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Intelligent Agricultural Hydroponic Production System

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Dedication

*To those who have been my light and guide,
To those who carried me with their prayers, patience, and hearts full of love,
To my dear parents,
Thank you for every moment of support, every quiet sacrifice, and every tear of joy and pride that accompanied
my journey.
You are the reason behind every success, and my first and greatest source of strength.
I pray that God grants you health, wellness, and a long, happy life.*

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peace, and may you always remain a bright spark in our hearts.*

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*To my dearest grandfathers **Si Lamine** and **Si Abdelhamid**, and my grandmothers **Hajja Rouqayya** and **Hajja
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May God have mercy on your souls and make your graves gardens of peace. You will never be forgotten.

*To my beloved grandmother **Aicha**,*

May God prolong your life and bless you, you remain our source of comfort, warmth, and endless prayer.

To my friends and everyone who supported me and stood by my side on this journey,

Thank you for every word of encouragement and every moment of help and companionship.

I pray that God blesses you all, and may success and fulfillment follow you in every step of your lives.

This work is dedicated to all of you

You are the light that guided me to this point.

All praise is due to Allah, always and forever. In Him alone we seek help.

BELALMI Maram

Dedication

*To my family, who have always been my shelter, my support, and my certainty,
To the roots from which I grew, and to which I return whenever life becomes heavy...*

To my beloved mother,

No words can ever truly describe you.

You are the prayer that opened doors for me, and the patience that helped me overcome every hardship.

You carried me with love, stayed up in silence, and supported me with grace.

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warmth and care.*

May God preserve you and bless your life you are the most precious and sincere gift I have.

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To my dearest grandmother,

The one who holds both wisdom and tenderness in one heart.

Your prayers sustain me, and your contentment is my peace.

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You have always been my refuge and my soft place to land in moments of weakness.

*Your prayers, your care, and even your spontaneous words
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To my uncles,

Thank you from the bottom of my heart for every sincere gesture and every quiet form of support.

Family will always be a priceless strength.

To every member of my extended family,

I dedicate this work with gratitude and appreciation.

You are my true treasure, and you believed in me even before I realized my own worth.

BETTAYEB Lina

Abstract :

This project presents an intelligent vertical hydroponic farming system that combines environmental control with automatic plant disease detection. The system is based on the ESP32 microcontroller and uses sensors to measure temperature and humidity, along with actuators such as a fan, heater, water pump, and LED grow lights. Environmental conditions are regulated using a fuzzy logic module to maintain an optimal environment for lettuce growth. For disease detection, a lightweight convolutional neural network (CNN) based on the MobileNetV2 model was trained on a dedicated dataset containing seven classes of healthy and diseased lettuce leaves. Real-time images are captured using a USB camera, allowing the system to react quickly to signs of disease. The system is designed to fit within vertical hydroponic farms, offering real-time monitoring and autonomous decision-making. The project aims to enhance crop productivity, reduce disease spread, and support smart and sustainable agriculture.

Keywords:

Smart agriculture; vertical hydroponics; lettuce disease detection; MobileNetV2; convolutional neural networks; fuzzy control; ESP32; environmental monitoring; embedded systems; sustainable farming.

Résumé :

Environnemental et la détection automatique des maladies des plantes. Le système repose sur un microcontrôleur ESP32 et utilise des capteurs pour mesurer la température et l'humidité, ainsi que des actionneurs comme un ventilateur, un chauffage, une pompe à eau et des lampes LED de croissance. Le contrôle des conditions environnementales est assuré par un module de logique floue, garantissant un environnement optimal pour la croissance de la laitue. Pour la détection des maladies, un réseau de neurones convolutifs léger basé sur MobileNetV2 a été utilisé, entraîné sur un ensemble de données spécifique contenant sept classes de feuilles de laitue saines et malades. Les images sont capturées en temps réel à l'aide d'une caméra USB, permettant une réaction rapide aux signes de maladies. Le système est conçu pour s'intégrer aux fermes d'agriculture hydroponique verticale, offrant une surveillance instantanée et une prise de décision autonome. Le projet vise à améliorer la productivité, limiter la propagation des maladies, et promouvoir une agriculture intelligente et durable.

Mots-clés:

Agriculture intelligente ; agriculture hydroponique verticale ; détection des maladies de la laitue ; MobileNetV2 réseaux de neurones convolutifs ; logique floue ; ESP32 ; surveillance environnementale ; systèmes embarqués ; agriculture durable.

