larger plants or those with high water and nutrient requirements due to its limited delivery capacity. Table 2.5 discusses the advantages and disadvantages of the wick system.

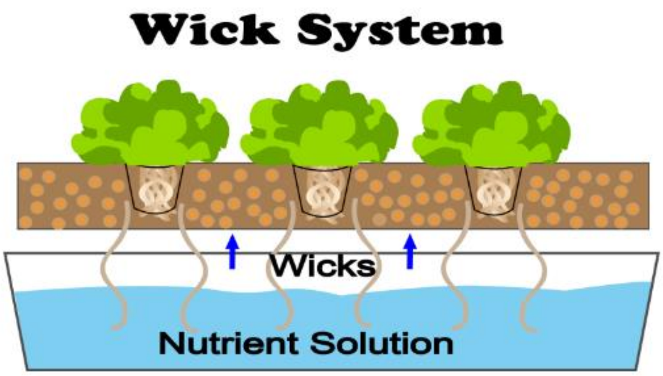


Figure 2.5: Wick System (Michael, 2023)

Table 2.5: Advantages and Disadvantages of the Wick System (McCandless, 2024)

Advantages	Disadvantages
Low cost	Not suitable for large plants due to limited delivery capacity
Once set up, only requires little maintenance	Need to be flushed out excess mineral salts in the growing medium with plain water regularly
Easy setup	
No external power needed	

2.4.4 Ebb and flow System

The Ebb and flow hydroponic systems refering to (Michael, 2023) shown in Figure 2.6 is a hydroponic setup where plants are grown in such a way that the nutrient solution is periodically pumped into the plant growing containers, flooding the root zone, and then drained back into a water reservoir. This process ensures plants receive water and nutrients while also allowing the roots to access oxygen during drainage. Timer control is needed to ensure that the water pumping cycle is suitable for the corresponding system to prevent over- or under-watering. Table 2.6 discusses the advantages and disadvantages of the Ebb and flow system.

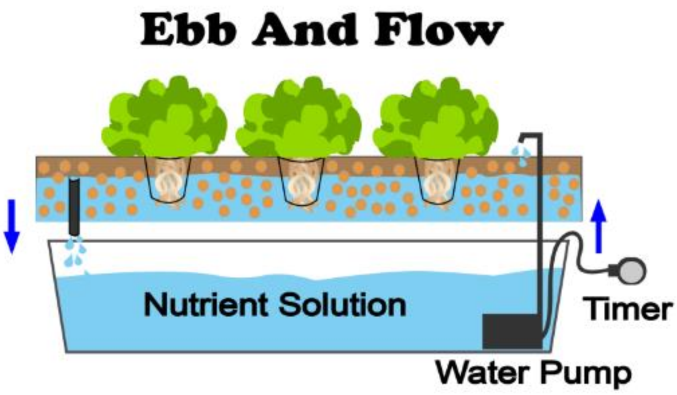


Figure 2.6: Ebb and flow System (Michael, 2023)

Table 2.6: Advantages and Disadvantages of the Ebb and flow System (Trees.com, 2022)

Advantages	Disadvantages
Low-cost	Depends on external power, pump breakdown may occur
Ensure the plants obtain just enough nuteients	Unstable pH level
Easy setup	

2.4.5 Drip System

The drip circulating systems refering to (Michael, 2023) shown in Figure 2.7 utilize individual pots for plants, connected to a water reservoir through a network of tubing. Pressure for water supply can come from either a water pump or a gravity-based system. Each plant receives water through dedicated drip emitters with adjustable flow mechanisms, allowing for customized watering levels. Regulation of water flow is crucial to prevent over-watering and drowning of plants, achieved through timer systems controlling pump operation. There are 2 types which are non-circulating and circulating systems. Circulating systems have a faster drip rate and can prevent excess nutrients from causing the death of the plants but it has a risk that the recirculated nutrient solution will contaminate the nutrient solution in the reservoir. Non-circulating systems have slower drip rates but they can prevent the contamination of the nutrient solution in the reservoir caused by recirculated solution (Trees.com, 2022). Table 2.7 discusses the advantages and disadvantages of the drip system.

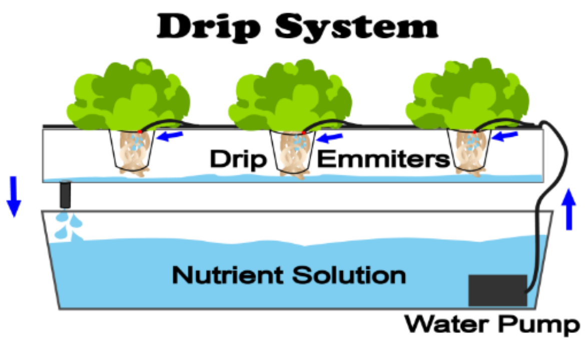


Figure 2.7: Drip System (Michael, 2023)

Table 2.7: Advantages and Disadvantages of the Drip System (Trees.com, 2022)

Advantages	Disadvantages
Offers enhanced control over the supply of water and nutrients.	Too complex for a very small growth operation
Scalable system is adaptable to varying growth needs.	Unstable pH level, for circulating system
	Waste of nutrients, for non-circulating system

2.4.6 Aeroponic System

The aeroponic hydroponic system refering to (Michael, 2023) shown in Figure 2.8 is a method in which the plant roots are suspended in the air and the nutrient-rich solution is directly sprayed at the root system. In this system, plants are typically housed in specialized trays or containers that support their growth while allowing their roots to hang freely. The nutrient solution is stored in a reservoir and delivered to the roots via misting nozzles positioned nearby. As the nutrient solution envelops the roots in a fine mist or spray, the plants absorb the necessary nutrients directly through their root systems. Hence, this method can reduce the waste of nutrient solution and prevent plant roots from downing. Table 2.8 discusses the advantages and disadvantages of the aeroponic system.

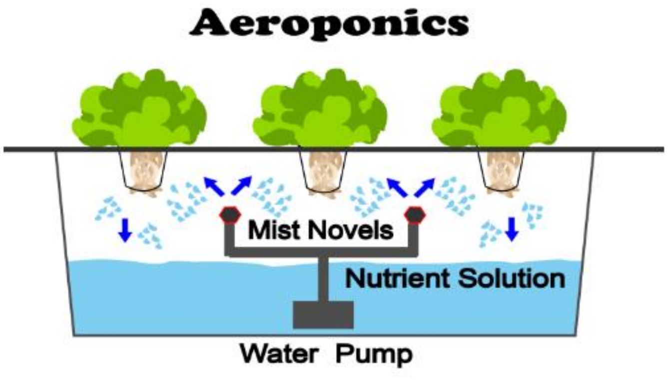


Figure 2.8: Aeroponics System (Michael, 2023)

Table 2.8: Advantages and Disadvantages of the Aeroponics System (Barth, 2018)

Advantages	Disadvantages
Faster growth of plants	Depending on power supply function, the breakdown of mist novels is severe
Water efficient	Expensive set up
Space efficient	Require continuous monitoring
	Require regular maintenance on the nozzles from becoming clogged by mineral deposits in the water

2.5 Fogger System

In this hydroponic system, the fogger system is implemented with the system aim of cooling down the plant temperature due to high-temperature regions or high-temperature periods. The fogger system uses an ultrasonic fogger which produces high frequency vibration causing the water to atomize. This atomised water will easily evaporate and bring the heat energy out from the plant, reducing the surrounding temperature as well as the plant temperature by up to 15 °F about 8.33 °C (MicroCool, 2023). Hence, having water fogging during the hottest part of the day will effectively reduce the surrounding temperature to maximize crop production.

2.6 Network Time Protocol (NTP)

Network Time Protocol (NTP) is a protocol used to synchronize the clocks of computers and other networked devices across the internet or local networks. Its primary purpose is to ensure that all devices maintain accurate timekeeping, which is essential for various network operations, such as logging events, scheduling tasks, and coordinating actions between different systems. With this NTP, the fogger shower time can be synchronized.

2.7 Mircocontroller

The two most well-known development boards for microcontrollers, ESP32 and Arduino, have had a big impact on DIY projects and embedded systems. In our hydroponic system design, Wifi, the number of GPIO pins and libraries greatly affect the ease of construction and implementation of the system. The comparison between ESP32 and Arduino microcontrollers are shown in Table 2.9.

Table 2.9: Comparison Between ESP32 and Arduino Microcontroller

ESP32	Uno R4 Minima (Arduino)
Dual-core Xtensa LX6, 240 MHz Higher processing power	ARM Cortex-M4, 48 MHz Lower processing power
520 kB RAM, 4 MB flash Larger memory	32 kB RAM, 256 kB flash, 8 kB data memory Lower memory
In-built Wi-Fi and Bluetooth	Need Wi-Fi and Bluetooth extension
34 GPIO pins	14 GPIO pins

2.8 Blynk

Blynk is an IoT platform that focuses on simplicity and ease of use. Blynk provides a mobile app and a cloud-based platform that allows users to quickly deploy IoT applications for monitoring the system. Blynk allows users to create custom dashboards to monitor and control connected devices, visualize sensor data, and trigger actions based on predefined rules. Blynk app can notify the user when an abnormal condition is detected and the user can monitor the system parameters no matter where. The example dashboard in the Blynk App is shown in Figure 2.9.

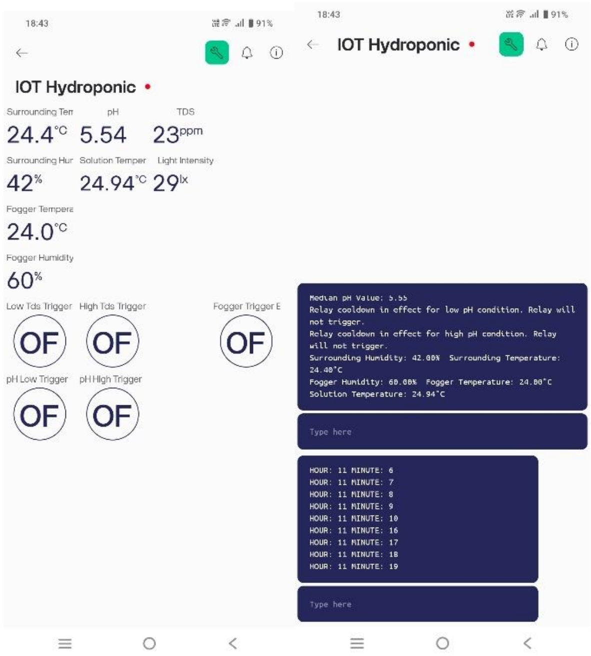


Figure 2.9: Blynk Mobile Dashboard

2.9 AI Models

In the context of hydroponic systems, where continuous monitoring and control of environmental parameters are crucial for optimizing plant growth, time series data plays a significant role. The data collected over time, such as temperature, humidity, pH levels, and TDS value, is essential for making accurate predictions and adjustments to the system.

Given the importance of these sequential data points, it is crucial to employ AI models that can effectively capture and analyze patterns over time. For this purpose, two advanced AI models—Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs)—are particularly well-suited. Both LSTM and GRU are types of Recurrent Neural Networks (RNNs) that are designed to handle long-term dependencies in sequential data, making them ideal for time series forecasting in hydroponic systems.

In this project, LSTM and GRU models will be implemented and compared to evaluate their performance in predicting future values based on the historical data collected from the hydroponic system. The goal is to determine which model provides better accuracy and reliability in forecasting, thus enabling more effective control and optimization of the hydroponic environment. This comparison will provide insights into the most suitable model for managing time-dependent variables in a hydroponic setup.

2.9.1 Long-Short-Term-Memory (LSTM) Machine Learning Model

Long Short-Term Memory (LSTM) is an improved type of recurrent neural network (RNN) architecture. Vanilla RNN cannot learn long-term dependencies due to its vanishing or exploding gradient problem on the weights caused by a large number of iterations of sequential data (GeeksforGeeks, 2023). Unlike convolutional neural networks (CNN), recurrent neural networks (RNN) have a feedback loop that feeds the output back into the network (Craig, 2023). LSTM excels at capturing long-term dependencies as well as short-term information in sequential data.

At the heart of LSTM networks are memory cells, which enable the network to retain and utilize information over extended periods of time. This memory cell consists of 3 gates which are the forget gate, input gate and output gate. The forget gates control the amount of information need to be forgotten from the previous cell state, the input gate controls the amount of new information added to the current cell state and the output gate controls the amount of information output from the cell state (Banoula, 2023). By selectively updating the cell state and hidden state based on the input data and the gating mechanisms, LSTM can effectively capture complex temporal patterns and dependencies in sequential data. This makes them well-suited for tasks including time-series prediction and sequential decision-making. This characteristic is suitable for our hydroponic system monitoring and prediction as our data is time-series based and needs prediction from long-term dependency and short-term information. Figure 2.10 shows the structure of LSTM. Table 2.10 discusses the advantages and disadvantages of the LSTM.

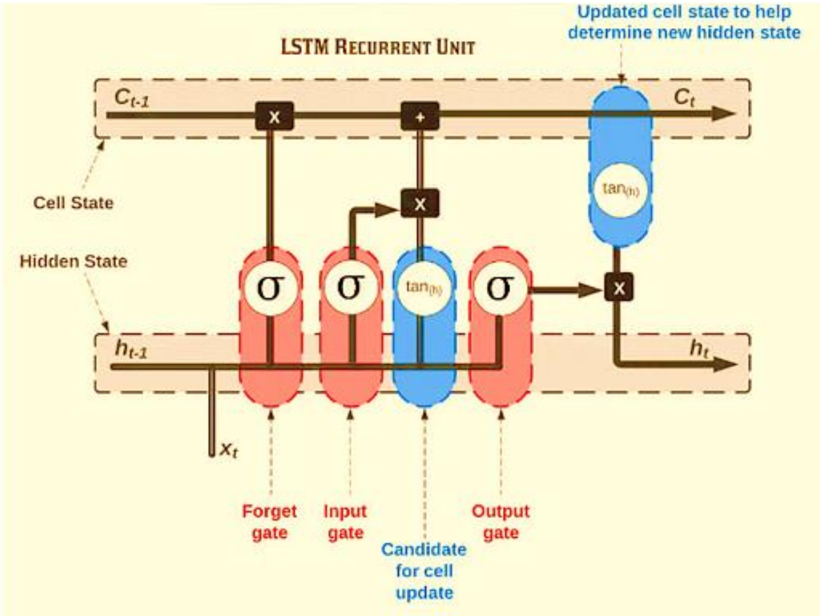


Figure 2.10: Long-Short-Term-Memory (LSTM) Structure (Banoula, 2023)

Table 2.10: Advantages and Disadvantages of LSTM (GeeksforGeeks, 2023)

Advantages	Disadvantages
Capture long-term dependencies	Computational complexity and expensive
Solve gradient problems by having gating mechanisms to recall or forget information selectively	Longer training time
Capture and remember the important information even a large time gap between relevant events in the sequence	Cannot deal with the parallel matter

2.9.2 Gated Recurrent Units (GRUs) Machine Learning Model

Gated Recurrent Units (GRUs) are a simplified variant of the Long Short-Term Memory (LSTM) networks, which also the family of Recurrent Neural Networks (RNNs). Like LSTM, GRUs are designed to tackle the vanishing gradient problem that typically affects Vanilla RNNs. GRUs excel in modeling sequential data by selectively remembered or forgotten information over time (Kostadinov, 2019). However, GRUs feature a simpler architecture with fewer parameters than LSTM, making them easier to train and more computationally efficient.

The key distinction between GRUs and LSTM lies in how they manage the memory cell state. In LSTM, the memory state is kept distinct from the hidden state and is modified through three gates: the input gate, output gate, and forget gate. On the other hand, GRUs simplify this by using a single state, which is updated with just two gates: the reset gate and the update gate (Anishnama, 2023).

The update gate in GRUs decides how much past information should be carried forward into the future, similar to the role of the Output Gate in an LSTM unit. Meanwhile, the reset gate manages how much past information should be forgotten, similar to the combined function of the Input Gate and Forget Gate in an LSTM unit (Anishnama, 2023). Overall, GRUs are a popular alternative to LSTM for sequential data modeling, particularly in scenarios where computational efficiency or a simpler model architecture is preferred. Figure 2.11 shows the structure of GRUs. Table 2.11 discusses the advantages and disadvantages of the GRUs.

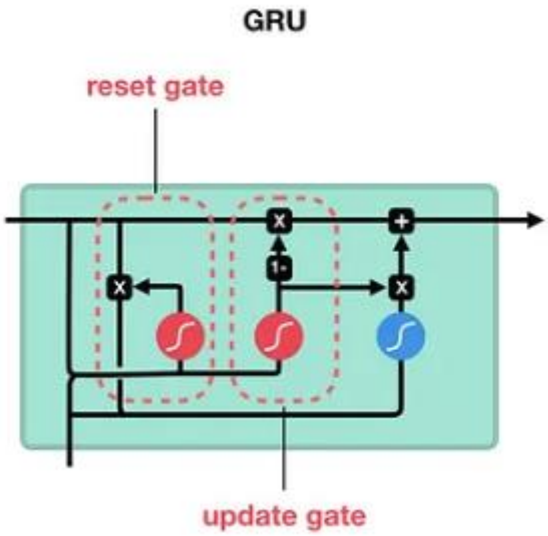


Figure 2.11: Gated Recurrent Units (GRUs) Structure (Phi, 2020)

Table 2.11: Advantages and Disadvantages of GRUs (Anishnama, 2023)

Advantages	Disadvantages
Efficient and faster to train than LSTMs.	May struggle with very long-term dependencies.
Can handle long-term dependencies by selectively remembering and forgetting inputs.	Can be prone to overfitting.
Effective for various sequential tasks.	Requires careful tuning of parameters.

2.10 Summary

In conclusion, based on the research and comparisons presented, the Deep Water Culture (DWC) method has been selected as the most suitable approach for growing lettuce in a hydroponic system. This method is favored for its simplicity of construction and its widespread use, making it accessible for public adoption. Additionally, the ESP32 microcontroller and the Blynk IoT platform were chosen for this project due to their advanced features, such as built-in Wi-Fi, numerous GPIO pins, and ease of integration, which make system monitoring and control efficient and cost-effective.

This chapter has explored various aspects of hydroponic farming systems and the technologies best suited for optimizing plant growth. It began by discussing key environmental parameters that significantly affect plant health, including pH levels, electrical conductivity (EC), temperature, light intensity, and surrounding temperature and humidity. Each of these factors plays a crucial role in ensuring optimal growth, especially for lettuce cultivation. The chapter also reviewed different hydroponic systems such as Nutrient Film Technique (NFT), Deep Water Culture (DWC), Wick, Ebb and Flow, Drip, and Aeroponics, highlighting their respective advantages and disadvantages. A fogger system's role in cooling plants and maintaining proper temperature was also discussed.

Furthermore, a comparison between ESP32 and Arduino microcontrollers was made, with ESP32 being favored due to its superior processing power, built-in Wi-Fi, and suitability for IoT applications. Blynk was selected as the IoT platform for its user-friendly interface and real-time system monitoring capabilities.

Lastly, the chapter emphasized the importance of machine learning models in hydroponic farming. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models were identified as ideal for analyzing time-series data from the system, enabling accurate monitoring and prediction of plant growth conditions. The chosen models will be evaluated to determine which offers better accuracy and reliability for system optimization. Overall, this chapter lays the groundwork for implementing a smart hydroponic system by addressing key environmental factors, technology choices, and predictive modeling techniques.

CHAPTER 3

METHODOLOGY AND WORK PLAN

3.1 Introduction

This chapter outlines the methodology and work plan for the project, which are broken down into three major parts:

1. Construction of an outdoor hydroponic prototype using the Deep Water Culture (DWC) method, integrated with various IoT sensors, controllable devices, and the Blynk IoT platform for user interface and data collection.
2. Experiments to investigate the impact of a water fogger system in lowering the temperature around plants and its effect on plant growth rate
3. Application of AI to analyze the collected data for predicting future environmental parameters and enabling proactive adjustments.