ملخص:

يقدم هذا المشروع نظامًا ذكيًا للزراعة العمودية المائية يجمع بين التحكم في البيئة المحيطة والكشف التلقائي عن أمراض النباتات. يعتمد النظام على المتحكم ESP32 ، ويستخدم مستشعرات لقياس درجة الحرارة والرطوبة، بالإضافة إلى مشغلات مثل المروحة، السخان، مضخة المياه، وأضواء LED للنمو. يتم التحكم في الظروف البيئية باستخدام وحدة منطق ضبابي للحفاظ على بيئة مناسبة لنمو نبات الخس. ولتشخيص الأمراض، تم استخدام شبكة عصبية التلافيفية (CNN) خفيفة مبنية على نموذج MobileNetV2 ، وتم تدريبها على مجموعة بيانات مخصصة تحتوي على سبع فئات من أوراق الخس السليمة والمصابة. يتم التقاط الصور في الوقت الحقيقي باستخدام كاميرا USB ، مما يسمح للنظام بالتفاعل السريع مع أي علامات مرض. تم تصميم النظام ليتناسب مع مزارع الزراعة العمودية المائية، ويوفر مراقبة لحظية واتخاذ قرارات تلقائية. يهدف المشروع إلى تحسين إنتاجية المحصول، والحد من انتشار الأمراض، ودعم الزراعة الذكية والمستدامة.

الكلمات المفتاحية :

الزراعة الذكية؛ الزراعة العمودية المائية؛ اكتشاف أمراض الخس؛ MobileNetV2 ؛ الشبكات العصبية الالتلافيفية؛ التحكم الضبابي؛ ESP32 ؛ مراقبة بيئية؛ أنظمة مدمجة؛ زراعة مستدامة.

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Table of abbreviations

°C	Degrees Celsius
%	Percent
ADC	Analog to Digital Converter
AI	Artificial Intelligence
CNN / CNNs	Convolutional Neural Network(s)
DC	Direct Current
DHT11	Digital Humidity and Temperature Sensor type 11
DL	Deep Learning
EC	Electrical Conductivity
ESP32	Espressif Systems 32-bit Microcontroller
FIS	Fuzzy Inference System
FLC	Fuzzy Logic Controller
GPIO	General Purpose Input/Output
GND	Ground
IDE	Integrated Development Environment
IoT / IOT	Internet of Things
LED	Light Emitting Diode
MQTT	Message Queuing Telemetry Transport
PH / pH	Potential of Hydrogen (Acidity/Alkalinity)
PID	Proportional-Integral-Derivative Controller
PWM	Pulse Width Modulation
RH	Relative Humidity
UART	Universal Asynchronous Receiver Transmitter
USB	Universal Serial Bus
V	Voltage

Chapter One: Introduction and Background

**Chapter One:
Introduction and Background**

Chapter 1 : Introduction and Background

1.1 Background of Hydroponics and Vertical Farming

Hydroponics is a farming technique where plants grow without soil, using water mixed with mineral nutrients. In this system, plants absorb everything they need directly from the solution, which often leads to faster growth, better yields, and more efficient use of space and water. Hydroponic setups can be found in greenhouses, indoor facilities, and even rooftops in cities. As soil quality declines and water becomes scarcer, hydroponics is gaining attention as a more sustainable way to grow food.

Vertical farming takes this a step further by growing plants in stacked layers, often inside buildings or containers. This helps save space, especially in crowded cities, and allows crops to be grown all year under controlled conditions like temperature, humidity, and lighting. With the UN estimating that 68% of the global population will live in urban areas by 2050, vertical farming could play a key role in producing food closer to where people live.

Environmental concerns also push the adoption of these systems. Traditional farming uses a lot of water and contributes to greenhouse gas emissions. In contrast, hydroponic systems can reduce water use by up to 90% and have a smaller environmental footprint. Companies like AeroFarms have shown how vertical systems using aeroponics can grow leafy greens efficiently and sustainably.

Still, there are challenges. Managing the climate inside these systems is not always easy, and detecting plant diseases in dense crops can be tricky. Smart technologies like fuzzy logic and machine learning are being used to tackle these problems by automating climate control and helping spot diseases early, which can lead to better results and healthier plants.

1.2 Problem Statement

As more people move into cities and farmland becomes scarce, there is increasing pressure to adopt new farming methods that use space and resources efficiently. Hydroponic and vertical farming offer promising solutions by allowing crops to grow year-round in small, controlled environments without soil. However, these systems need accurate control of environmental factors like temperature and humidity. Even small changes in these conditions can harm plant growth and reduce yields. Manual control is often not reliable and can be time-consuming (Sharma et al., 2018) [1].

Another issue is the spread of plant diseases in high-density hydroponic setups. Many farms still rely on visual inspection to detect diseases, but this method is slow and depends on experienced workers. In large farms, delays in spotting diseases like downy mildew or bacterial wilt can lead to major crop losses. Lee et al. (2020) [2] stressed the importance of using automated systems to monitor plant health in controlled environments for faster disease detection.

While technologies like IoT and machine learning are starting to improve hydroponic farming, many systems still treat climate control and disease detection as separate problems. There is a clear

Chapter One: Introduction and Background

research gap in building a single intelligent system that can do both: manage temperature and humidity using fuzzy logic, and detect plant diseases using efficient deep learning algorithms like convolutional neural networks (CNNs).

Solving this problem could lead to smarter and more self-sufficient farming systems that produce high-quality crops while saving labor and resources especially in crowded urban areas (Al-Kodmany, 2018) [3].

1.3 Research Objectives

The main goal of this project is to create a smart hydroponic system that can automatically control important environmental conditions mainly temperature and humidity using fuzzy logic. In greenhouses, these conditions often change quickly and unpredictably, which makes traditional control methods like on/off or PID less effective. Fuzzy logic is better suited because it can deal with uncertainty and uses rules based on real-world knowledge to keep the climate stable for healthy plant growth.

Another goal is to build a machine learning model using convolutional neural networks (CNNs) to detect plant diseases from images. In dense hydroponic farms, especially those using vertical setups, diseases can spread fast due to high humidity. By using CNNs to recognize signs of disease early, farmers can act quickly to stop the spread, reduce damage, and avoid using too many chemicals. CNNs are a good choice because they work well with images, don't require large training datasets, and can run on devices with limited computing power.

A third goal is to design a complete system where sensors collect data, fuzzy logic controls the environment, and the CNN model detects diseases all working together in real time. This system should make decisions automatically and process data efficiently. By combining IoT sensors, smart control, and machine learning, the system could reduce the need for manual work and make urban or remote farming more practical and scalable.

Lastly, the project will test the system through experiments. It will measure how well fuzzy logic keeps temperature and humidity stable, and how accurately the CNN model detects diseases. The system's performance will be evaluated using common metrics like precision, recall, and F1-score. These results will help show the real benefits of using intelligent technologies in modern hydroponic farming.

1.4 Thesis Structure

This thesis is structured into six chapters, each addressing a specific aspect of the research to ensure a comprehensive understanding of the system's design, implementation, and evaluation:

Chapter 1: Introduction and Background

This chapter introduces the concepts of hydroponics and vertical farming, outlines the key problems in climate regulation and disease management, and defines the main objectives of the research project.

Chapter One: Introduction and Background

Chapter 2: Literature Review and Related Work

This chapter provides an overview of previous studies related to smart hydroponic systems, environmental control strategies using fuzzy logic, and plant disease diagnosis using convolutional neural networks (CNNs). It identifies existing research gaps that this thesis aims to fill.

Chapter 3: System Architecture and Methodology

The third chapter explains the architecture of the proposed smart hydroponic system. It describes the hardware and software components used, how environmental sensing and actuation are achieved, and details the fuzzy logic methodology implemented for environmental control.

Chapter 4: Implementation and Results

This chapter presents the physical assembly and integration of the system components, the configuration of the Node-RED dashboard, and experimental results evaluating the performance of the fuzzy logic controller under varying environmental conditions.

Chapter 5: Crop Disease Diagnosis Using CNN

This chapter details the implementation of the MobileNet CNN model used to detect and classify lettuce diseases based on image data. It covers data collection, preprocessing, model training, performance evaluation, and integration into the overall system.

Chapter 6: Conclusion and Future Work

The final chapter summarizes the major findings of the thesis, discusses challenges encountered during the research, and suggests possible directions for future improvements and extensions of the system.

Chapter two: Literature Review and Related Work

**Chapter two:
Literature Review and Related Work**

Chapter 2: Literature Review and Related Work

2.1 Introduction

In recent years, the global trend toward sustainable food systems has led to growing interest in modern agricultural methods, particularly hydroponics and vertical farming. These soil-free techniques are known for their efficient use of water, nutrients, and space, making them ideal for densely populated and resource-limited regions. With the addition of smart technologies—like sensors, actuators, embedded controllers, and automation tools—hydroponic systems have become more productive, scalable, and adaptive to changing environmental needs. Since climate conditions inside these systems directly affect plant health and yield, researchers are increasingly focusing on building intelligent platforms that can monitor and regulate such factors in real time.