Firstly, the hydroponic system employs various sensors and controllable devices to maintain optimal environmental parameters. These parameters are displayed on the user interface of the IoT platform and the controllable devices can be controlled automatically or manually. It's crucial that users have the ability to adjust these parameters, as the optimal conditions can vary depending on the plant growth stage, external environmental factors, and the specific region.

Secondly, an experiment is conducted to evaluate whether water fogger system can improve plant development during periods of high ambient temperature. Two hydroponic setups—one with a fogger system and one without—are operated concurrently to ensure that both sets of plants are exposed to the same environmental conditions. The fogger system is controlled by Network Time Protocol (NTP) coordinated with the ESP32 microcontroller. Plant growth parameters are measured and recorded to evaluate the effectiveness of the fogger system.

Lastly, the data collected from environmental sensors is continuously analyzed by AI models, specifically LSTM and GRU model. These models are trained to monitor the system, provide predictive insights for proactive control, and identify potential abnormal conditions. By comparing the performance of LSTM and GRU, the system ensures the most effective approach is used for accurate monitoring and prediction.

3.2 Hydroponic Circuit Design

In this outdoor DWC hydroponic system, a large box container (45 cm × 50 cm × 15 cm) is used as a nutrient solution reservoir, as shown in Figure 3.1. The plants are supported by a modified waterproof plastic board placed on top of the container, as illustrated in Figure 3.2.

Figure 3.1: Nutrient Solution Reservoir

Figure 3.2: Modifted Waterproof Plastic Board

The nutrient solution reservoir can store approximately 20 liters of nutrient solution. According to K (2021), for every 4 liters of nutrient solution, 1 liter of air per minute is required. Thus, the air pump capacity needed is $\frac{20}{4} = 5\ liter\ per\ minute$. The air pump used in this setup provides 2 × 4 liters of air per minute, as shown in Figure 3.3, which is more than sufficient for our DWC hydroponic system. Figure 3.4 shows the equipment required for aerating the solution, including pipes, an air stone, and the air pump. Apart from providing aeration, the air pump and air stone aid in the circulation of the nutrient solution, ensuring uniform pH and TDS levels across the reservoir.

Figure 3.3: Capacity of Air Pump

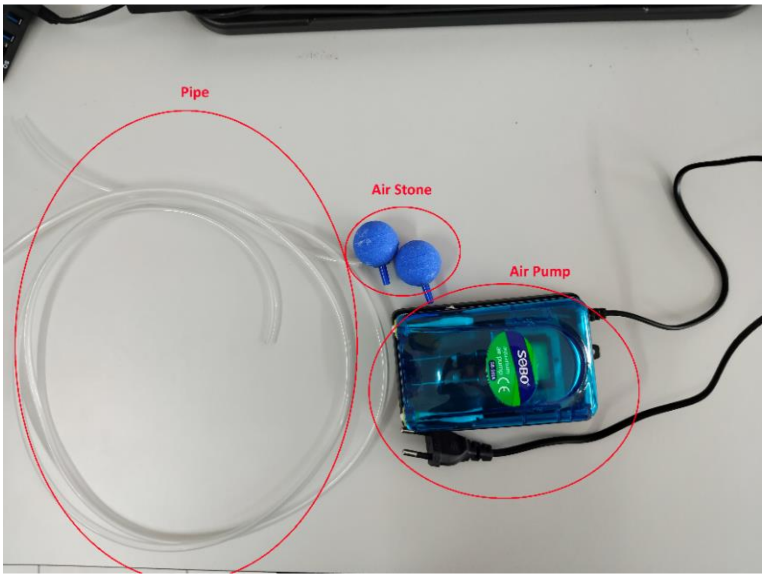


Figure 3.4: Pipes, Air Stone and Air Pump

Besides, to protect the outdoor hydroponic setup from rain, the ESP32 circuit and sensors must be housed in a rainproof container. A container modified with holes and cable glands serves this purpose, as shown in Figures 3.5 and 3.6, which illustrate the interior and exterior of the container, respectively. This container houses the main ESP32 circuit, all sensor circuits, adapters, and extensions. The sensor cables and wires for controllable devices pass through the cable glands. This setup ensures accurate measurement of environmental parameters by placing sensors in their optimal locations. Proper sealing of the container and cable glands is essential to protect the electronics from moisture and environmental exposure, enhancing the system's reliability and longevity.

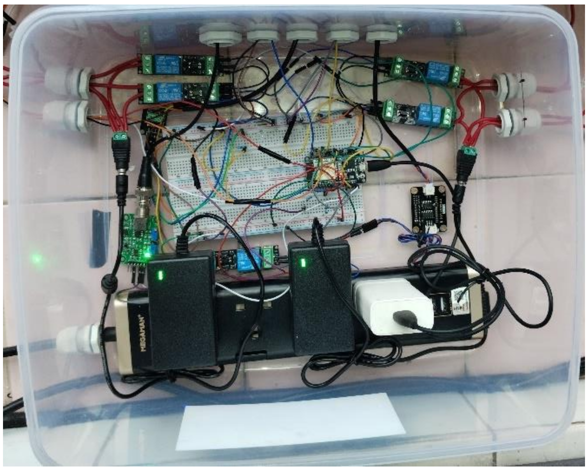


Figure 3.5: Interior of Container

Figure 3.6: Exterior of Container

3.2.1 Block Diagram

Figure 3.7 illustrates the entire flow of data and instructions between sensors, the ESP32 microcontroller, controllable devices, and the IoT platform. The block diagram shows that all real-time environmental parameters are continuously measured by their corresponding sensors and transmitted to the ESP32. Additionally, the ESP32 acquires the current time through NTP (Network Time Protocol).

The received data is sent to the IoT platform or cloud via the Internet for user interface access and data collection for further analysis. Users can control the controllable devices through a mobile or web dashboard via the Blynk Cloud Interface. The ESP32 receives these instructions and activates the relay to control the devices, such as peristaltic pumps and fogger setup.

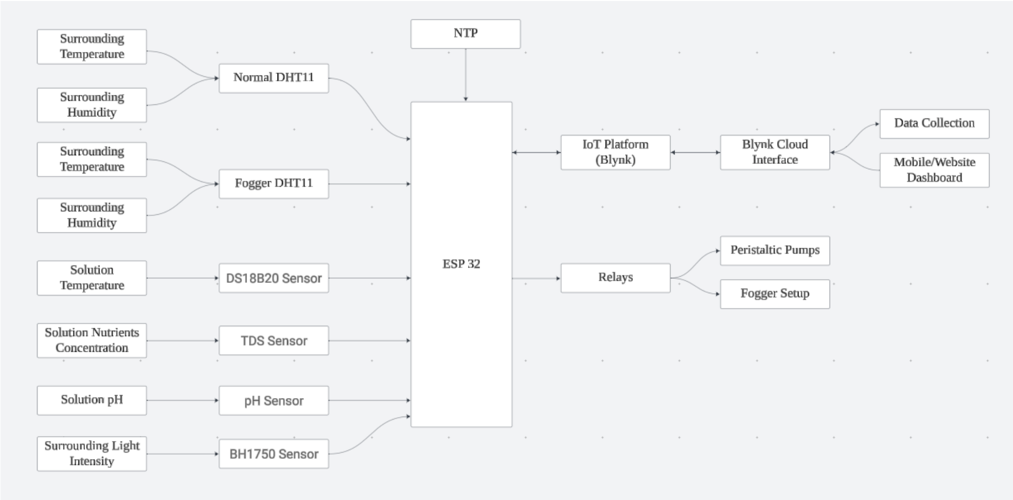


Figure 3.7: Block Diagram of IoT Hydroponic Setup

3.2.2 Sensors Circuit Design

To continuously monitor environmental parameters, several sensors are integrated with the ESP32 microcontroller. Real-time data is transmitted to the IoT platform, Blynk, for user observation and data collection for further analysis. The sensors utilized include the DHT11 for monitoring surrounding humidity and temperature, a pH sensor to measure the pH value of the nutrient solution, a TDS sensor for determining the TDS or EC value of the nutrient solution, a DS18B20 sensor for tracking the nutrient solution temperature, and a BH1750 ambient light sensor for measuring light intensity.

3.2.2.1 Temperature and Humidity Sensor (DHT11)

DHT11 Specification:

- Humidity Range: 20-80% RH
- Humidity Accuracy: ±5% RH
- Temperature Range: 0-50 °C
- Temperature Accuracy: ±2% °C
- Operating Voltage: 3V to 5.5V

As shown in Figure 3.8, two DHT11 sensors are used for different purposes. One sensor, referred to as "normal surrounding DHT11" measures the surrounding temperature and humidity without the fogger system. The other sensor, "fogger DHT11" measures the surrounding temperature and humidity with the fogger system active. Figure 3.8 illustrates the circuit configuration, where the normal DHT11 data pin is connected to GPIO23 of the ESP32, and the fogger DHT11 sensor data pin is connected to GPIO19 of the ESP32.

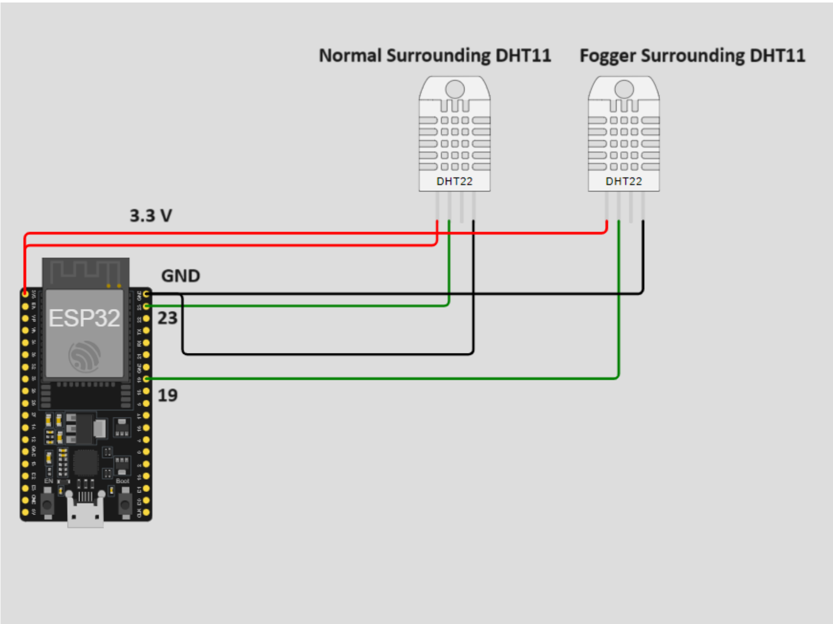


Figure 3.8: Circuit for the DHT11 sensors (GPIO23 and GPIO19)

3.2.2.2 pH Sensor

pH Sensor Specification:

- Module Power : 5.00V
- Module Size : 43 x 32mm(1.69x1.26")
- Measuring Range :0 - 14PH
- Measuring Temperature: 0 - 60 ℃
- Accuracy : ± 0.1pH (25 ℃)
- Response Time : ≤ 1min
- pH Sensor with BNC Connector

Based on the specification of the pH sensor circuit, a 5V input is required, which is provided by connecting the sensor's V_{cc} to the V_{in} of the ESP32. Based on initial testing, the sensor output is clipped at 5V. Since the maximum input voltage for the ESP32 GPIO analog inputs is 3.3V, a voltage divider circuit is necessary to reduce the voltage to a safe level for the GPIO34 pin. This voltage divider, composed of two resistors, ensures that the maximum output voltage of 5V from the pH sensor is appropriately scaled down to within the 3.3V limit of the ESP32's analog input.

According to Espressif Systems, a 0.1µF capacitor is used to reduce noise from the pH circuit and the ESP32 input voltage. Figure 3.9 shows the circuit for the pH sensor connected to GPIO34.

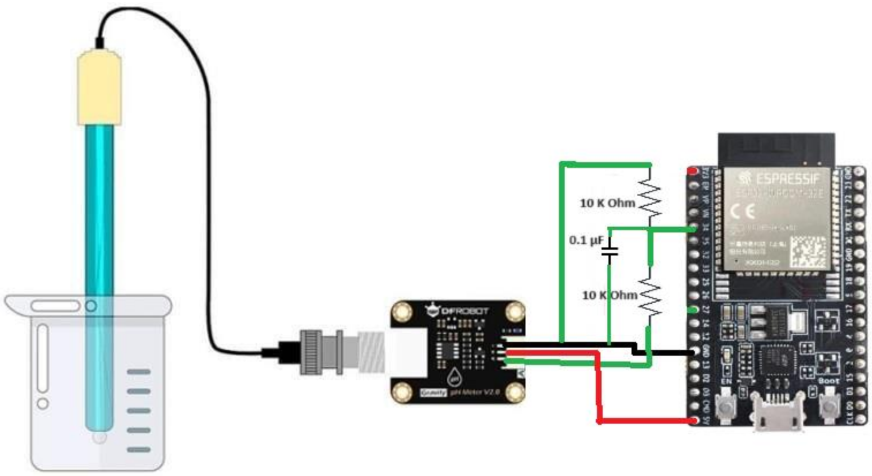


Figure 3.9: Circuit for the pH sensor (GPIO34)

The pH sensor must be calibrated to ensure accurate measurements. Buffer powders, as shown in Figure 3.10, are used for this calibration. The following is the calibration procedure:

1. Preparation:
   - Mix 250 mL of distilled water with standard pH buffer powders (4.00, 6.86, and 9.18).
   - Use the Arduino IDE to interface with the pH probe.
2. Initial Calibration:
   - Insert the pH probe into the 6.86 pH solution.
   - Using a voltage divider composed of two 10 kΩ resistors, adjust the pH offset calibration varistor as shown in Figure 3.11 until the analog voltage input to GPIO35 of the ESP32 is approximately half of 3.3V, which is 1.65V. This adjustment ensures that the pH meter can accurately measure the full pH range from 0 to 14. According to Figure 3.12, a higher output voltage corresponds to a lower pH value.

Figure 3.10: Standard pH Buffer Powder

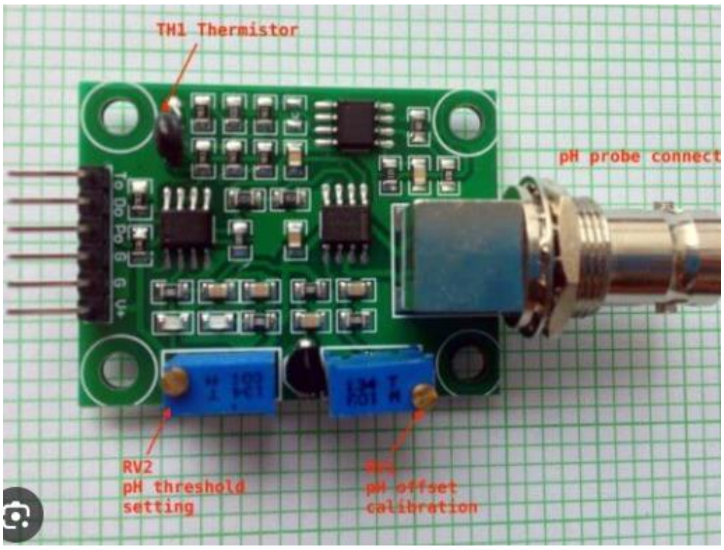


Figure 3.11: Circuit of pH Sensor

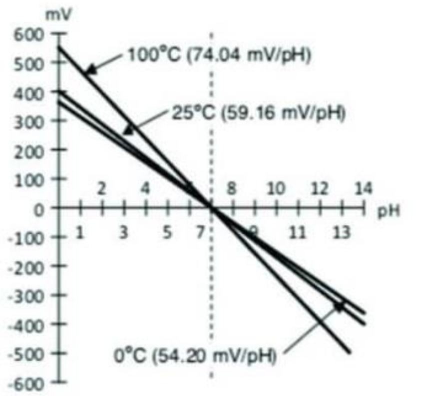


Figure 2. pH-Electrode Transfer Function

Figure 3.12: Transfer Function of pH Electrode

3. Gradient Calculation:
   - Insert the pH probe into the 4.00 pH solution.
   - Measure the voltage output by the pH probe and calculate the gradient (m) using the formula: $m = (pH_{6.86} - pH_4) / (V_{ph6.86} - V_{ph4})$.
   - From the testing, the calculated gradient is: $m = \frac{6.86-4.01}{1.645-1.840} = -14.615$.
4. Transfer Function and Final pH Calculation:

- Calculate the pH value using the formula: $pH = pH_{6.86} - (V_{ph6.86} - Po) * m$.
- In this case, $pH = 6.86 - (1.645 - Po) * -14.815$.

3.2.2.3 TDS Sensor

TDS Sensor Specification:

- Input Voltage: 3.3 ~ 5.5V
- Output Voltage: 0 ~ 2.3V
- Working Current: 3 ~ 6mA
- TDS Measurement Range: 0 ~ 1000ppm
- TDS Measurement Accuracy: ± 10% F.S. (25 °C)
- Module Size: 42 * 32mm

As shown in Figure 3.13, the data pin of the TDS sensor is connected to GPIO35, with the maximum output voltage being 2.3V, which is within the safe input range for the ESP32 GPIO35 pin. This setup allows the sensor to be directly interfaced with the ESP32 without the need for additional voltage regulation. Similar to the pH sensor, the TDS sensor must be calibrated to ensure accurate measurements. The following is the calibration procedure:

1. Preparation:
    - Mix 1000 mL of distilled water with 0.5 g of NaCL salt to form 500 ppm or 1 mS/cm solution.
    - Use the Arduino IDE to interface with the TDS sensor.
2. Calibration:
    - Calculate the TDS value using the formula:
        I. $Temperature\_Compensation = 1.0 + 0.02 * (solution\_temperature - 25.0)$
        II. $Compensation\_Voltage = \frac{Voltage\_Measured}{Temperature\_Compensation}$
        III. $TDS\ Value = (133.42 * Compensation_{Voltage}{}^{3} - 255.86 * Compensation\_Voltage^{2} + 857.39 * Compensation\_Voltage) * 0.5 * kValue$

- Adjust the kValue to fit the 500 ppm. After my testing, the kValue should be 1.10.

Based on Figure 3.13, a relay is used to control the ON/OFF state of the TDS sensor. This is crucial because when the TDS probe and pH probe are placed in the same solution, the TDS probe generates an AC signal that can interfere with pH measurements. The relay is employed to turn off the TDS sensor when the pH sensor is active and vice versa. This approach helps to avoid electrochemical interference, ensuring accurate readings from both sensors.

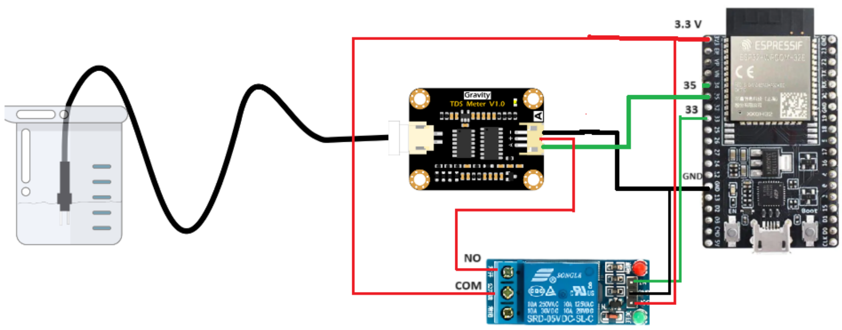


Figure 3.13: Circuit for the TDS sensor (GPIO35)

An alternative solution to the interference problem is using an Analog Signal Isolator, as shown in Figure 3.14. An Analog Signal Isolator can effectively isolate the signals from the two sensors, preventing interference and ensuring accurate measurements. However, this component is relatively expensive, costing about RM93, excluding delivery fees. Given the high cost, the relay method remains a more cost-effective solution, while still effectively mitigating interference between the TDS and pH sensors.