This chapter reviews existing research on smart hydroponic systems. It starts by examining current implementations of hydroponics and their technological enhancements. It then explores environmental control strategies, highlights the application of fuzzy logic in greenhouse and indoor agriculture, and discusses recent progress in plant disease detection using convolutional neural networks (CNNs). The chapter concludes by identifying the research gaps that this thesis intends to address.

2.2 Smart Hydroponic Systems

Hydroponics has become a practical solution to conventional agriculture, especially in areas affected by water shortages, poor soil fertility, or urban expansion. It works by supplying a nutrient solution directly to plant roots, allowing for faster growth with reduced resource use. The adoption of smart components has made these systems even more efficient by enabling automation and continuous monitoring.

Sensors are commonly used to track environmental variables like pH, EC, temperature, and humidity. Based on this data, actuators can adjust lighting, ventilation, and nutrient delivery in real time. These smart responses lead to better plant performance, less waste, and reduced need for human supervision (Grewal et al., 2011) [4].

With the emergence of IoT (Internet of Things), smart hydroponics have advanced further. Data from multiple sensors can now be transmitted wirelessly and processed using microcontrollers. This allows farmers or users to remotely monitor system performance, receive alerts, and automate responses. One notable example is the system by Samijayani et al. (2020) [5], which used a wireless sensor network to automatically adjust the nutrient and environmental settings in a hydroponic setup.

On the commercial side, AeroFarms in the U.S. uses aeroponics and machine learning to grow leafy greens in stacked layers under optimized conditions (AeroFarms, 2023) [6]. On the academic side, researchers have built low-cost hydroponic systems using platforms like Arduino and Raspberry Pi, making smart agriculture more accessible and affordable (Kowser et al., 2020) [7]. These initiatives reflect a wider movement toward intelligent, sustainable farming methods.

Chapter two: Literature Review and Related Work

2.3 Environmental Control Techniques

Environmental control plays a central role in hydroponics. In earlier systems, it was done manually using thermostats and timers to control heat and light. These methods, although affordable, are not responsive enough to match the dynamic changes in temperature or humidity that can affect plant growth (Resh, 2022) [8].

To improve performance, many greenhouses use PID controllers, which calculate the difference between a desired setpoint and the current value of a variable, then adjust it accordingly. However, these controllers often struggle in complex environments like greenhouses, where temperature and humidity can fluctuate unpredictably (Gouadria et al., 2017) [9]. PID systems also require tuning and don't adapt easily to multiple variables at once.

In contrast, fuzzy logic controllers offer more flexibility. Instead of exact values, they rely on rules and linguistic terms like "slightly high" or "very low" to make decisions similar to human reasoning. According to Thomopoulos et al. (2024) [10], fuzzy systems have shown better stability than PID controllers in maintaining greenhouse conditions during unexpected changes.

More recent solutions combine fuzzy logic with IoT and machine learning tools to create adaptive control systems. Sahour et al. (2022) [11], for instance, built an IoT-based fuzzy controller that managed temperature and humidity in a hydroponic greenhouse, improving water use and plant growth. These innovations push us closer to fully automated and intelligent growing environments.

2.4 Applications of Fuzzy Logic in Agriculture

Since it was introduced by Lotfi Zadeh in 1965 [12], fuzzy logic has been widely applied in agriculture. Its main advantage is the ability to handle uncertainty and vague data, making it perfect for agricultural environments where measurements are not always precise. In greenhouses and hydroponic farms, fuzzy logic systems can simulate human-like decisions by using "if-then" rules.

One of the most common applications is climate control. For example, Revathi et al. (2016) [13] developed a fuzzy logic system for managing greenhouse temperature, which outperformed basic on/off controls. Their system responded more smoothly to environmental changes, reducing overshoot and improving stability. Other models go further by managing multiple variables at once, such as temperature, humidity, and ventilation.

Fuzzy logic has also been used for irrigation scheduling. Bukhari et al. (2024) [14] created a fuzzy decision support system to optimize water use in olive farming, using soil moisture, evaporation rates, and weather forecasts. Similarly, Cardenas-Lailhacar and Dukes (2012) [15] used fuzzy logic to improve irrigation efficiency in turfgrass systems.