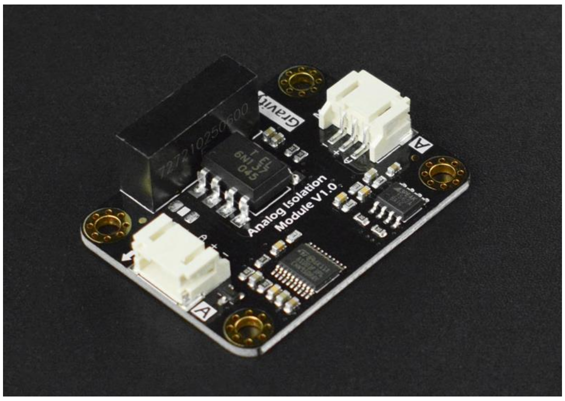


Figure 3.14: Analog Signal Isolator

3.2.2.4 Solution Temperature Sensor (DS18B20)

DS18B20 Specification:

- Temperature sensor supply voltage: 3.0V ~ 5.5V
- Temperature sensor resolution: 9 to 12 adjustable resolution
- Temperature range: -55 ~ +125 ° (lead can only withstand the highest temperature of 85 degrees)

As shown in Figure 3.15, the data pin of the DS18B20 temperature sensor is connected to GPIO17 of the ESP32. A pull-up resistor with a value of 4.7 kΩ is required to maintain the data line in a high state when the bus is idle. This configuration ensures reliable communication between the DS18B20 sensor and the ESP32, enabling accurate temperature measurements.

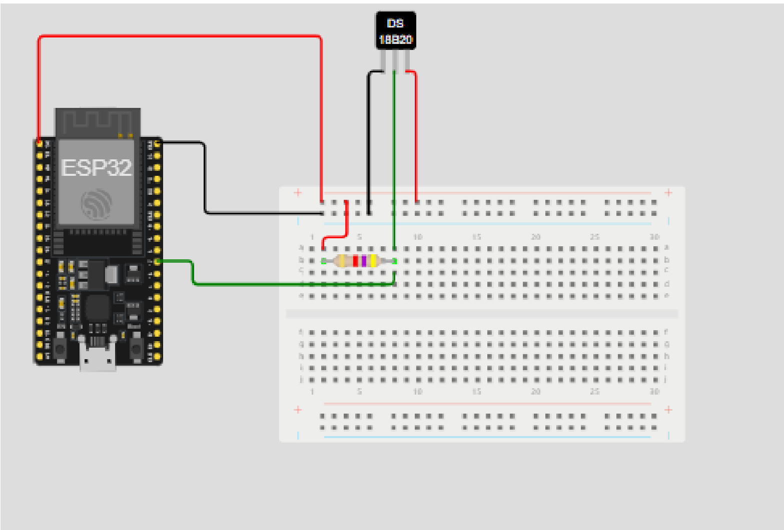


Figure 3.15: Circuit for the DS18B20 sensor (GPIO17)

3.2.2.5 Light Intensity Sensor (BH1750)

BH1750 Specification:

- I2C bus Interface
- Range: 1 – 65535 lux
- Low current by power down function
- 50Hz / 60Hz Light noise reject-function
- It is possible to select 2 different I2 C slave addresses
- Small measurement variation (+/- 20%)

Based on Figure 3.16, the SCL (Serial Clock Line) and SDA (Serial Data Line) pins of the BH1750 light sensor are connected to the GPIO22 and GPIO21 pins of the ESP32, respectively. This connection enables I2C communication between the sensor and the microcontroller, allowing for efficient data transfer and sensor control. By leveraging the I2C protocol, multiple sensors can be connected to the same bus, simplifying the wiring and expanding the system's capability to monitor various environmental parameters.

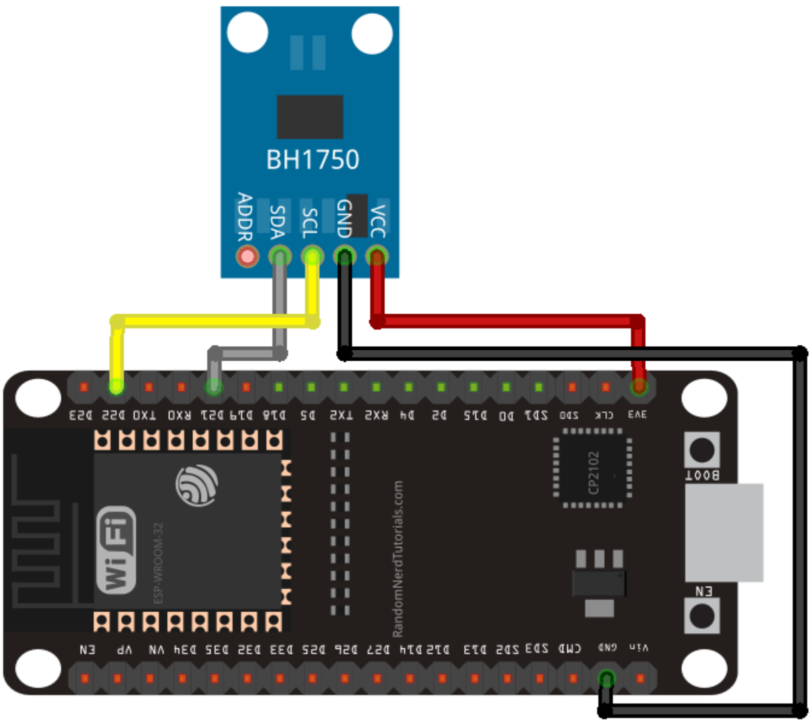


Figure 3.16: Circuit for the BH1750 Ambient Light Sensor (GPIO22 and GPIO21)

3.2.3 Controllabel Devices Circuit Design

The pH and TDS values of the nutrient solution are automatically controlled by actuators, specifically peristaltic pumps. Figure 3.17 shows the appearance of a peristaltic pump. Four peristaltic pumps are used, with each environmental parameter having two pumps: one to increase the value and one to decrease it. For TDS control, an 850 ppm TDS up solution is used along with a 50 ppm TDS down solution. For pH control, a pH 3 (phosphorous acid) solution is used to decrease pH, and a pH 9 (potassium hydroxide) solution is used to increase pH.

Each solution is stored in its corresponding container, as shown in Figure 3.18. The peristaltic pumps are programmed to dispense the appropriate solution into the nutrient solution reservoir as needed, based on real-time measurements from the sensors. When the pH sensor detects that the pH level is outside the desired range, the appropriate pump is activated to adjust the pH. Similarly, when the TDS sensor detects an out-of-range TDS level, the corresponding pump adjusts the TDS.

Due to the high current requirements of the peristaltic pumps, an external power supply is necessary, and relays are used to control their operation. Figure 3.19 illustrates the circuit setup, which involves four GPIO pins and four relays to manage the four peristaltic pumps. The ESP32 microcontroller controls the system, using GPIO pins (12, 13, 4, and 18) to interface with the relays. Each relay, acting as a switch, allows the external 12V power supply to power the peristaltic pumps when activated by the ESP32. The positive terminal of each adapter connects to the common (COM) terminal of the relay, while the normally open (NO) terminal connects to the positive terminal of the pump. The negative terminals are directly connected.

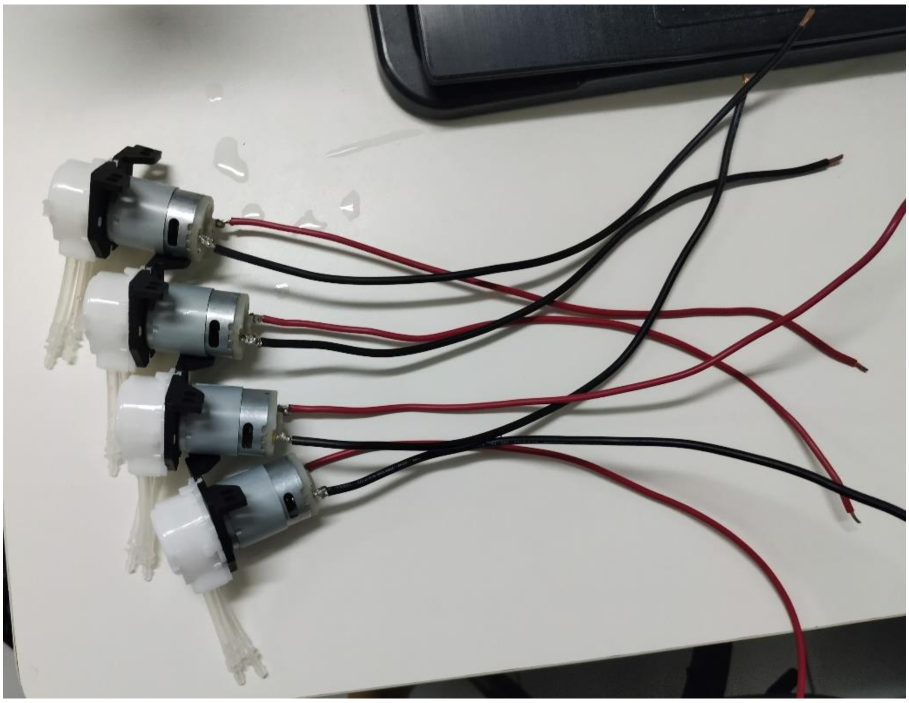


Figure 3.17: Peristaltic Pump

Figure 3.18: Containers Filling pH and TDS Up/Down Solution

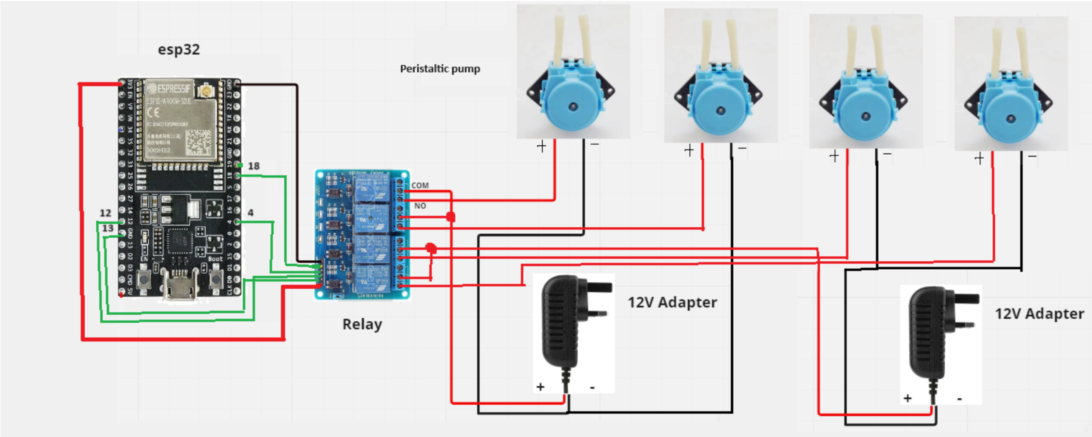


Figure 3.19: Circuit for the Peristaltic Pump

Figure 3.20 "Relay Control Logic Flowchart" is designed for pH and TDS control. It ensures that the relay operates only when specific time intervals and input conditions, such as pH or TDS levels, are met. The system checks if the required cooldown time has passed, evaluates the median pH or TDS value, and increments a count status when necessary. If the count status reaches a predefined setting, the relay is activated to adjust the pH or TDS levels, followed by a brief delay, and then the relay is turned off. This process helps maintain optimal pH and TDS levels efficiently.

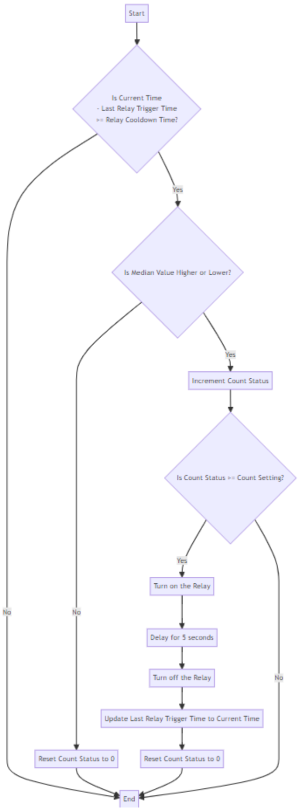


Figure 3.20: Relay Control Logic Flowchart

3.2.3.1 Fogger System Implementation

For the fogger system, due to time and cost constraints, the fogger module shown in Figure 3.21 will be purchased from an online shop. This module will be directly applied to the plants that require fogging for temperature reduction. The fogger with the absorbent wick can operate for up to 10 minutes, ensuring efficient cooling during this period. The circuit setup, as illustrated in Figure 3.22, connects the fogger setup to the ESP32 microcontroller, with the relay controlled via GPIO 27, allowing for precise on/off control of the fogger.

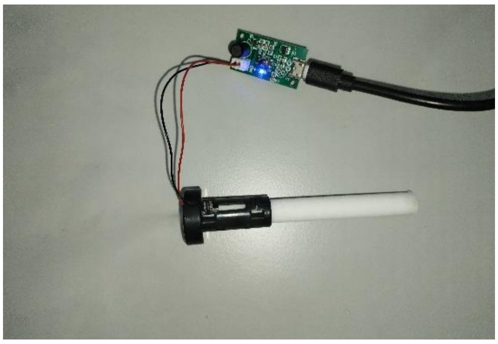


Figure 3.21: Fogger Module

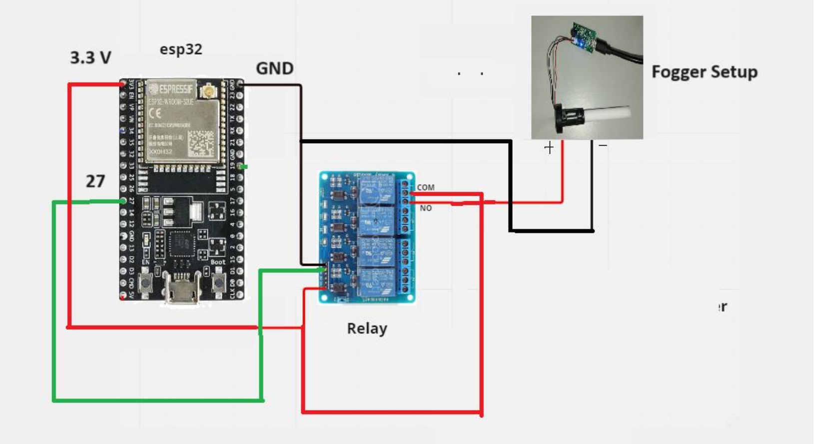


Figure 3.22: Circuit for the Fogger Setup

3.2.4 IoT Platform Design and Data Collection

The IoT platform design for this project is implemented using Blynk, which provides both a website and mobile dashboard. Figures 3.23 and 3.24 showcase the user interface on both platforms. All environmental parameters, such as surrounding temperature, humidity, pH, TDS, and light intensity, will be continuously updated based on sensor outputs and displayed on the user dashboard. Additionally, users can manually control pH and TDS levels via the control buttons provided. Sensor error detection and NTP (Network Time Protocol) time are displayed in the terminal sections, ensuring that users are informed of any discrepancies or issues in real-time. Table 3.1 outlines the key environmental parameters collected during the experiment, which are continuously monitored through the IoT platform for real-time updates and manual control options.

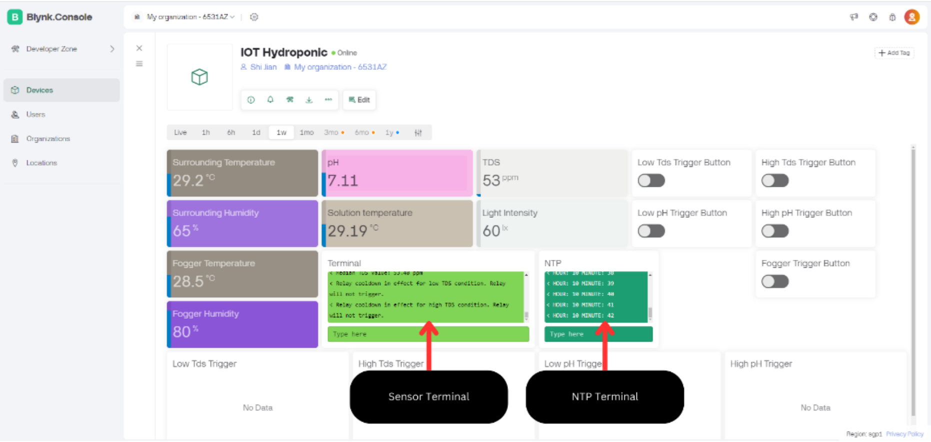


Figure 3.23: Blynk Website User Dashboard

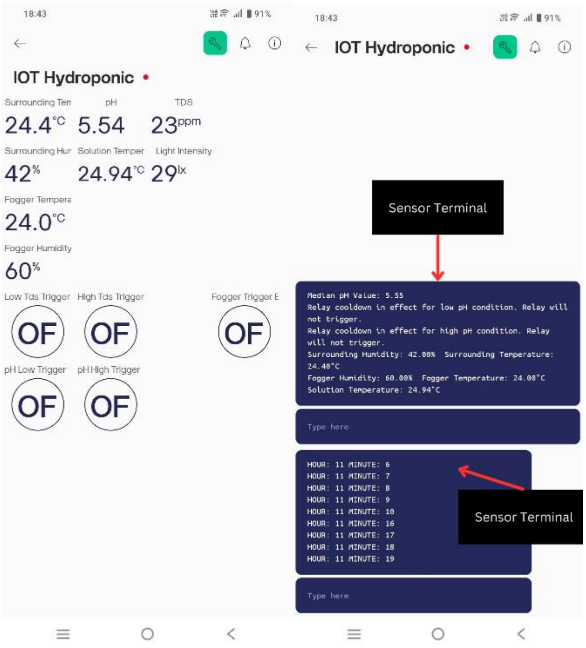


Figure 3.24: Blynk Mobile Dashboard

Table 3.1: Data Collection Parameters

No	Envirenmental Parameters
1	Surrounding Temperature
2	Surrounding Humidity
3	Light Intensity
4	pH Value
5	TDS Value
6	Nutrient Solution Temperature
7	Low pH Trigger
8	High pH Trigger
9	Low TDS Trigger
10	High TDS Trigger
11	Fogger Temperature
12	Fogger Humidity
13	Fogger Trigger

3.2.5 Sensor Error Detection

Enhancing reliability is crucial, and this includes implementing sensor error detection. When a sensor reading appears unrealistic, the system will automatically retry data retrieval from the corresponding sensor. If the number of retries exceeds the preset limit, the system will prompt a message to the Blynk terminal, clearly indicating which sensor is experiencing a problem or error. Hence, corrective actions can be taken immediately. This approach ensures that the system remains accurate and dependable, even when faced with potential sensor malfunctions. Figure 3.25 shows that an error was detected with the fogger DHT11 sensor.

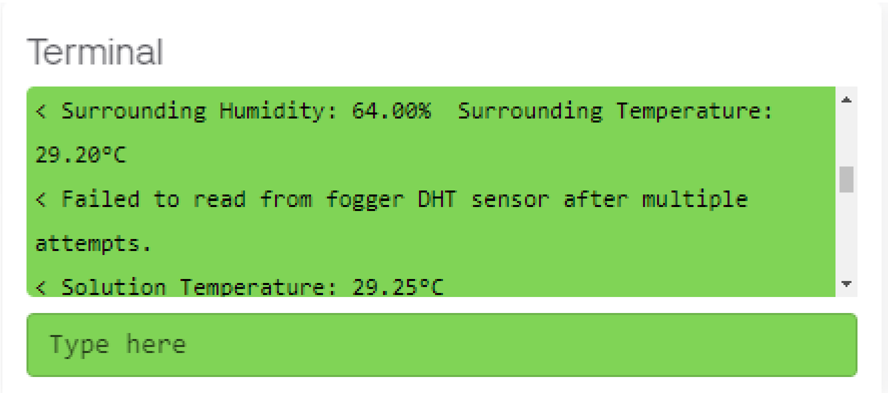


Figure 3.25: Fogger DHT11 Sensor Detected Error

3.2.6 Sensor Accuracy Enhancement Using Median Filtering

The median method was used to process the sensor data in order to increase the accuracy of the sensors in the hydroponic system.Sensors can sometimes produce inaccurate readings due to factors like electrical interference or sudden environmental changes. Instead of relying on a single reading, 10 samples were taken, and the median value, which is the middle value when the numbers are sorted, was used.