Recently, researchers have been combining fuzzy logic with IoT and machine learning to develop systems that are both reactive and adaptive. One example is Hamza et al. (2019) [16], who implemented a fuzzy-based control system with real-time sensor data to regulate climate conditions. These hybrid systems show how fuzzy logic can play a key role in modern, automated farming.

Chapter two: Literature Review and Related Work

2.5 Plant Disease Diagnosis Using Convolutional Neural Networks (CNNs)

In closed environments like hydroponics, plant diseases can spread rapidly due to high humidity and limited airflow. Traditional inspection methods such as visual checking or lab testing can be slow, subjective, and labor-intensive. As a solution, machine learning, especially CNNs (convolutional neural networks), has become an effective tool for automated disease detection.

CNNs are ideal for image classification tasks. They can extract and learn features from leaf images such as color changes, spots, and texture abnormalities without needing manual feature selection. Ferentinos (2018) [17] showed that CNN-based models could detect a wide range of plant diseases with over 98% accuracy.

In this thesis, we use a MobileNet CNN model due to its lightweight design. It works well on basic hardware with limited processing power, which is important in small-scale hydroponic farms. The CNN analyzes images captured by a USB camera and detects whether leaves are healthy or infected. This allows early action and helps reduce the use of pesticides.

By combining CNN disease detection with IoT sensors, the system becomes more autonomous and less dependent on expert growers. It can detect problems early and notify the user, improving crop quality and making smart farming more accessible.

Tabel2-1: Performance Comparison of CNN Models for Plant Disease Detection.

Model	Accuracy	Parameters	Mobile-Compatible
VGG16	98.5%	~138 million	✘ No
ResNet50	99.1%	~25 million	✘ Limited
MobileNet	97–99%	~4 million	✔ Yes

Chapter two: Literature Review and Related Work

2.6 Summary and Identified Gaps

The literature shows that smart hydroponic systems have made strong progress in both climate control and plant disease detection. The integration of fuzzy logic, IoT, and CNNs has improved system automation, stability, and crop health.

However, most research still treats climate control and disease monitoring as separate systems. While fuzzy logic is commonly used for managing environmental conditions, and CNNs for identifying diseases, very few projects combine both in a unified, real-time platform. This separation limits the system's potential to function autonomously in complex and changing conditions.

Also, many CNN-based models are designed for high-performance cloud platforms. They often require powerful processors and large datasets. While MobileNet is a lighter alternative, it has not been widely explored in real-world systems that also include fuzzy control logic.

This research aims to bridge that gap by building an integrated system that uses fuzzy logic to manage climate and CNNs to detect plant diseases all in one cost-effective, modular platform. The proposed system is tailored for small urban farms or remote areas, such as those found in Algeria, where smart, sustainable farming is urgently needed.

Conclusion

This chapter has presented an overview of the key technologies and research efforts related to smart hydroponic systems. It began by reviewing the implementation of hydroponics and how integrating IoT, automation, and sensor-based control has improved system performance. The chapter also examined various environmental control strategies, highlighting the benefits of using fuzzy logic for maintaining optimal conditions in complex greenhouse environments. Furthermore, it explored the growing role of machine learning particularly CNNs in diagnosing plant diseases through image analysis.

While significant progress has been made in both environmental regulation and disease detection, most studies address these functions separately. Few have proposed a unified system that combines fuzzy logic for climate control with CNNs for real-time plant health monitoring. Additionally, although lightweight CNN models such as MobileNet offer promising results on low-resource devices, their use in practical hydroponic environments alongside fuzzy logic remains underexplored.

The identified gap highlights the need for an integrated solution that can support automation, reduce human intervention, and work efficiently in small-scale or resource-constrained settings. This research responds to that need by developing a smart vertical hydroponic system that combines fuzzy control and CNN-based disease detection into one scalable and affordable platform paving the way for sustainable urban agriculture, particularly in countries like Algeria.

**Chapter Three:
System Architecture and Methodology**

Chapter 3 : System Architecture and Methodology

3.1 Introduction

This chapter outlines a smart, sustainable hydroponic agricultural system designed for efficient crop production in controlled environments. It integrates IoT sensors, automated actuators, and an intelligent control unit for real-time monitoring and precise regulation of temperature, humidity, and nutrients.

Using fuzzy logic control, the system adaptively manages environmental changes by adjusting lighting, ventilation, and water flow to optimize plant growth. A user-friendly Node-RED dashboard provides real-time data visualization and automated logging for continuous evaluation and improvement.