The median is preferred over the average in this case because the average can be skewed by a few outlier readings, which can lead to less accurate results. In contrast, the median yields a result that more accurately depicts the actual circumstances because it is unaffected by these extreme values. This approach ensures that the data used to monitor and control the hydroponic system is more accurate and reliable.

3.3 Experiments Set Up for effectiveness of the Fogger System

This experiment aims to evaluate the effectiveness of utilizing a water fogging system to enhance plant development during periods of high surrounding temperatures within a hydroponic setup. The experiment focuses on growing lettuce, a common crop in hydroponic systems. Due to time constraints, the experiment was divided into single phases. There are a total of eight growing trays, with four trays growing without the fogger system and four trays growing with the presence of the fogger system. The trays were positioned as shown in Figure 3.26, where the fogging process is scheduled to begin on day 7, as the fogger does not affect the germination of lettuce seeds. The purpose of this setup was to observe and compare the growth and development of lettuce in the presence and absence of the fogger system.

In this experiment, it was crucial to conduct both setups simultaneously to ensure that the lettuce growth was affected by the same environmental parameters, excluding surrounding temperature and humidity. While environmental parameters such as the nutrient solution temperature and light intensity were left uncontrolled and regulated naturally by the surrounding environment, the growing trays without the fogger system were also left unmanaged, allowing them to be influenced by external conditions. However, in the growing trays with the fogger system, the surrounding temperature and humidity were influenced by the fogger. Beginning on day 7 of the 1-month experiment, the 4 lettuce plants were fogged for approximately 10 minutes during peak temperature periods, 5 times per week.

All environmental parameters, including temperature, humidity, pH level, and Total Dissolved Solids (TDS) values, were gathered by corresponding sensors. This data was uploaded to the IoT cloud platform Blynk, allowing for real-time monitoring. The collected data could be downloaded from the Blynk cloud for further analysis and comparison.

To ensure accurate and comprehensive results, data collection was performed for both setups which are one with the fogger system and one without. Environmental parameters such as temperature, humidity, pH level, and Total Dissolved Solids (TDS) values were closely monitored. For example, the pH level of the nutrient solution was maintained between 5.5 and 6.5, while the TDS value was kept within 500-800 ppm to provide an optimal growing environment for the lettuce.

Throughout both phases of the experiment, plant growth parameters are measured and recorded. The effectiveness of the fogger system is evaluated based on these growth parameters.

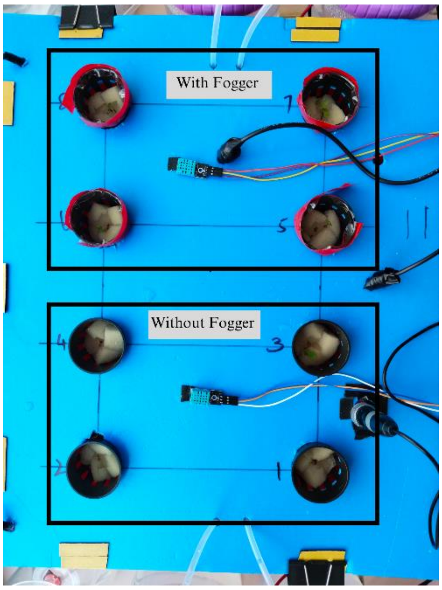


Figure 3.26: Experimental Setup of Hydroponic Lettuce Growth Trays With and Without Fogger System

3.4 Machine Learning

Machine learning is implemented in the system to enhance the monitoring of plant growth conditions. The input to the LSTM and GRU models consists of sequences of time series environmental parameters and controllable devices' control intensity status, and the output is the predicted environmental parameters for the next time step. A Final Year Project (FYP) student majoring in Software Engineering, and I are collaborating to implement this machine learning model. First, the time-series dataset shown in Table 3.2 is collected from the experiments described in Section 3.3. The AI model training is conducted using Google Colab, leveraging its computational resources for efficient development and testing.

Table 3.2: Time-Series Data Collection

No	Envirenmental Parameters
1	Surrounding Temperature
2	Surrounding Humidity
3	Light Intensity
4	pH Value
5	TDS Value
6	Nutrient Solution Temperature
7	Low pH Trigger
8	High pH Trigger
9	Low TDS Trigger
10	High TDS Trigger
11	Fogger Temperature
12	Fogger Humidity
13	Fogger Trigger

After data collection, the dataset undergoes preprocessing to ensure compatibility with the model's requirements. This involves tasks such as normalization, scaling, and handling missing values, which prepare the data for training. Normalization and scaling data are aim to improve the accuracy of machine learning algorithms. Min-max scaling and Z-score normalization methods are employed, which can be implemented using scikit-learn library functions MinMaxScaler and StandardScaler. The MinMaxScaler uses Equation 3.1 to normalize the feature values between the maximum and minimum values, resulting in normalized values within the range of 0 and 1. The StandardScaler uses Equation 3.2, subtracting the mean value to normalize the data. This method transforms the data into a format where the mean is 0, and the standard deviation is 1.

$$x_{scaled} = \frac{x - min}{max - min} \qquad \text{(Equation 3.1)}$$

where

x_{scaled} = normalized value

x = original value

min = minimum value of the input feature

max = maximum value of the input feature

$$z = \frac{x - \mu}{\sigma} \qquad \text{(Equation 3.2)}$$

where

z = standardized value

x = original value

μ = mean value of the input feature

σ = standard deviation of the input feature

Next, the data is organized into sequences, as LSTM and GRU models excel at capturing sequential patterns. This step involves defining input sequences (features) and corresponding output (targets) based on the problem at hand. Once the data is prepared, the model architecture is designed, specifying the number of LSTM or GRU layers and the number of units (neurons) in each layer. The model is then compiled, configured for training by setting up the optimizer, loss function, and evaluation metrics. The model is trained using the prepared data, where it learns to capture patterns and dependencies within the sequences.

During training, the model's performance is monitored on a separate validation set to prevent overfitting. Overfitting occurs when the model is too complex, as shown in the third diagram of Figure 3.27, while underfitting occurs when the model is too simple, as illustrated in the first diagram of Figure 3.27.

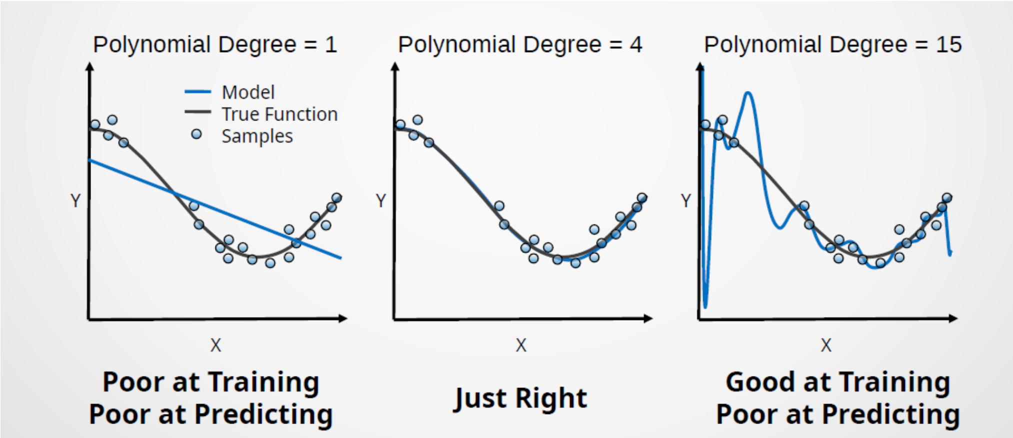


Figure 3.27: Complexity of the Training Model

After training is complete, evaluation metrics are used to evaluate the model's performance. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are commonly used evaluation metrics for LSTM and GRU models. MAE measures the average of the sum of absolute differences between the actual and predicted values in the dataset, as shown in Equation 3.3. MSE measures the average of the sum of the squared differences between the actual and predicted values in the dataset, as shown in Equation 3.4.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \qquad \text{(Equation 3.3)}$$

where

N = Total number of data

y_i = ith actual output value

$\hat{y}_i$ = ith predicted output value

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad \text{(Equation 3.4)}$$

where

N = Total number of data

y_i = ith actual output value

$\hat{y}_i$ = ith predicted output value

To compare the LSTM and GRU models, their performance is primarily evaluated based on accuracy and predictive capabilities. Both models are trained on the same preprocessed time-series dataset, and their predictions are assessed using evaluation metrics like Mean Absolute Error (MAE) and Mean Square Error (MSE). Since the dataset is small, training time is not a significant factor in this comparison. Instead, the focus is on the models' ability to capture sequential patterns and dependencies in the data. By comparing the MAE and MSE values, we can determine which model provides more accurate predictions. The comparison will highlight which model performs better for proactive control and accurate prediction in this context.

3.5 Summary

The methodology detailed in this chapter covers three key components: the construction of a IoT- enabled hydroponic system prototype, experimentation with a water fogger system, and the implementation of machine learning model.

The hydroponic system design includes detailed circuit setups for each sensor and control unit, such as a peristaltic pump, which automate the adjustment of pH levels and EC values in the nutrient solution. The water fogger system experiment is designed to evaluate its effectiveness in promoting plant growth under high-temperature conditions, providing valuable insights into its potential for improving agricultural yields in challenging climates.

Additionally, the continuous data collection from environmental IoT sensors is leveraged to train an LSTM and GRU machine learning model, which aims to predict future environmental conditions within the hydroponic setup. This approaches not only real-time monitoring but also proactive responses to changing environmental conditions.

The user interface on the Blynk platform, which displays real-time environmental data, further empowers users to make informed decisions regarding the hydroponic environment. By integrating hardware with IoT technology and advanced machine learning techniques, this methodology presents a comprehensive framework for optimizing and monitoring hydroponic environments. It holds significant potential for real-world applications, particularly in regions facing challenges related to climate change and food security.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

In this project, three major components were completed, and the details will be discussed. This project aimed to design and develop an IoT-enabled Deep Water Culture (DWC) hydroponic prototype, experimentally evaluate the impact of a fogger-based cooling system on lettuce growth, discuss the water efficiency of hydroponic farming compared to traditional soil farming, and integrate AI models to predict environmental parameters using real-time environmental data.

First, a fully functional IoT-enabled DWC hydroponic prototype was designed and developed. This prototype consists of eight growing trays, IoT sensors for environmental parameters real-time monitoring, and controllable devices that can adjust key environmental parameters such as surrounding temperature, humidity, solution pH level and solution TDS level either automatically or manually. The prototype system successfully facilitated the growth of lettuce over a 30-days period, with environmental parameters and lettuce growth data from this growing period were collected for further analysis and AI training purposes.

Secondly, with the fully functional hydroponic system in place, an experiment was conducted to investigate the impact of a fogger-based cooling system on lettuce growth. Lettuce plants thrive in temperatures between 22°C and 25°C. The goal of the fogger system was to reduce the temperature difference between the ambient environment and the optimal temperature range, especially during peak heat periods. The cooling effect of the fogger was evaluated by monitoring key growth parameters such as plant height and total leaf area, with data being recorded every three days.

Thirdly, the project involved the integration of AI models for future prediction of environmental parameters. The environmental parameters data were collected via the IoT cloud platform Blynk. Two models, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), were trained using the environmental data collected during the experiment. These models were developed to forecast future environmental parameters by analyzing both real-time and historical environmental conditions. The performance of the models was assessed using various metrics, and the best-performing model was selected based on its predictive accuracy and reliability.

Lastly, to enhance the innovation of the IoT-enabled hydroponic system, I worked together with a software engineer to develop an application capable of real-time monitoring, control actions, and AI-driven predictions based on the current environmental parameters. For real-time monitoring and AI-driven predictions, the hydroponic system was designed to transmit data to an application server, enabling the application to retrieve this data. Additionally, for control actions via the application, the hydroponic system continuously communicated with the application server using HTTP functions to retrieve the status of each controllable device. Based on the status received, the system would simply turn the controllable devices on or off to manage the growing environment.

This chapter provides a detailed overview of the project's key components, which include designing and developing an IoT-enabled Deep Water Culture (DWC) hydroponic prototype, evaluating the impact of a fogger-based cooling system on lettuce growth, comparing water efficiency between hydroponic and traditional farming, and integrating AI models for predicting environmental parameters.

4.2 IoT-enabled Hydroponic Prototype

The IoT-enabled hydroponic prototype, as shown in Figure 4.1, consists a completed hydroponic setup, equipped with various environmental sensors, controllable devices, and a waterproof container for housing electronic components. The sensors are responsible for monitoring all environmental parameters, while the controllable devices allow for both automatic and manual adjustments to maintain optimal growing conditions. The system is enclosed in a waterproof container to safeguard the sensitive electronic components, ensuring the sensors and controls function efficiently without the risk of water damage, such as short circuits or corrosion.

Figure 4.1: IoT-enabled DWC Hydroponic System Prototype

The prototype was effectively used to grow a batch of lettuce, showcasing its ability to maintain optimal conditions for plant growth. The system's real-time monitoring and adjustment of environmental conditions ensured ideal settings for plant development, as evidenced by the successful growth of lettuce throughout the experiment. The entire lettuce plant growth process was documented with photos taken on day 1, day 5, day 10, day 15, day 20, day 25, and day 30, as shown in Figures 4.2 to 4.8. The system's performance is further validated by the successful collection of environmental data through the sensors, with the data being transmitted and gathered via the IoT platform, as detailed in Section 4.2.1.

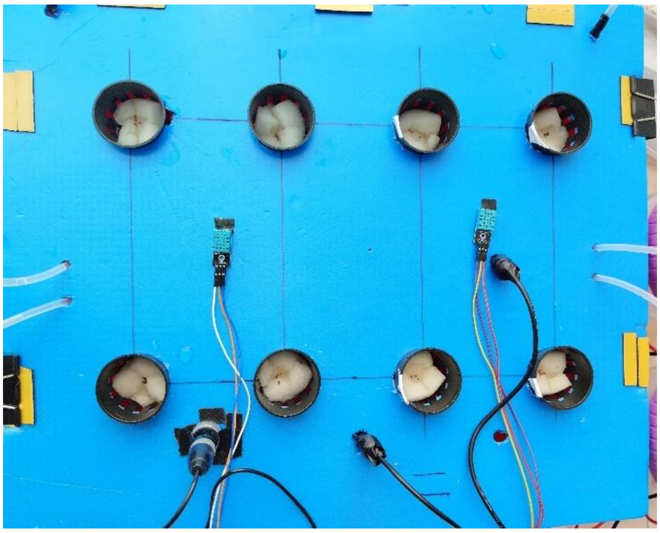


Figure 4.2: Lettuce Growth on Day 1

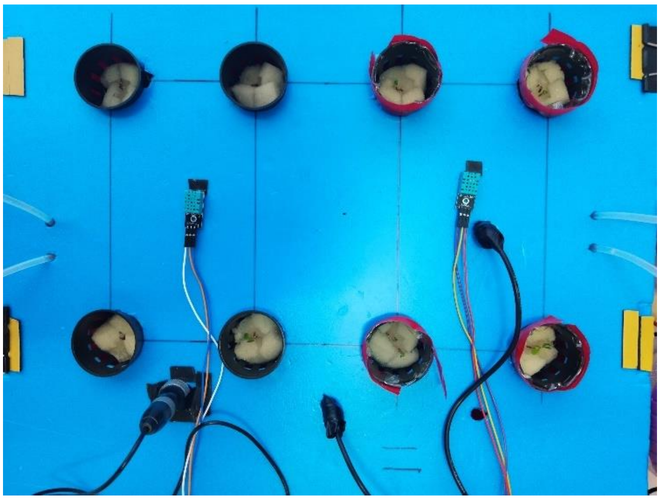


Figure 4.3: Lettuce Growth on Day 5

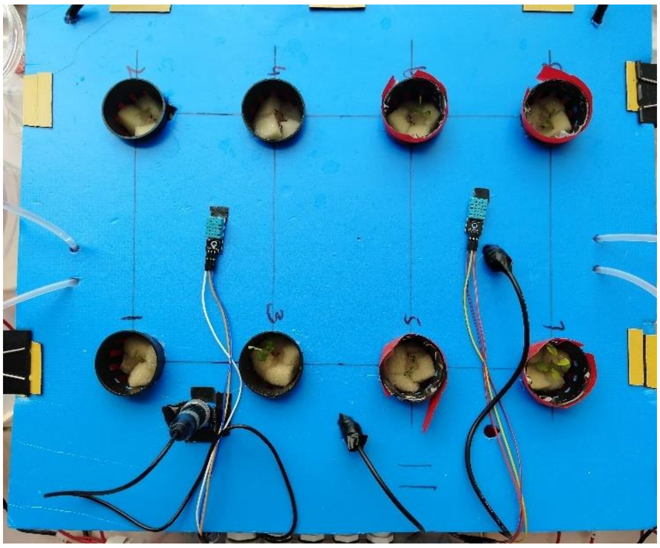


Figure 4.4: Lettuce Growth on Day 10

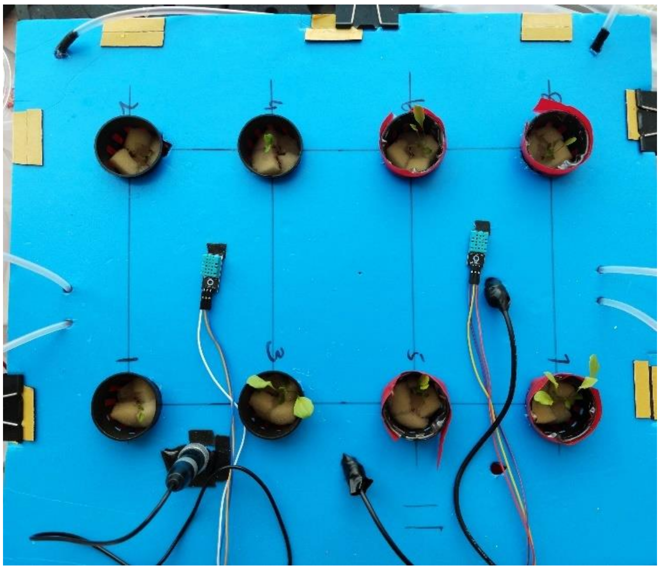


Figure 4.5: Lettuce Growth on Day 15

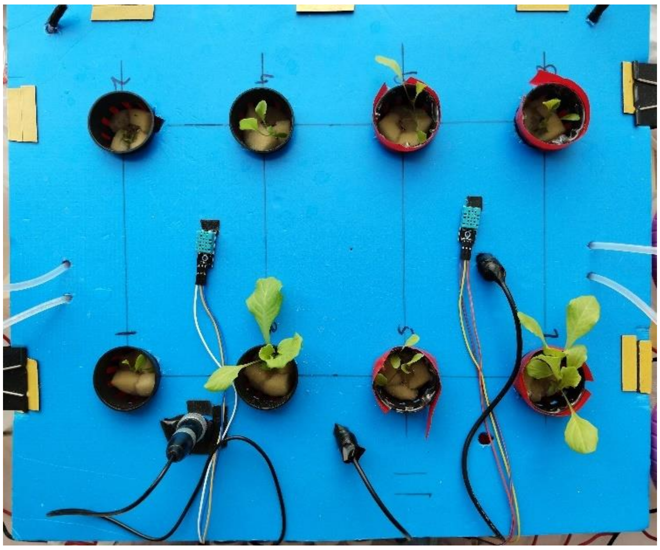


Figure 4.6: Lettuce Growth on Day 20

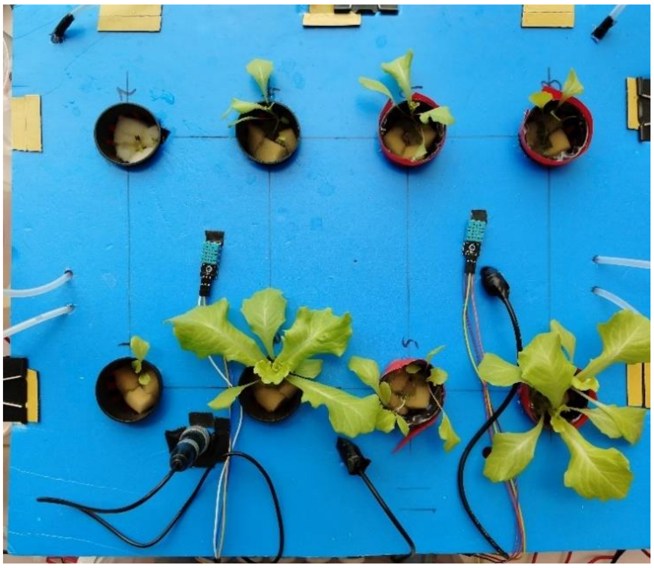


Figure 4.7: Lettuce Growth on Day 25

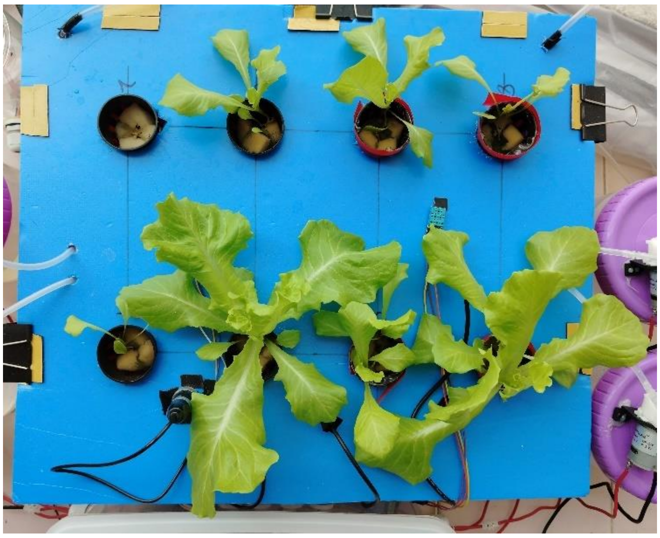


Figure 4.8: Lettuce Growth on Day 30

4.2.1 Environmental Parameters Data Collection

Throughout the 30-day period, environmental parameters were continuously monitored by the sensors and automatically uploaded to the IoT cloud. This consistent data collection provided a comprehensive and precise record of environmental fluctuations over time. Once collected, the data was downloaded from the IoT platform for thorough analysis of the environmental fluctuations and their effect on lettuce plant growth.