This combination of intelligent control and IoT technology offers a scalable sustainable solution for modern agriculture.

3.2 The production system parameter detectors

3.2.1 The sensor

A sensor is a device that perceives variations in environmental conditions and generates a corresponding output signal to another system Fig 3.1 It functions by transforming a physical phenomenon into a quantifiable analog voltage or in some cases, a digital signal, which can then be displayed in a human readable format or transmitted for further analysis and processing [18].

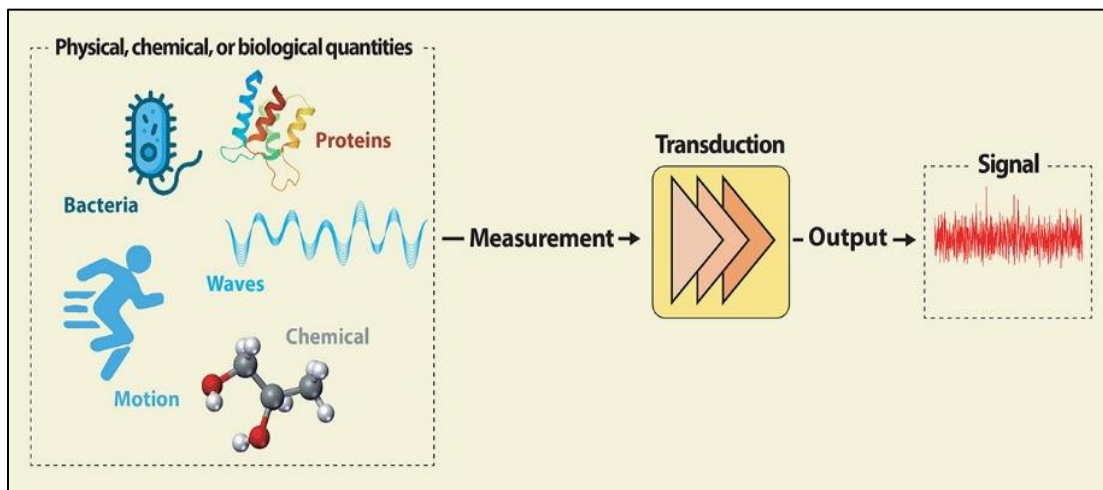


Figure 3-1: The sensing process.

Chapter Three: System Architecture and Methodology

3.2.2 The different types of sensor

- Passive sensors:

Passive sensors rely on an external energy source as strain gauges, thermistors, and are typically characterized by their impedance. A change in the measured physical phenomenon alters this impedance, producing a detectable signal only when an external voltage is applied. At the output, these sensors behave as passive dipoles—resistive, capacitive, or inductive, depending on the measurand and the underlying physical effect exploited for measurement.

- Active Sensors:

Active sensors directly convert the measured physical phenomenon into an electrical signal as voltage, current, or charge, without requiring external excitation. Here, the transduction is governed by fundamental physical laws, and the sensor itself acts as an active dipole, like a current or voltage generator. Examples include piezoelectric sensors as charge output and thermocouples as voltage output.

3.2.3 Signal classification:

- Analog signal

An analog signal is a continuous-time, continuous-amplitude representation of a physical phenomenon (e.g., temperature, light intensity). It can take any value within a defined range and is susceptible to noise and degradation over long distances.

- Logical signal

Logical (Binary) Signal

A logical signal has only two discrete states: HIGH (1, typically +5V or +3.3V) and LOW (0, 0V), representing Boolean logic (true/false, on/off). It is immune to noise when thresholds are properly defined.

- Digital signal

A digital signal is a discrete-time, discrete-amplitude representation of data, encoded as a series of binary bits (0s and 1s). Unlike analog signals, digital signals are robust against noise and can be processed by microcontrollers.

TABEL3.1: Signal classification.