4.2.1.1 Analysis of Temperature and Humidity (Surrounding and Fogger)

Figures 4.9 and 4.10 display the temperature and humidity data gathered from both the surrounding environment and the area influenced by the fogger system. The DHT11 sensors used in this experiment effectively captured the trends in ambient conditions, as well as the variations caused by the fogger, illustrating its impact on the local environment. The optimum temperature range for lettuce growth is between 22°C and 25°C, although lettuce can still grow at higher temperatures, though with a reduced growth rate. The primary function of the fogger system is to lower the surrounding temperature to the optimal range, particularly during peak heat periods, to promote faster lettuce growth. Additionally, the fogger increases local humidity, which is beneficial for lettuce, as it reduces water loss through transpiration. By simultaneously lowering temperature and raising humidity, the fogger creates a more favorable microclimate, promoting healthier lettuce growth, especially under hot conditions.

Although the data in Figures 4.9 and 4.10 capture these trends, the reduction in temperature due to the fogger is not immediately evident. This is because the fogger operates for only 10 minutes at a time, resulting in a single data point being collected, with the hourly data being averaged over six points. As a result, the immediate temperature drop caused by the fogger is less noticeable in these figures. However, the cooling effect is more clearly observed in Figure 4.19, which captures the short-term reduction in temperature during the fogger's active periods.

While the fogger system effectively reduces the surrounding temperature and raises humidity, the temperature in Figure 4.9 still largely remains outside the optimal range for lettuce growth (22°C to 25°C). Nonetheless, the temperature reduction can bring the environment closer to the optimal range, enhancing the fogger's overall cooling effect and creating more favorable conditions for lettuce growth during the hottest periods.

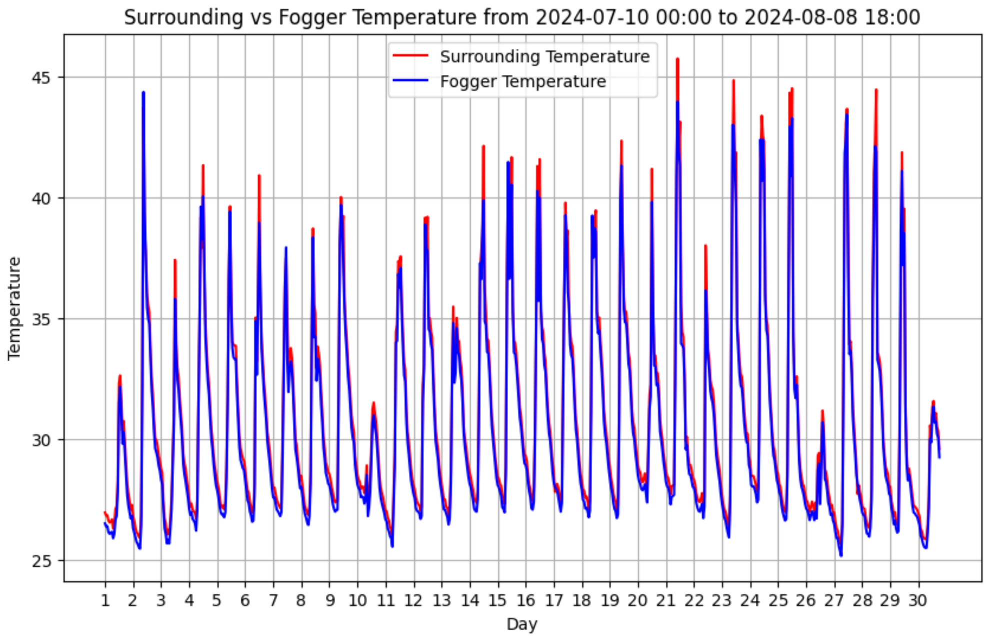


Figure 4.9: Comparison of Surrounding vs Fogger Temperature Over 30 Days

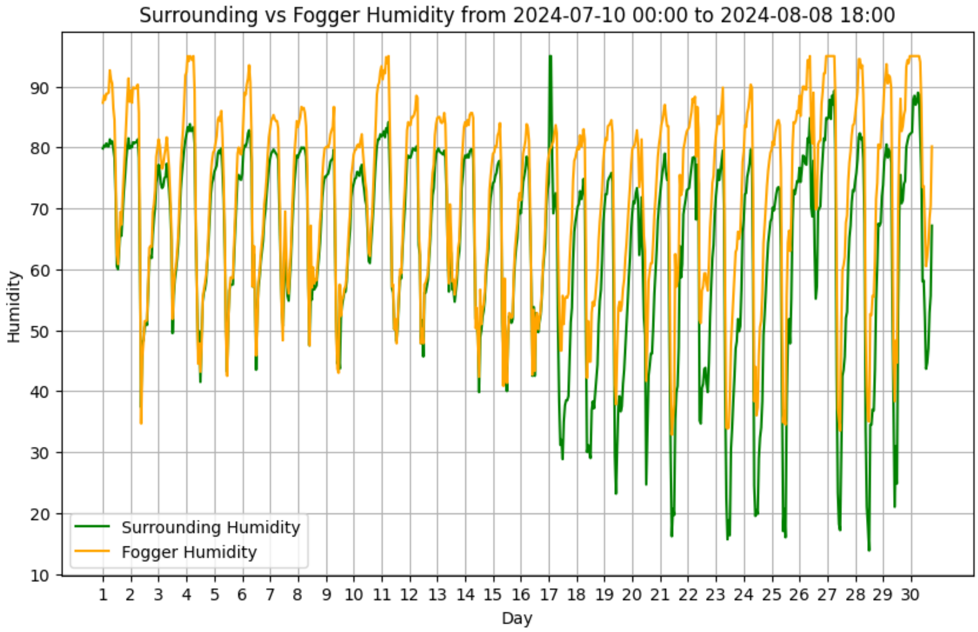


Figure 4.10: Comparison of Surrounding vs Fogger Humidity Over 30 Days

4.2.1.2 Analysis of Solution Temperature and Light Intensity

The data for solution temperature and light intensity, as shown in Figures 4.11 and 4.12, provide a comprehensive view of the environmental conditions within the hydroponic system over the 30-day period. The solution temperature remained relatively stable, with minor fluctuations about 4°C influenced by external temperature changes as shown in Figure 4.11. While these fluctuations were minimal, they can still affect nutrient absorption rates in lettuce plants, potentially impacting their growth. Lettuce is sensitive to thermal changes in its growing medium, and fluctuations in solution temperature, especially if they exceed optimal levels, could reduce nutrient uptake efficiency and slow plant growth. To improve the system's overall efficiency and reduce temperature variations, implementing a cooling mechanism or improved temperature regulation could help keep the solution temperature within the ideal range (20°C-25°C) for lettuce growth.

The light intensity data showed considerable variation, primarily due to the day-night cycle. Additionally, lower peaks on certain days indicated reduced sunlight during rainy or cloudy weather, which decreased the amount of light reaching the plants and could impact photosynthesis. Lettuce plants require consistent light exposure for steady growth, and fluctuations in light intensity could hinder this process. To address this, supplemental artificial lighting, such as LED grow lights, could be installed to maintain consistent light levels. Automated lighting systems could be used to compensate for periods of reduced natural light, ensuring that the plants receive adequate light for optimal growth. At higher temperatures (30°C), lettuce requires light intensity between 20,000 and 30,000 lux for optimal growth. However, as observed from Figure 4.12, the light intensity in the current setup only remains above this range for about five hours per day, which is likely insufficient for optimal growth. This suggests that the location of the lettuce plants may not be ideal. On the positive side, the maximum light intensity observed is below 100,000 lux, which ensures the plants are safe from potential photodamage.

Both solution temperature and light intensity are critical to healthy lettuce growth, and fluctuations in these parameters can negatively affect plant development, resulting in slower growth rates or lower-quality yields. By improving control over solution temperature and light intensity, the hydroponic system can provide a more stable environment, promoting better plant health and higher yields. Therefore, addressing these fluctuations through enhanced technological solutions would significantly improve the system's overall effectiveness.

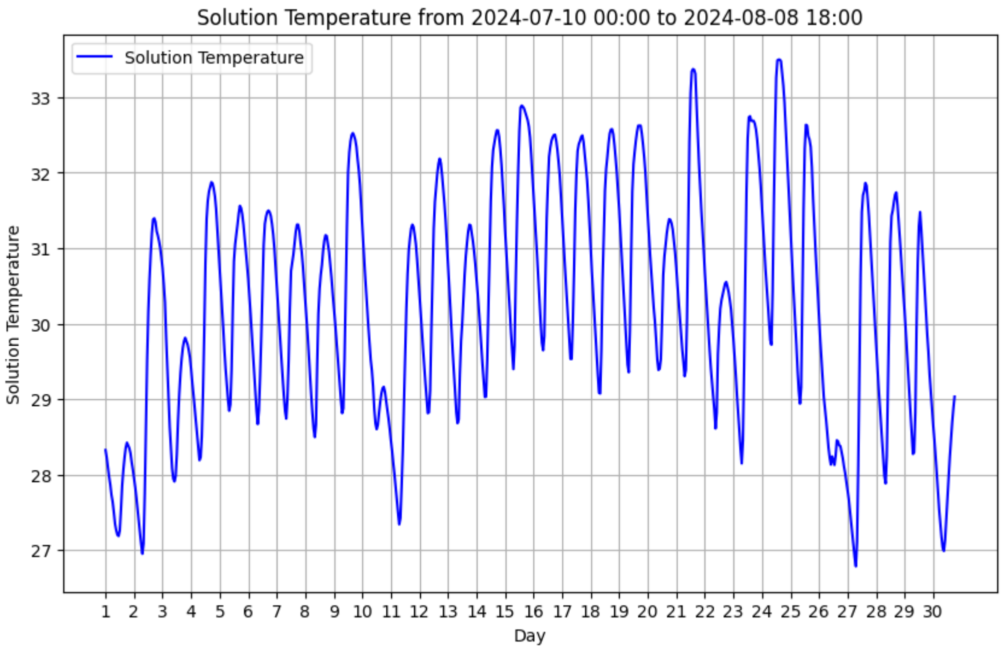


Figure 4.11: Solution Temperature Over 30 Days

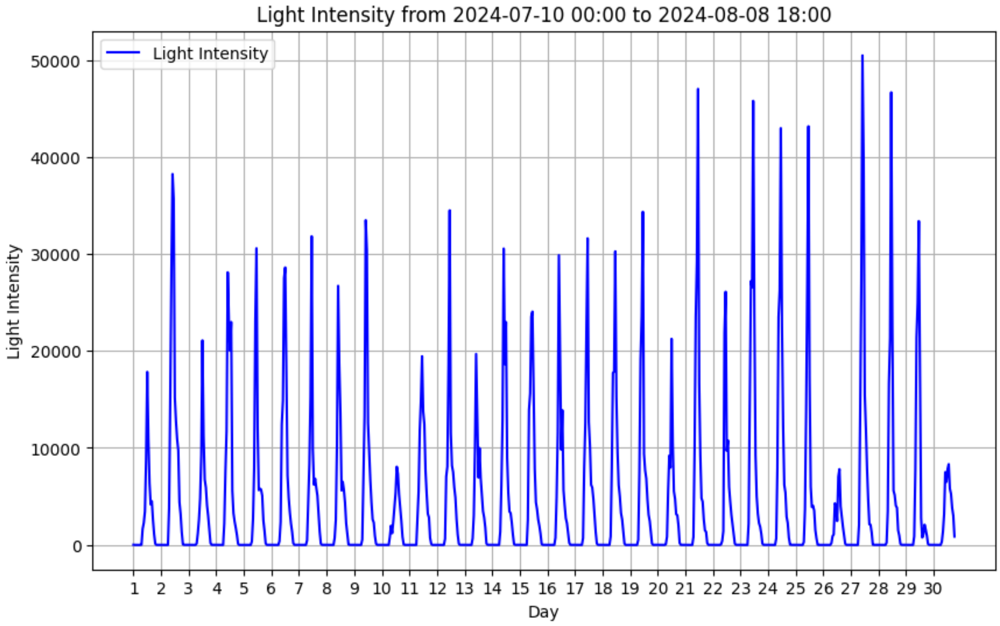


Figure 4.12: Light Intensity Over 30 Days

4.2.1.3 Analysis of Solution TDS Value

The Total Dissolved Solids (TDS) value, as shown in Figure 4.13, reflects the concentration of dissolved substances in the hydroponic solution over 30 days. The graph shows a generally stable trend, with a gradual increase in TDS levels. This increase is due to the more nutrients such as pH-down solution (phosphoric acid) were added to maintain optimal growing conditions, which contributes to the rising TDS concentrations over time.

However, there were occasional sharp drops in TDS readings, which were linked to intermittent power supply issues affecting the TDS sensor circuit board. These low readings did not represent the actual conditions, but instead resulted from technical malfunctions in the sensor's power supply. Although the control signal was sent to the relay, the relay switch did not close the circuit properly, causing the TDS circuit board fail to receive power.

Despite these occasional errors, the solution's TDS is maintained within the optimal range for lettuce plant growth, which is 500 ppm to 1000 ppm. This indicates that the controllable devices successfully performed their job in maintaining the nutrient concentration for healthy plant development.

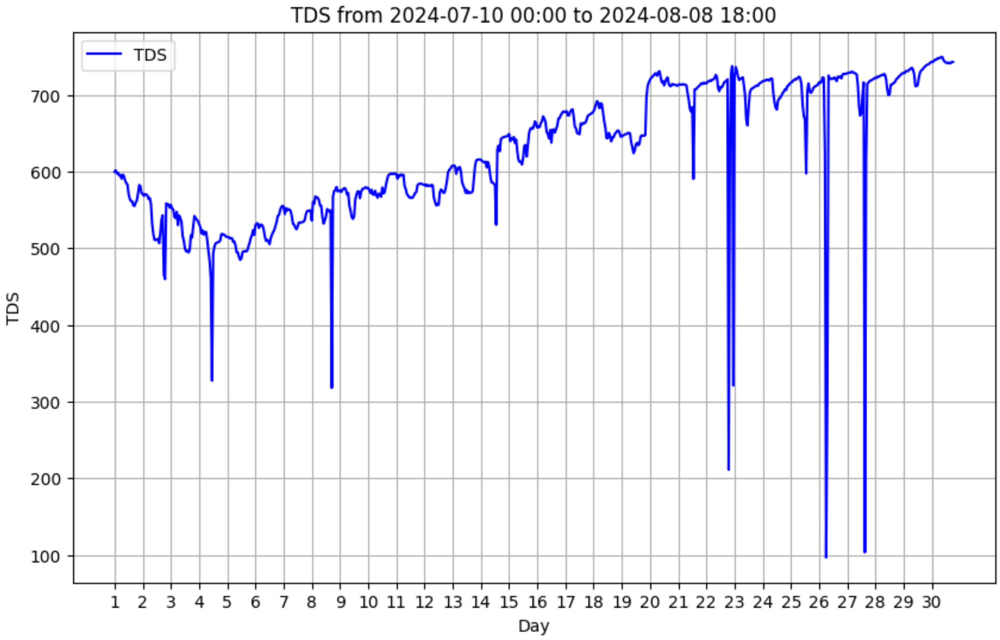


Figure 4.13: Solution TDS Value Over 30 Days

4.2.1.4 Analysis of Solution pH Level

Figure 4.14 presents the trend of changes in the solution pH level within the hydroponic system over a 30-day period. The majority of the pH values are maintained within the optimal range for lettuce growth, which is between 5.5 and 6.5. However, there are some outliers where the pH exceeds the optimum range, but these values were later adjusted back to the ideal range by the controllable device. This indicates the effectiveness of the pH control mechanism in maintaining the solution's pH level. Some of the outliers could also be attributed to several factors, which will be discussed later.

The instability of the pH values observed in Figure 4.14 can be attributed to several factors, including sensor limitations and the variability in the power supply used for the pH sensor circuit. The pH sensor circuit relies on a voltage divider to determine the analog reading of the pH sensor. For calibration purposes, a stable 5V DC supply from my PC was used. This stable 5V DC supply from PC also introduced a very small fluctuations in the pH readings.

To ensure the accuracy of the pH readings and address the instability issues, various power sources were tested to identify the most stable solution. Figures 4.16 to 4.18 showcase the three different power sources evaluated during the experiment. Initially, a power extension socket with USB ports

(Figure 4.16) was used to supply 5V DC power for the ESP32. However, the low-quality AC to DC converter in the USB ports led to fluctuations in the pH readings. Although the measured voltage ranged between 4.98V and 4.99V, the instability in the readings remained a consistent issue.

. Next, the power source was switched to a budget USB adapter, as shown in Figure 4.17. The voltage meter indicated a slightly higher output of 5.11 to 5.12V. Although this adapter provided more stable readings compared to the previous setup, the deviation from the calibrated 5V still affected the accuracy of the pH sensor readings, ultimately making this power source unsuitable for the system.

For optimal performance, a high-quality USB adapter, as shown in Figure 4.18, was selected. The voltage meter displayed a stable reading of 4.99 – 5.00V, providing the most consistent pH readings among the tested power sources. Although using a power bank yielded the most stable pH readings during testing, it was not a viable option for continuous 24-hour operation due to its limited energy capacity.