Type	Characteristics	Project Use Case
Analog	Continuous, infinite resolution	Raw sensor readings (ph)
Logical	Two states (HIGH/LOW)	On/off controls (relays)
Digital	Discrete, multi-bit encoding	Sensor data transmission

Chapter Three: System Architecture and Methodology

3.2.4 Internal structure of a sensor

The internal structure of the sensor consists of 3 elements:

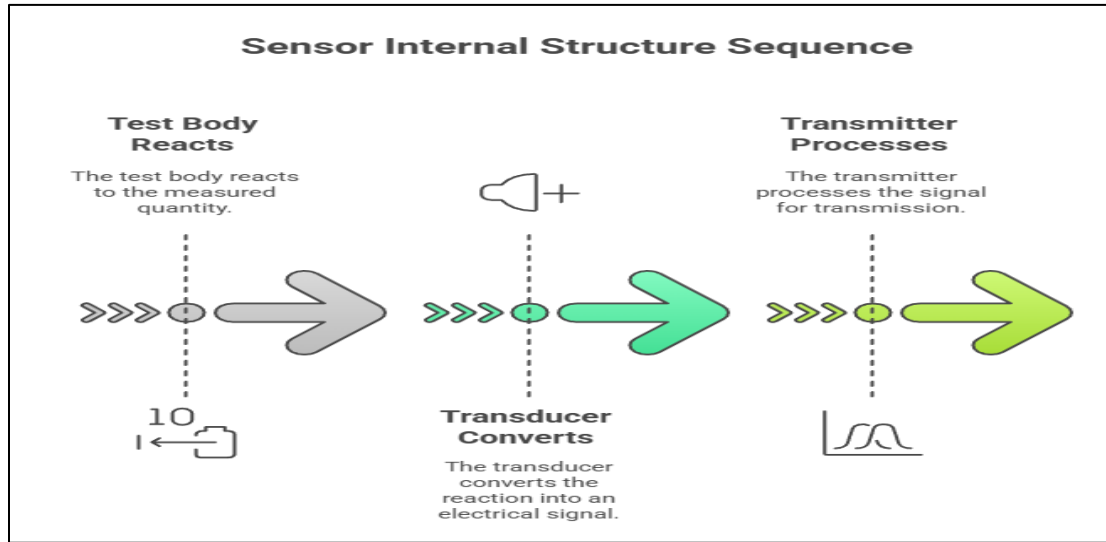


Figure 3-2: Internal structure of a sensor.

- The Test Body

A component that specifically reacts to the quantity being measured, converting this quantity into another physical quantity that can be measured.

- The Transducer

Converts the test body's reactions into an electrical signal, which forms the output signal.

- The Transmitter

Amplifies, filters, and standardizes the output signal for remote transmission. It may be integrated into the transducer or function as a separate component.

3.3 Hardware Components / Software requirements: Sensors, Actuators, and Controllers

The proposed smart hydroponic vertical farming system relies on several essential hardware components that work together to create a stable and intelligent growing environment. Each component has been selected based on its suitability for ensuring efficient plant growth, environmental control, and real-time monitoring. The following section explains the role of each device, its function within the system, and the rationale behind its inclusion [19].

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Sensing Layer:



Figure 3-3: Sensing Layer.

-DHT11 Sensor (Temperature & Humidity) (Fig 3-3):

The DHT11 sensor operates using a thermistor to measure temperature and a humidity-sensing element whose resistance varies with moisture levels. It outputs calibrated digital signals for both parameters. The sensor measures temperature within the range of 0°C to 50°C with an accuracy of $\pm 2^\circ\text{C}$, and relative humidity from 20% to 90% with an accuracy of $\pm 5\%$. This sensor is crucial for maintaining an optimal microclimate for plant growth by enabling precise monitoring and control of temperature and humidity, thereby preventing issues such as mold development and heat stress.

In this system, the sensor provides real-time data to the ESP32 microcontroller, which uses this information to activate actuators such as the heater or the fan. The DHT11 was chosen for its simplicity, low cost, and adequacy in applications that do not require highly precise measurements—making it suitable for a resource-conscious, small-scale farming setup like our .

-USB Camera Module (Plant Imaging) (Fig 3-3):

This module features a 720p resolution camera equipped with a fixed-focus lens, typically interfaced via USB 2.0. It captures high-quality still images of plant leaves and stems, facilitating early detection of leaf discoloration and diseases. Additionally, it supports tracking of plant growth progress and enables remote visual inspection, which is essential for timely intervention and effective crop management.

Its integration supports the project's secondary objective: early disease detection through image-based analysis. The use of a basic USB camera is a low-cost, practical choice that aligns with the system's aim of being deployable in resource-limited environments.