Furthermore, to minimize fluctuations in the pH readings, the frequency of data collection was increased, and an averaging method was applied to the collected pH levels. Figure 4.15 illustrates the pH levels over a one-hour period, demonstrating that while fluctuations and outliers are still present, the signal's overall stability has greatly improved. Some outliers, such as the spike above pH 9.0, can be observed in the data. These anomalies may be the result of sensor noise or momentary environmental changes. However, by applying the averaging method over the one-hour interval, the accuracy of the pH readings has increased significantly, as the short-term fluctuations are smoothed out, providing a more reliable overall measurement. The averaging technique not only helps to reduce the impact of transient outliers but also ensures that the pH levels remain within the optimal range for lettuce growth. The average pH level during this period was calculated to be 6.27, which falls well within the ideal range for plant health and nutrient absorption, reinforcing the effectiveness of the control system in maintaining consistent conditions in the hydroponic system.

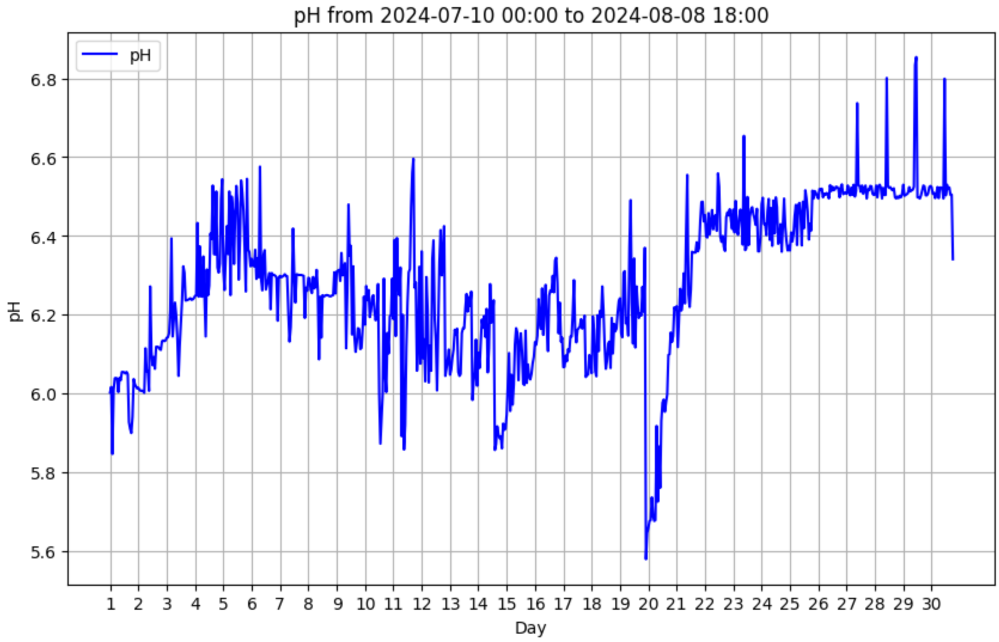


Figure 4.14: Solution pH Level Over 30 Days

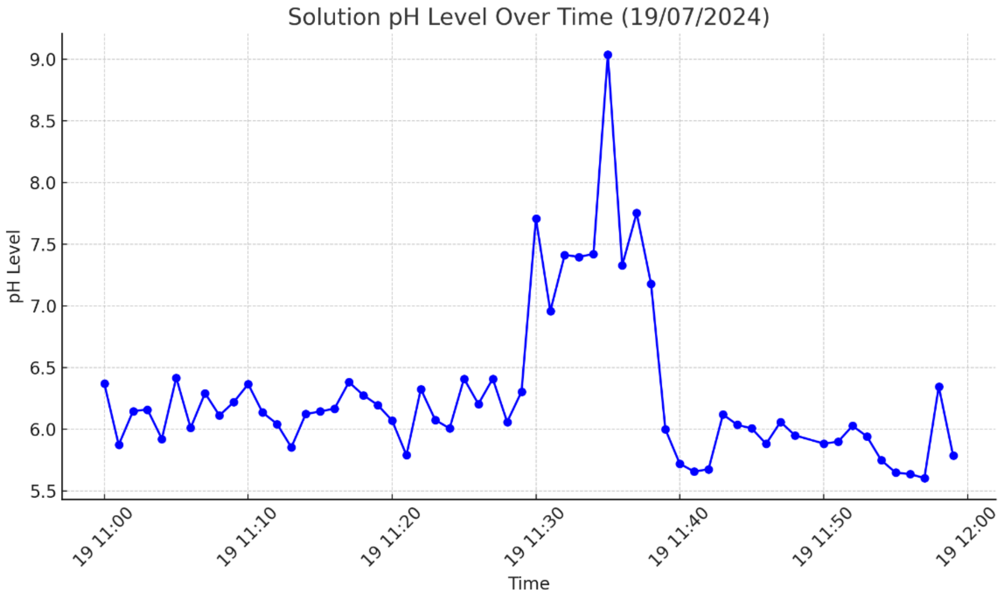


Figure 4.15: Solution pH Level on 19/07/2024 from 11:00 to 12:00

Figure 4.16: Power Extension Socket with USB Ports

Figure 4.17: Budget USB Adapter

Figure 4.18: High-Quality USB Adapter

4.2.2 Summary

Table 4.1 highlights the environmental conditions monitored throughout the 30-day period and their respective effects on lettuce growth.

Table 4.1: Summary of Environmental Conditions and Impact on Lettuce Growth

Parameter	Optimal Range	Observed Range	Impact on Plant Growth
Temperature (Fogger)	22°C-25°C	Often > 25°C	Fogger helps lower temperature, leading to an increased lettuce growth rate compared to normal ambient conditions.
Humidity (Fogger)	50% - 70%	Often > 50%, < 70%	High humidity reduces water loss through transpiration, promoting growth.
Temperature (Normal)	22°C-25°C	Often > 25°C	Higher ambient temperatures negatively affect growth without intervention.
Humidity (Normal)	50% - 70%	Often > 35%, < 70%	Low humidity can increase water loss through transpiration, slowing growth.
Solution Temperature	20°C-25°C	Stable, ±4°C	Stable temperature supports nutrient absorption, slight fluctuation affects growth.
Light Intensity	20,000 - 30,000 lux	Peaks ~5 hrs/day	Limited exposure can hinder photosynthesis and slow growth.
TDS Value	500 - 1000 ppm	Within optimal range	Consistent nutrient levels support healthy growth.
pH Level	5.5 - 6.5	Slight fluctuations	Small pH fluctuations managed by control system, minimal impact on growth.

4.3 Experimental Setup and Evaluation of Plant Cooling System

This section provides a detailed evaluation of the fogger system's effectiveness in mitigating high-temperature stress on lettuce plants over a one-month period. Beginning on day 7, four lettuce plants were subjected to a cooling process in which the fogger system was activated for approximately 10 minutes during high-temperature intervals. This cooling cycle was repeated five times per week. The data collected over the course of the experiment were analyzed to evaluate the impact of the fogger system on key plant growth parameters, such as plant height and total leaf area. The lettuce plant height and lettuce plant leaf area with and without fogger cooling were recorded, with the results shown in Table 4.2 and Table 4.3.

Table 4.2: Growth Measurements of Lettuce Plants Without Fogger Setup Over Time

Day	Without Fogger Setup									
	Plant Height (cm)				Average (cm)	Total Plant Leaf Area (cm2)				Average (cm2)
	1	2	3	4		1	2	3	4	
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	1.00	0.50	2.00	0.00	0.88	0.00	0.00	1.27	0.00	0.32
9	1.30	0.55	3.60	0.20	1.41	0.06	0.00	1.42	0.00	0.37
12	2.50	0.60	5.80	2.20	2.78	0.23	0.02	2.32	0.30	0.72
15	3.70	0.70	6.20	2.50	3.28	0.44	0.25	4.23	0.53	1.36
18	4.00	0.80	7.70	5.00	4.38	0.57	0.35	8.80	0.98	2.68
21	4.70	1.50	10.00	6.80	5.75	1.55	0.52	22.80	3.57	7.11
24	5.40	1.70	11.00	8.50	6.65	3.00	0.70	54.32	8.40	16.61
27	6.40	1.70	15.80	9.50	8.35	4.48	0.70	140.00	16.32	40.38
30	9.30	0.00	18.40	12.50	10.05	9.00	0.00	266.70	43.87	79.89

Table 4.3: Growth Measurements of Lettuce Plants With Fogger Setup Over Time

Day	With Fogger Setup									
	Plant Height (cm)				Average (cm)	Total Plant Leaf Area (cm2)				Average (cm2)
	5	6	7	8		5	6	7	8	
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	1.50	1.40	2.00	1.30	1.55	0.25	0.39	0.49	0.06	0.30
9	2.60	2.40	3.50	2.00	2.63	0.82	0.75	0.99	0.38	0.73
12	4.20	4.10	6.00	3.10	4.35	0.84	0.82	2.10	0.62	1.10
15	4.80	4.50	6.00	3.60	4.73	0.86	1.05	3.11	0.71	1.43
18	5.30	6.00	8.00	3.90	5.80	1.80	2.00	8.55	1.89	3.56
21	6.90	7.00	9.70	6.10	7.43	5.63	5.28	15.20	4.73	7.71
24	7.50	8.50	11.00	7.00	8.50	7.90	12.00	43.20	6.30	17.35
27	11.20	12.30	16.00	9.00	12.13	19.68	30.78	116.40	14.30	45.29
30	13.00	14.50	20.20	11.10	14.70	37.80	65.20	241.50	25.20	92.43

4.3.1 Impact of Fogger System on Temperature Control

Figure 4.19 shows the effect of the fogger system on the surrounding temperature during different time intervals. The fogger was activated during periods of high ambient temperature to reduce heat stress on the plants. Across all intervals, the fogger system consistently lowered the temperature, providing a cooler environment for plant growth.

On average, the fogger system effectively reduces temperature by an average of 9.2°C, which helps reduce the risk of heat-related issues. This temperature drop is beneficial for lettuce plants, as it prevents the adverse effects of prolonged exposure to high temperatures, such as slowed growth, and leaf wilting. The reduced temperature helps sustain healthier plants, ensuring better development and overall productivity. Overall, the fogger system demonstrates its potential as a valuable tool for temperature control, offering a practical solution to manage heat stress and promote consistent, healthy plant growth.

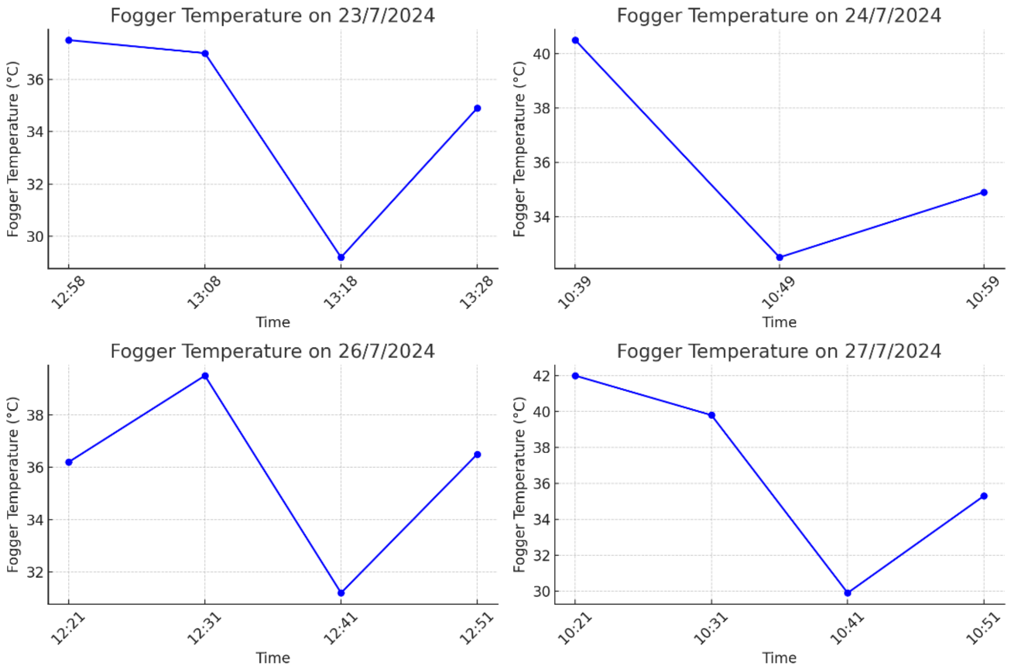


Figure 4.19: Fogger Operation Leading to Decrease in Temperature Across Different Time Intervals

4.3.2 Data Analysis Steps

Evaluating the effect of the fogger system on lettuce growth involved measuring plant height (in cm) and leaf area (in cm²) in two setups: one with the fogger system and one without. The procedure for data collection and evulation followed these steps:

Data Collection: Plant height (in cm) and total leaf area (in cm²) were recorded for four plants in each setup on days 1, 3, 6, 9, 12, 15, 18, 21, 24, 27, and 30. This allowed consistent tracking of growth progression over time for both setups.

Data Organization: The recorded data were organized into tables (Table 4.1 and Table 4.2), detailing individual plant heights and leaf areas for each setups. To simplify analysis and present overall growth trends, average values were calculated for each measurement period.

Data Visualization: Graphs (Figures 4.20 and 4.21) were used to plot the average plant height and leaf area for both the fogger and non-fogger setups. These visual representations facilitated a direct comparison of growth trends, making it easier to observe how the plants responded to the different environmental conditions.

Statistical Analysis: A comparison of the daily growth rates for both plant height and leaf area was conducted to evaluate whether the fogger system had a measurable effect on plant growth.

4.3.3 Results and Discussion of Effectiveness of Fogger System

The results of the analysis indicate that the fogger system had a significant positive impact on the growth of the lettuce plants. The figures provided (Figure 4.20 and Figure 4.21) visually demonstrate the growth trends for both plant height and leaf area. By comparing the plant height and leaf area between the fogger and non-fogger setups, a clear difference in growth patterns was observed, offering strong support for the fogger system's effectiveness.

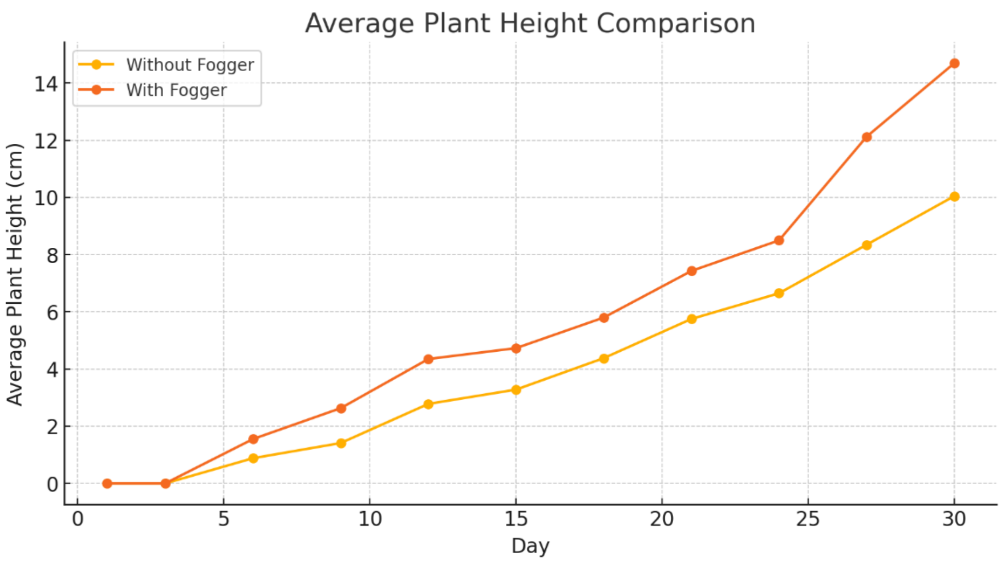


Figure 4.20: Average Plant Height Comparison Between Fogger and Non-Fogger Setups

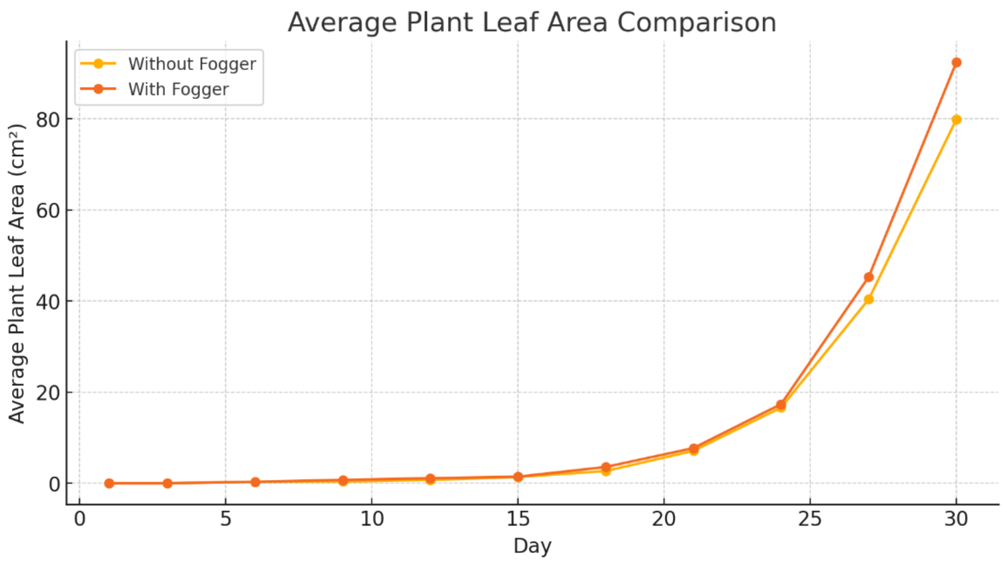


Figure 4.21: Average Plant Leaf Area Comparison Between Fogger and Non-Fogger Setups

4.3.3.1 Average Lettuce Plant Height

By observing Figure 4.20, the lettuce plants in the fogger setup exhibited faster and more consistent growth compared to those grown without the fogger. In the early days of the experiment (day 1 and day 3), there was no noticeable difference in height between the two setups, as both recorded an average height of 0 cm. However, by day 6, the lettuce plants in the fogger began to grow at a faster rate compared to the non-fogger setup, and this trend continued throughout the 30-day period. Additionally, the effect of the fogger system was more evident during the vegetative stage of lettuce growth, as can be seen in Figure 4.20. By day 24, the plant height growth rate in the fogger setup increased rapidly, reflecting the system's enhanced ability to support growth during this critical stage.

By day 30, the lettuce plants in the fogger setup reached an average height of 14.70 cm compared to 10.05 cm in the non-fogger setup. The continuous upward trend observed in the fogger setup as highlighted in Figure 4.20 suggests that the fogger system provided a more conducive growing environment, likely through better control of humidity and temperature, which led to accelerated lettuce plant growth.

4.3.3.2 Average Lettuce Plant Leaf Area

By observing Figure 4.21, a similar trend was observed in the average leaf area. During the first few days of the experiment, both setups showed no significant leaf development. However, by day 9, the lettuce plants in the fogger setup began to display a greater increase in leaf area. Additionally, by day 24, during the vegetative stage of growth, the lettuce plants in the fogger setup show a rapid increase in leaf area, indicating that the fogger system becomes more effective in promoting leaf development during this critical phase. This trend persisted throughout the experiment, and by day 30, the average leaf area in the fogger setup was 92.43 cm^2, compared to 79.89 cm^2 in the non-fogger setup.

The increased leaf area in the fogger setup, as shown in Figure 4.21, is a positive indicator of plant health and development. Larger leaves enhance the plant’s ability to perform more efficient photosynthesis, which is essential for the overall growth and vitality of the lettuce plants. This suggests that the fogger system not only promoted faster height growth but also contributed significantly to the development of healthier and larger leaves.

4.3.3.3 Rate of Growth

The fogger setup showed a faster and more steady growth rate for both lettuce plant height and leaf area. Throughout the experiment, the lettuce plants in the fogger system was consistently higher rate of growth in the fogger setup than those in the non-fogger system, as seen in Figure 4.20 and Figure 4.21.

This consistent lead in both parameters indicates that the fogger system provided improved growth conditions, likely through better control of environmental factors such as temperature and humidity. The enhanced growth rate, especially during the vegetative stage, suggests that the fogger system played a crucial role in optimizing plant development and overall health, leading to larger plants with greater leaf area. These results highlight how the fogger system created better conditions for lettuce growth compared to the non-fogger setup.

4.3.3.4 Conclusion

In conclusion, the fogger system increased the average lettuce plant height by 46.26% (from 10.05 cm to 14.70 cm) and the total leaf area by 15.70% (from 79.89 cm^2 to 92.43 cm^2) by the end of the 30-day period. These results demonstrate that the fogger system significantly improved lettuce growth, particularly during the vegetative stage, when rapid growth is most critical. In environments with high temperatures, the fogger system proved to be a valuable tool for enhancing lettuce plant growth by providing more favorable environmental conditions, resulting in improved overall growth and development of the lettuce plants.

4.3.4 Comparison of Water Efficiency Between Hydroponic Farming and Traditional Soil Farming Methods for Lettuce

Water conservation is crucial, especially in regions with high temperatures and limited water resources, such as Malaysia. According to Zuraini Anang et al. (2019), the growing demand for agricultural goods due to population growth and economic development is expected to put additional strain on already limited water resources. The agricultural sector consumes 76% of Malaysia's water resources, particularly for irrigation, which can lead to water shortages during dry seasons. Traditional soil farming consumes a significant amount of water, contributing to resource depletion, especially during these dry periods. In contrast, hydroponic farming utilizes a recirculating water system, making it a more sustainable and water-efficient approach.

A case study by Barbosa et al. (2015), conducted in Arizona, explored water usage in both traditional soil-based and hydroponic lettuce production. The focus here is on water usage, measured in liters per kilogram per year (L/kg/y). As shown in Figure 4.22, hydroponic production demonstrated significantly greater water efficiency when normalized by yield. On average, hydroponic systems used 13 ± 2.7 times less water than conventional farming. Specifically, hydroponic lettuce production required 20 ± 3.8 L/kg/y, while conventional lettuce farming demanded 250 ± 25 L/kg/y (Barbosa et al., 2015).

This substantial difference highlights the potential of hydroponic farming to significantly reduce water consumption, especially in regions like Malaysia, where water availability fluctuates due to seasonal variability and dry weather. By adopting hydroponic methods, Malaysia can align its agricultural practices with the goals set out in the 12th Malaysia Plan (12MP), which emphasizes sustainability and efficient resource management. The 12MP highlights the importance of integrated water resource management and sustainable agriculture to achieve long-term environmental protection while supporting economic growth (United Nations Development Programme, 2021).

Hydroponic farming directly supports SDG 6 (Clean Water and Sanitation) by promoting efficient water use, especially through recirculating systems that drastically reduce water waste compared to traditional soil-based farming. This is crucial for conserving water in agriculture, which consumes a large portion of Malaysia's water resources. Furthermore, hydroponics also aligns with SDG 12 (Responsible Consumption and Production) by encouraging sustainable farming practices that minimize the use of chemical inputs and reduce environmental impact. According to Toclan, hydroponic systems require fewer pesticides and fertilizers, leading to more sustainable food production.

In high-temperature zones where water is a precious resource, implementing hydroponic systems helps conserve water while maintaining or even improving crop productivity. This approach supports Malaysia's broader sustainability goals outlined in the 12MP, which focus on reducing resource depletion, fostering green growth, and enhancing food security. By integrating hydroponic farming, Malaysia can make substantial progress toward reducing agricultural water consumption, contributing to its national sustainability agenda while tackling the challenges of climate change and resource scarcity.

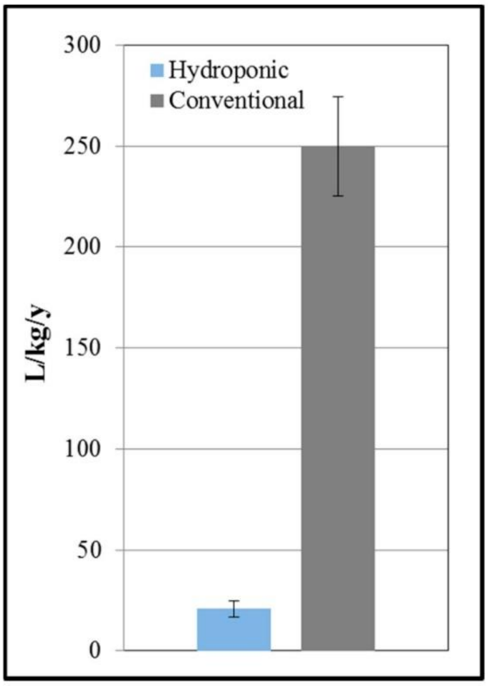


Figure 4.22: Modeled Annual Water Use in Liters Per Kilogram of Lettuce Grown in Southwestern Arizona Using Hydroponic vs. Traditional Methods (Barbosa et al., 2015)

4.4 AI Model Training and Evaluation

This section focuses on the training and evaluation of AI models to predict future environmental condition which involved using a hydroponic dataset collected over 30 days from an IoT-enabled hydroponic system. The dataset was collected and preprocessed into one-hour intervals, capturing detailed environmental parameters and the activation status of various controllable devices within the hydroponic setup. The AI model training utilized both LSTM and GRU models, with the objective of comparing and evaluating their performance. The goal is to evaluate and compare the performance of these AI models in forecasting future environmental conditions, allowing for proactive system management to enhance plant growth.

4.4.1 Data Preparation

Data preparation is a critical process for ensuring the accuracy and performance of LSTM and GRU models. The dataset, collected from the hydroponic prototype, needs to be properly cleaned and organized before model training. The training data is the first 3 weeks whereas the test data is the last 1 week. Before feeding the data into the LSTM and GRU models, it is crucial to ensure that the dataset is clean and consistent. This process can be divided into three key steps:

Data Cleaning and Consistency: Addressing missing values and sensors error readings, standardizing data types to ensure the dataset is reliable and ready for analysis.

Data Scaling: Features (surrounding temperature, pH level and etc) are scaled using StandardScaler to standardize the range of values, ensuring balanced model learning and preventing larger values from dominating the training process.

Data Sequencing: LSTM and GRU models rely on previous time steps to make predictions, so the time-series data is organized into time-dependent sequences. This allows the models to learn temporal patterns and relationships for accurate forecasting.

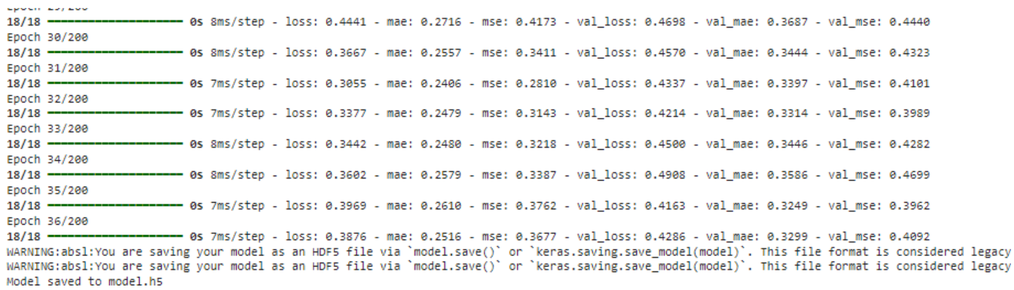
4.4.2 LSTM and GRU Model Structure and Training

The LSTM and GRU models are constructed and trained to predict future values based on past data sequences. Both models follow a similar structure, beginning with the creation of data sequences from the input dataset. These sequences are then split into training and validation sets, typically using 80% of the data for training and 20% for validation.

The LSTM model is built with two layers: the first LSTM layer contains 64 units that return sequences, followed by a second LSTM layer with 32 units that output the final hidden state for predictions. To prevent overfitting, a dropout layer is added, and a dense output layer generates the final prediction. The LSTM model uses the Adam optimizer with a learning rate of 0.001 to adjust the model's weights during training.

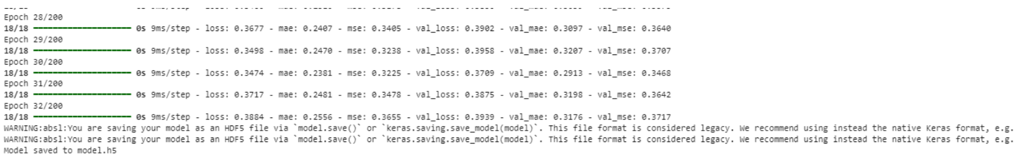
The GRU model follows a similar structure to the LSTM model but uses GRU layers instead of LSTM layers. It includes a first GRU layer with 64 units returning sequences, followed by a second GRU layer with 32 units that produce the final output. Like the LSTM model, it has a dropout layer and a dense output layer. The GRU model is compiled using the Adam optimizer with a learning rate of 0.001. GRU layers have a simpler structure compared to LSTM, making them faster and sometimes more effective for specific tasks where fewer parameters are needed. This allows the GRU model to be computationally efficient while still delivering accurate predictions.

The models use Mean Squared Error (MSE) as the loss function, with Mean Absolute Error (MAE) as an additional metric. Early stopping is implemented to halt training if the validation loss does not improve after 10 epochs, ensuring the model does not overfit. The models are trained for 200 epochs by default, and their performance is validated using a separate validation set. After training, the best version of each model, based on validation performance, is saved for future use. This process ensures that the LSTM and GRU models are optimized to accurately predict future data points from time series data, making them effective tools for analysis and predicting. Figures 4.23 and 4.24 show the training process and results for the LSTM and GRU models, respectively. The final models are saved after training.



```
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.4441 - mae: 0.2716 - mse: 0.4173 - val_loss: 0.4698 - val_mae: 0.3687 - val_mse: 0.4440
Epoch 30/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.3667 - mae: 0.2557 - mse: 0.3411 - val_loss: 0.4570 - val_mae: 0.3444 - val_mse: 0.4323
Epoch 31/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - loss: 0.3055 - mae: 0.2406 - mse: 0.2810 - val_loss: 0.4337 - val_mae: 0.3397 - val_mse: 0.4101
Epoch 32/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - loss: 0.3377 - mae: 0.2479 - mse: 0.3143 - val_loss: 0.4214 - val_mae: 0.3314 - val_mse: 0.3989
Epoch 33/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.3442 - mae: 0.2480 - mse: 0.3218 - val_loss: 0.4500 - val_mae: 0.3446 - val_mse: 0.4282
Epoch 34/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.3602 - mae: 0.2579 - mse: 0.3387 - val_loss: 0.4908 - val_mae: 0.3586 - val_mse: 0.4699
Epoch 35/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - loss: 0.3969 - mae: 0.2610 - mse: 0.3762 - val_loss: 0.4163 - val_mae: 0.3249 - val_mse: 0.3962
Epoch 36/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - loss: 0.3876 - mae: 0.2516 - mse: 0.3677 - val_loss: 0.4286 - val_mae: 0.3299 - val_mse: 0.4092
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy
Model saved to model.h5
```

Figure 4.23: Training Results of the LSTM Model



```
Epoch 28/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.3677 - mae: 0.2407 - mse: 0.3405 - val_loss: 0.3902 - val_mae: 0.3097 - val_mse: 0.3640
Epoch 29/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.3498 - mae: 0.2470 - mse: 0.3238 - val_loss: 0.3958 - val_mae: 0.3207 - val_mse: 0.3707
Epoch 30/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.3474 - mae: 0.2381 - mse: 0.3225 - val_loss: 0.3709 - val_mae: 0.2913 - val_mse: 0.3468
Epoch 31/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.3717 - mae: 0.2481 - mse: 0.3478 - val_loss: 0.3875 - val_mae: 0.3198 - val_mse: 0.3642
Epoch 32/200
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.3884 - mae: 0.2556 - mse: 0.3655 - val_loss: 0.3939 - val_mae: 0.3176 - val_mse: 0.3717
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g.
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g.
Model saved to model.h5
```

Figure 4.24: Training Results of the GRU Model

4.4.3 LSTM and GRU Model Evaluation

The LSTM and GRU models underwent a thorough process of evaluation to determine their effectiveness in predicting future environmental condition based on the provided data. The performance of these models was assessed by comparing their prediction errors and analyzing how closely their predictions matched the actual data. Figure 4.25 illustrates the comparison of Mean Squared Error (MSE) and Mean Absolute Error (MAE) between the two models. The GRU model slightly better than the LSTM model, as it shows that GRU model having a lower MSE and MAE. This indicating that the GRU model made more accurate predictions on average. This suggests that the GRU model was better at capturing the patterns in the data for this hydroponic system data.

Figure 4.26 visually compares the actual versus predicted values for the surrounding temperature using both the LSTM and GRU models. The plot shows that both models closely follow the actual temperature trends, with the GRU model's predictions being slightly more aligned with the actual values, particularly during sharp changes in temperature. This visual analysis supports the numerical evaluation, further indicating that the GRU model performed better in predicting the time series data in this case.

Overall, these evaluations demonstrate that while both LSTM and GRU models are effective in time series prediction, the GRU model showed a slight advantage in this particular scenario.

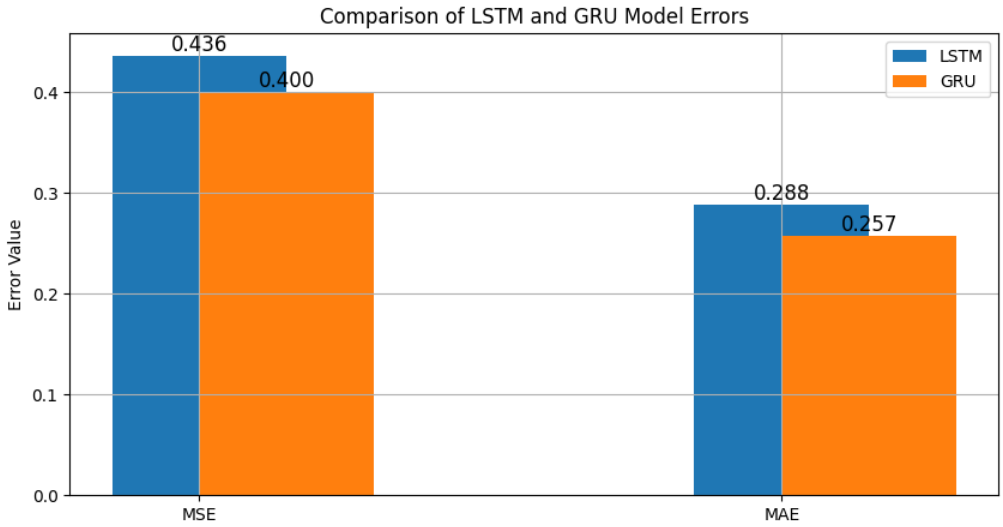


Figure 4.25: Comparison of MSE and MAE Between LSTM and GRU Models

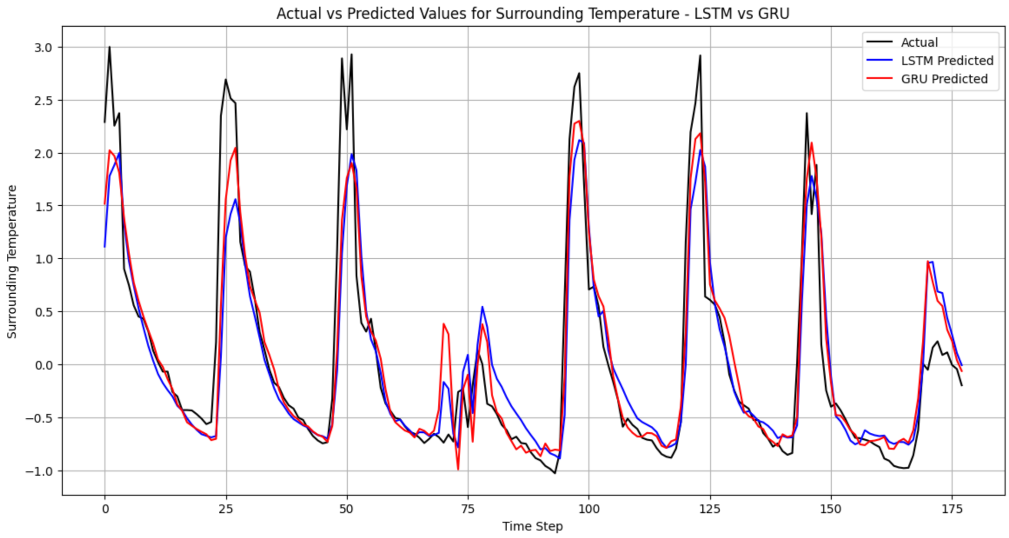


Figure 4.26: Actual vs Predicted Values for Surrounding Temperature - LSTM vs GRU

4.4.4 AI Model Limitations

The LSTM and GRU models demonstrated well results, but their performance was limited by the small amount of data available for training (30 days). Due to time constraints, the data collection period was short, which means the dataset may not fully represent the variety of patterns and conditions that the models could encounter in real-world scenarios. As a result, the models may not perform as accurately when faced with situations that differ from those in the training data. Collecting data over a longer period would enable the models to capture a broader variety of patterns and scenarios, leading to more accurate and reliable predictions.

The limited dataset also restricted the models' ability to learn from a wide range of scenarios, which could impact their accuracy in predicting uncommon or extreme conditions. The AI models trained are specific to this particular hydroponic system and location, which further limits their ability to generalize to other setups. To improve accuracy and reliability, collecting a longer period and more diverse dataset, including different hydroponic systems and locations, would allow the models to learn better and make more accurate predictions. Retraining the models with this new data would make them more effective in different environments.

4.5 Enhancing the Innovation of the IoT-Enabled Hydroponic System

The innovation of the IoT-enabled hydroponic system is driven by real-time data monitoring and collection, AI model integration, and automation capabilities. To further enhance the innovation and functionality of the IoT-enabled hydroponic system, I worked in collaboration with a software engineer, to develop a user-friendly application capable of real-time monitoring, control actions for controllables like pH adjustment pump and fogger setup, and AI-driven predictions based on the collected environmental data.

The communication between the IoT-enabled hydroponic system and the Application Server is established using the HyperText Transfer Protocol (HTTP). The ESP32 microcontroller is programmed to continuously loop and retrieve the status of various controllable devices, such as the peristaltic pump and fogger, as illustrated in Figure 4.27. When a change in the status of a device is detected compared to its previous state, the corresponding device is triggered to operate based on the new status. After executing the operation, the ESP32 posts the updated status back to the Application Server for data logging purposes, which includes triggers like Low pH Trigger, Fogger Trigger, and others. These trigger statuses are crucial for training the AI model, as they provide essential operational data. Figure 4.28 shows that the ESP32 successfully checked the device trigger status, specifically the High pH Trigger, and updated the application server.

Figure 4.27: Serial Monitor Output Showing ESP32 Loop Retrieving and Device Trigger Status

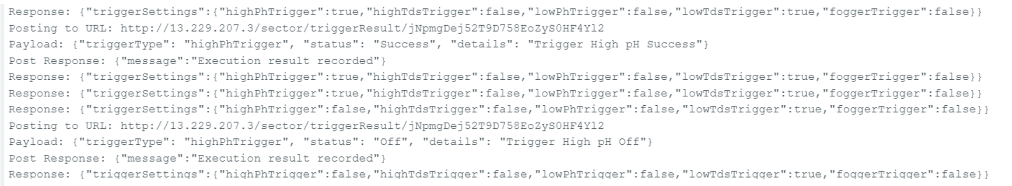


Figure 4.28: Serial Monitor Output Showing ESP32 Successfully Checked the Device Trigger Status (High pH Trigger)

Next, the ESP32 updates the environmental parameters collected from sensors to the Application Server, as shown in Figure 4.29. These environmental parameters, such as temperature, humidity, and pH levels, are essential for real-time monitoring through the application. Moreover, the data is utilized for future predictions based on the AI model trained with historical data. Once the AI model is trained, it is integrated into the Model Server to enable real-time predictions and provide insights to the user via the application based on current environmental conditions. Figure 4.30 shows the JSON Payload successfully updated to Firebase Cloud.

```
// Create JSON payload
String payload = "{"
  "\"userId\": \"" + linkUser + "\","
  "\"sectorId\": \"" + linkSector + "\","
  "\"parameters\": {"
    "\"surroundingTemperature\": " + float(air_temp) + ","
    "\"surroundingHumidity\": " + float(air_hum) + ","
    "\"solutionTemperature\": " + float(solution_temp) + ","
    "\"pH\": " + float(medianpH) + ","
    "\"tds\": " + float(medianTds) + ","
    "\"lightIntensity\": " + float(lux) + ","
    "\"foggerTemperature\": " + float(fogger_air_temp) + ","
    "\"foggerHumidity\": " + float(fogger_air_hum) + ","
    "\"foggerTrigger\": 0,"
    "\"lowTdsTrigger\": 0,"
    "\"highTdsTrigger\": 0,"
    "\"lowPhTrigger\": 0,"
    "\"highPhTrigger\": 0"
  "}}";

int httpResponseCode = http.POST(payload); // Send the POST request
```

Figure 4.29: Code Snippet for Creating JSON Payload and Posting Environmental Data to Firebase Cloud

```
Median TDS Value: 43.61 ppm
Relay cooldown in effect for low TDS condition. Relay will not trigger.
Relay cooldown in effect for high TDS condition. Relay will not trigger.
Response code: 400
Response: <!DOCTYPE html>
<html lang="en">
<head>
<meta charset="utf-8">
<title>Error</title>
</head>
```

Figure 4.30: Serial Monitor Output Showing the JSON Payload Successfully Updated the Firebase Cloud

This integration of real-time data, control actions, and AI-driven predictions elevates the functionality of the IoT-enabled hydroponic system, making it a powerful tool for optimized plant management.

4.6 Summary

This chapter detailed the findings and progress of the IoT-enabled hydroponic system, highlighting the design, a detailed analysis on the impact of the fogger-based cooling system towards the lettuce plant growth, comparison of water efficiency between hydroponic and traditional farming, and the development of AI models for predicting environmental parameters.

The IoT-enabled hydroponic system shown in Figure 4.1 was designed with eight growing trays, sensors for real-time environmental monitoring, and controllable devices. It effectively managed and controlled parameters such as temperature, humidity, pH, and TDS, optimizing conditions for lettuce growth over 30 days.

The fogger-based cooling system reduced the temperature by an average of 9.2°C, creating a cooler environment for lettuce growth. Figures 4.20 and 4.21 demonstrated the significant increase in plant height and leaf area in the fogger setup compared to the non-fogger setup, resulting in a 46.26% increase in plant height and 15.70% increase in leaf area. This underscores the effectiveness of the fogger system in mitigating heat stress and promoting optimal plant growth.

Additionally, the comparison between hydroponic farming and traditional soil-based farming revealed substantial water savings, as illustrated in Figure 4.22. Hydroponic systems used up to 13 times less water than conventional methods, making it a more sustainable choice for regions like Malaysia where water conservation is crucial. This aligns with the 12th Malaysia Plan (12MP) and supports SDG 6 (Clean Water and Sanitation) and SDG 12 (Responsible Consumption and Production).

The AI models (LSTM and GRU) were developed to predict future environmental conditions, enhancing the system's ability to manage plant growth. After training and evaluation process, the results in Figures 4.25 show that the GRU model performed slightly better, making more accurate predictions based on time-series data. However, both models would benefit from longer data collection periods to improve accuracy and generalization.

Furthermore, the innovation of the system was advanced through collaboration with a software engineer to develop a user-friendly application capable of real-time monitoring, AI-based predictions, and control actions. This integration of IoT and AI elements contributed to a highly efficient, sustainable, and scalable hydroponic solution.

Overall, this chapter demonstrates the potential of integrating IoT, AI, and hydroponic technologies to enhance system efficiency, reduce human intervention, and increase crop yield while minimizing resource waste. By combining real-time data monitoring and predictive AI models, the system optimizes growing conditions, conserves resources, and promotes more sustainable agricultural practices.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

This project successfully developed a fully functional IoT-enabled Deep Water Culture (DWC) hydroponic system capable of growing lettuce plants while providing real-time monitoring and automation for environmental control. The system empowers users to efficiently manage and maintain optimal growth conditions through automated adjustments based on collected data, significantly reducing the need for manual intervention. By integrating AI models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), the system can make proactive predictions of future environmental conditions, further optimizing resource usage and plant growth.

The project had three main objectives, all of which were successfully achieved:

- **To develop and design a fully functional IoT-enabled hydroponic farming system**

  This objective was met by designing and building an IoT-enabled DWC hydroponic system that includes sensors for monitoring environmental parameters such as temperature, humidity, pH, and Total Dissolved Solids (TDS). The system allows for real-time data collection and remote monitoring through an IoT platform, giving users control over their hydroponic setup.

- **To investigate the effectiveness of a plant cooling system using fogger setups to help cool plants during peak heat periods and to assess the water efficiency of hydroponic farming through research**

  The project demonstrated the effectiveness of a fogger-based cooling system designed to mitigate the effects of high ambient temperatures on plant growth. The fogger system significantly improved lettuce plant growth by reducing temperature stress during peak heat periods. Additionally, the water efficiency in the hydroponic system was also discussed and compared. This demonstrating that hydroponic method uses water more efficiently compared to traditional soil-based methods.

- **To integrate IoT technologies into the hydroponic farming system for real-time environment monitoring, data collection of environmental parameters, and implementation of AI for future prediction**

  This objective was achieved by integrating IoT technologies to continuously monitor and collect environmental data. The system uses this data to train AI models such as LSTM and GRU, enabling the prediction of future conditions and proactive adjustments to the hydroponic system. This approach minimizes human intervention and ensures that optimal conditions are maintained for plant growth.

In conclusion, all objectives of the project were successfully met, demonstrating the potential of IoT and AI in enhancing the sustainability, automation, and efficiency of hydroponic farming systems. This project is highly relevant to Malaysia’s push for sustainable and smart agriculture, aligning with initiatives outlined in the 12th Malaysia Plan. The plan, in Theme 1 (Resetting the Economy), emphasizes the adoption of modern technologies such as IoT, robotics, and precision agriculture to boost productivity. Technologies like indoor vertical farming and plant factories, which are compatible with hydroponic systems, are specifically highlighted as offering opportunities for controlled-environment farming. This approach directly supports the project's objective of automating and optimizing hydroponic farming systems, ensuring that resources are used efficiently while meeting the increasing demand for high-quality produce.

Additionally, the project supports the promotion of sustainable agriculture practices as outlined in the plan, where farmers are encouraged to adopt good agricultural practices (myGAP) and organic farming. Hydroponic systems, which minimize water use and reduce the need for chemical inputs, directly align with these sustainability goals. By utilizing IoT and AI, this project enhances automation and promotes environmental sustainability in hydroponic farming, demonstrating the scalability of the system for both small-scale urban farms and larger commercial operations. The system thus contributes to Malaysia's agricultural industry by promoting resource-efficient and environmentally friendly farming practices, consistent with the 12th Malaysia Plan’s objectives for modern, smart, and sustainable agriculture (Economic Planning Unit, Prime Minister's Department, 2021).

5.2 Limitations

Although the project achieved its goals, there are a few limitations that need to be addressed in future developments.

The first limitation is the limited data size and duration, as the dataset used for training the machine learning model only spanned one month. This short timeframe may have impacted the results, particularly in assessing the fogger system's effect on lettuce growth, which could be influenced by external factors like weather fluctuations or natural variations in the seeds themselves. Such a limited dataset also affects the AI model’s training, as machine learning models generally perform better with larger datasets that capture a broader range of conditions. Without collecting more data over time, the model's ability to give accurate predictions in different or extreme environmental conditions is limited, which may reduce the system’s overall effectiveness.

The second limitation is the specificity of the dataset. The dataset used for training the machine learning model was collected from a hydroponic system growing lettuce in Malaysia, which limits its adaptability to other crops and regions. Different vegetables, such as cabbage or chili, grown in diverse climates or regions, have unique environmental requirements and nutrient needs that the current model does not accommodate. Additionally, location-specific factors like temperature, humidity, and sunlight can vary significantly, further affecting the model’s performance in different regions. Hence, to make the system applicable to a wider range of crops and locations, future research should focus on collecting crop-specific data for different vegetables and environmental settings, improving the model's adaptability across a broader range of crops and geographic locations.

The third limitation is the accuracy of the pH sensor used in the system. The pH sensors, particularly low-cost models, can be prone to fluctuations due to external factors such as temperature variations, electrical interference, and sensor calibration drift. In this project, these factors could lead to inconsistent pH readings, affecting the accuracy of nutrient solution adjustments in the hydroponic system. This inconsistencies in pH measurements can result in impact the effectiveness of nutrient adjustments and overall plant health. Additionally, any inaccuracies in pH measurements can negatively impact the AI model's ability to make accurate predictions and adjustments based on real-time data. Regular calibration, the use of higher-quality pH sensors, or additional filtering techniques may be necessary to improve pH measurement reliability and ensure consistent environmental control for optimal plant growth.

5.3 Recommendations for future work

To further enhance the functionality and effectiveness of the IoT-enabled hydroponic system, several key improvements can be made for future research and development:

1. **Enhance IoT Sensor Accuracy**

   One key area for improvement is the precision of the IoT sensors, particularly those measuring temperature, pH, and nutrient levels. Future work could involve using higher-quality sensors with better calibration to provide more reliable and accurate real-time monitoring. This would reduce the likelihood of inconsistent data and ensure optimal growing conditions are maintained at all times.

2. **Expand the Dataset for Enhanced Model Accuracy**

   Collecting a larger dataset over a longer period is critical for improving the accuracy of the AI models. By gathering more data, the models will be able to recognize a wider range of patterns and environmental variations, leading to more accurate predictions and better anomaly detection. Expanding the dataset will also enable the system to generalize across a broader range of environmental conditions, improving its adaptability to different scenarios.

3. **Refine AI Models**

   Continuous optimization of the LSTM and GRU models is essential to improve prediction accuracy and anomaly detection. Future efforts could involve training these models on larger, more diverse datasets to increase their robustness and adaptability. This would help the system predict and address potential issues before they impact plant growth, ensuring more reliable system performance.

REFERENCES

Adelmann, T. (2023) *What is the hydroponic nutrient-film-technique (NFT), Diy build your own hydroponics system*. Available at: https://hydroplanner.com/blog/hydroponic-nutrient-film-technique-nft (Accessed: 19 March 2024).

Ahmed, H.A., Yu-Xin, T. and Qi-Chang, Y. (2020) 'Optimal control of environmental conditions affecting lettuce plant growth in a controlled environment with artificial lighting: A Review', *South African Journal of Botany*, 130, pp. 75–89. doi:10.1016/j.sajb.2019.12.018.

Anishnama (2023) *Understanding gated recurrent unit (GRU) in deep learning, Medium*. Available at: https://medium.com/@anishnama20/understanding-gated-recurrent-unit-gru-in-deep-learning-2e54923f3e2 (Accessed: 03 September 2024).

Banoula, M. (2023) *Introduction to long short-term memory(lstm): Simplilearn, Simplilearn.com*. Available at: https://www.simplilearn.com/tutorials/artificial-intelligence-tutorial/lstm (Accessed: 22 April 2024).

Barbosa, G., Gadelha, F., Kublik, N., Proctor, A., Reichelm, L., Weissinger, E., Wohlleb, G., & Halden, R. (2015). Comparison of land, water, and energy requirements of lettuce grown using hydroponic vs. conventional agricultural methods. *International Journal of Environmental Research and Public Health*, *12*(6), 6879–6891. https://doi.org/10.3390/ijerph120606879

Barth, B. (2018) *How does aeroponics work?, Modern Farmer*. Available at: https://modernfarmer.com/2018/07/how-does-aeroponics-work/ (Accessed: 02 April 2024).

Begum, T. (2021). Soil degradation: the problems and how to fix them. Natural History Museum, London. [online] 16 Apr. Available at: https://www.nhm.ac.uk/discover/soil-degradation.html.
Climate and temperature development in Malaysia. (n.d.). Retrieved March 4, 2024, from https://www.worlddata.info/asia/malaysia/climate.php

Cooper, E. (2023) *What should the EC be for hydroponics?, Bitponics*. Available at: https://www.bitponics.com/what-should-the-ec-be-for-hydroponics/ (Accessed: 19 April 2024).

Craig, L. (2023) *CNN vs. RNN: How are they different?: TechTarget, Enterprise AI*. Available at: https://www.techtarget.com/searchenterpriseai/feature/CNN-vs-RNN-How-they-differ-and-where-they-overlap (Accessed: 22 April 2024).

Dubaniewicz, K. (2021) *Four plant health checks you should be doing every day, The art of growing blog*. Available at: https://blog.bluelab.com/four-plant-health-checks-you-should-be-doing-every-day (Accessed: 19 April 2024).

Economic Planning Unit, Prime Minister's Department (2021) *Twelfth malaysia plan, 2021-2025*. Available at: https://pulse.icdm.com.my/wp-content/uploads/2021/09/Twelfth-Plan-Document_compressed-1.pdf (Accessed: 16 September 2024).

Espressif Systems (no date) *Analog to digital converter, ESP*. Available at: https://docs.espressif.com/projects/esp-idf/en/v4.2.3/esp32/api-reference/peripherals/adc.html#:~:text=The%20ESP32%20ADC%20can%20be,mitigate%20the%20effects%20of%20noise. (Accessed: 21 August 2024).

GeeksforGeeks (2023) *Deep learning: Introduction to long short term memory, GeeksforGeeks*. Available at: https://www.geeksforgeeks.org/deep-learning-introduction-to-long-short-term-memory/ (Accessed: 22 April 2024).

Godge, M. (2022) *Hydroponics: Getting to the root of the myths*, *Food for Thought*. Available at: https://www.sfa.gov.sg/food-for-thought/article/detail/hydroponics-getting-to-the-root-of-the-myths (Accessed: 05 March 2024).

Hatfield, J.L. and Prueger, J.H. (2015) 'Temperature extremes: Effect on plant growth and development', *Weather and Climate Extremes*, 10, pp. 4–10. doi:10.1016/j.wace.2015.08.001.

Henry, J. *et al.* (2018) *Lettuce nutritional monitoring factsheet.pptx, Nutritional Monitoring Series*. Available at: https://hortamericas.com/wp-content/uploads/2018/04/e-gro-Nutritional-Factsheet-Lettuce.pdf (Accessed: 08 April 2024).

Horticulture, A. (2023) *The role of ph and EC in maintaining plant health in Hydroponic Systems, Acorn Horticulture*. Available at: https://acornhorticulture.com/the-role-of-ph-and-ec-in-maintaining-plant-health-in-hydroponic-systems/#Understanding_pH_Levels_in_Hydroponics (Accessed: 08 April 2024).

IPCC. (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press. In Press.

K, B. (2021) *Dwc - how much air do I need, One Stop Grow Shop*. Available at: https://www.onestopgrowshop.co.uk/blogs/news/dwc-how-much-air-do-i-need#:~:text=The%20answer%20to%20that%20is,4%20litres%20of%20nutrient%20solution. (Accessed: 16 July 2024).

Kostadinov, S. (2019) *Understanding GRU networks*, *Medium*. Available at: https://towardsdatascience.com/understanding-gru-networks-2ef37df6c9be (Accessed: 03 September 2024).

Lee, J.-Y. *et al.* (2020) 'Effects of concentration and temperature of nutrient solution on growth and camptothecin accumulation of Ophiorrhiza pumila', *Plants*, 9(6), p. 793. doi:10.3390/plants9060793.

Lou, M. *et al.* (2022) 'Growth parameter acquisition and geometric point cloud completion of lettuce', *Frontiers in Plant Science*, 13. doi:10.3389/fpls.2022.947690.

Mattson, N. (2018) *Monitoring is crucial for growing lettuce and leafy greens year round*, *Hort Americas*. Available at: https://hortamericas.com/blog/news/monitoring-is-crucial-for-growing-lettuce-and-leafy-greens-year-round/#:~:text=Mattson%20said%20the%20relative%20humidity,the%20physiological%20disorder%20tip%20burn. (Accessed: 22 April 2024).

McCandless, J.G. (2024) *Hydroponic wick system: The best system for beginners*, *Ponics Life*. Available at: https://ponicslife.com/hydroponic-wick-system-the-best-system-for-beginners/ (Accessed: 02 April 2024).

McDonald, C. (2023) *How does humidity affect plant growth? we researched it*, *Happy Hydro*. Available at: https://www.happyhydro.com/blogs/gardening/how-does-humidity-affect-plant-growth#:~:text=In%20high%20humidity%20conditions%2C%20the,thereby%20affecting%20growth%20and%20yield. (Accessed: 22 April 2024).

Michael (2023) *7 different types of hydroponic systems*, *NoSoilSolutions*. Available at: https://www.nosoilsolutions.com/6-different-types-hydroponic-systems/ (Accessed: 21 March 2024).

MicroCool (2023) *Fogging system for greenhouses: How evaporative fog cooling impacts the health of your crops*, *LinkedIn*. Available at: https://www.linkedin.com/pulse/fogging-system-greenhouses-how-evaporative-fog-cooling-impacts#:~:text=Fogging%20systems%20lower%20the%20temperature,effectively%20reducing%20ambient%20temperatures%20immediately. (Accessed: 22 April 2024).

Phi, M. (2020) *Illustrated guide to LSTM's and GRU's: A step by step explanation*, *Medium*. Available at: https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21 (Accessed: 03 September 2024).

Thompson, H.C. *et al.* (1998) 'Shoot and root temperature effects on lettuce growth in a floating hydroponic system', *Journal of the American Society for Horticultural Science*, 123(3), pp. 361–364. doi:10.21273/jashs.123.3.361.

Toclan (no date a) *SDG's, Toclan Asia | Malaysia Urban Farming & Hydroponics Specialist*. Available at: https://www.toclanasia.com/pages/sdg-s (Accessed: 16 September 2024).

Trees.com (2022a) *Ebb & flow (flood and drain) hydroponic system, Trees.com*. Available at: https://www.trees.com/gardening-and-landscaping/ebb-and-flow-hydroponics (Accessed: 02 April 2024).

Trees.com (2022b) *Hydroponic drip system explained*, *Trees.com*. Available at: https://www.trees.com/gardening-and-landscaping/hydroponic-drip-system#:~:text=A%20drip%20system%20is%20an,solution%20directly%20onto%20your%20plants. (Accessed: 02 April 2024).

United Nations Development Programme (2021) *The 12th Malaysia plan: Advancing sustainability*, *UNDP*. Available at: https://www.undp.org/malaysia/blog/12th-malaysia-plan-advancing-sustainability (Accessed: 16 September 2024).

Worlddata.info. (n.d.). That's how warm it is in Malaysia: 32.1 °C on average per year and over 2100 hours of sunshine! [online] Available at: https://www.worlddata.info/asia/malaysia/climate.php#:~:text=The%20average%20annual%20temperature%20was.

Zhou, J., Li, P. and Wang, J. (2022) 'Effects of light intensity and temperature on the photosynthesis characteristics and yield of lettuce', *Horticulturae*, 8(2), p. 178. doi:10.3390/horticulturae8020178.

Zuraini Anang *et al.* (2019b) 'Factors affecting water demand: Macro evidence in Malaysia', *Jurnal Ekonomi Malaysia*, 53(1). doi:10.17576/jem-2019-5301-2.