- EC/pH Sensor (Nutrient Monitoring) (Fig 3-3):

The EC/pH sensor system comprises an electrical conductivity (EC) probe that measures the ion concentration in nutrient solutions by assessing conductivity, and a pH electrode that detects hydrogen ion activity to determine solution acidity or alkalinity. The EC measurement typically ranges from 0 to 20 mS/cm, indicating nutrient strength, while the pH scale spans from 0 to 14. This sensor is vital for preventing nutrient lockout, optimizing fertilizer absorption, and maintaining a healthy root zone environment, all of which are critical for robust plant development

The sensor data helps detect when the solution becomes either too acidic, too alkaline, or diluted in nutrients, prompting necessary corrective actions. We selected this sensor because it provides vital insights into the root environment and yields.

Chapter Three: System Architecture and Methodology

Actuation Layer:



Figure 3-4: Actuation Layer.

-DC Water Pump (Figure 3-4):

The 3–6V submersible DC water pump provides reliable nutrient circulation with a flow rate of 120 liters per hour. Its low-voltage operation ensures energy efficiency while maintaining consistent distribution of the hydroponic nutrient solution. The fully submersible design allows direct placement inside nutrient reservoirs, preventing stagnation and ensuring optimal delivery to the root zone.

- Cooling Fan (Figure 3-4):

The 12V DC brushless cooling fan offers effective temperature regulation through forced air circulation. Its brushless motor design ensures quiet operation and a longer lifespan. Adjustable speed control allows precise environmental management to prevent heat build-up from other system components, thereby maintaining stable growing conditions.

Proper ventilation is vital in dense vertical systems to prevent mold, mildew, and other humidity-related diseases. The fan was selected for its low power consumption and reliability in maintaining airflow.

- LED Grow Lights (Figure 3-4):

The full-spectrum LED array (400–700 nm) delivers photo synthetically optimized illumination suitable for all plant growth stages. By emitting both blue (450 nm) and red (660 nm) wavelengths, it supports vegetative growth and flowering phases while maintaining energy efficiency compared to traditional lighting .

The decision to use LED technology was based on its high energy efficiency, long lifespan, and ability to deliver light tailored to the specific needs of lettuce cultivation.

- Heating System (Figure 3-4):

A 50W waterproof heating pad equipped with an adjustable thermostat (range: 15–30°C ±1°C) is incorporated for temperature maintenance. The heating pad features a durable, corrosion-resistant surface, an integrated temperature sensor for closed-loop control, and operates on 12V DC compatible with the system’s power architecture. An automatic shut-off safety mechanism is included to prevent overheating.

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Control Layer:

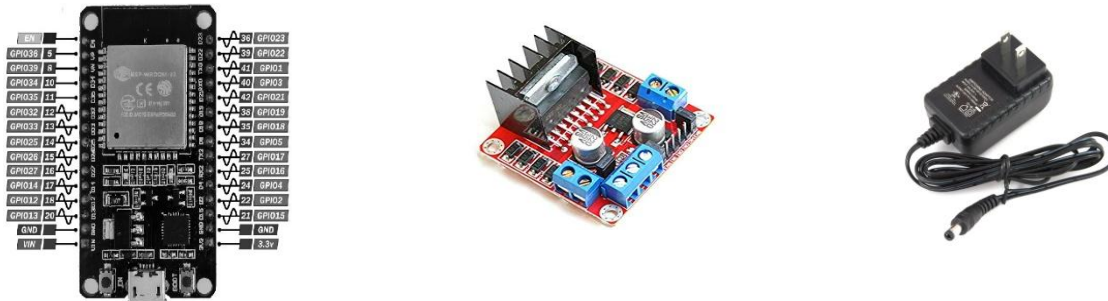


Figure 3-5: Control Layer.

- ESP32 ESP-WROOM-32 Microcontroller (Figure 3-5):

The ESP32 ESP-WROOM-32 is a powerful and versatile microcontroller widely used in IoT and embedded systems. It features a dual-core 240 MHz processor that supports efficient multitasking and fast data processing. Integrated Wi-Fi and Bluetooth connectivity enable wireless communication and remote control of devices.

The ESP32 offers numerous GPIO pins and supports multiple communication protocols such as SPI, I2C, and UART, allowing easy connection to various sensors and actuators. It also includes built-in analog-to-digital converters (ADC), digital-to-analog converters (DAC), and capacitive touch sensors. Designed for low power consumption, the ESP32 supports deep sleep modes, making it ideal for battery-powered applications.

Additionally, it incorporates hardware security features like secure boot and encryption to protect data and firmware.

The ESP32 provides a compact, energy-efficient, and competent platform for smart agricultural systems and many other IoT applications.

- Motor Driver (Figure 3-5):

The motor driver acts as a vital interface between the ESP32 microcontroller and electromechanical actuators. It amplifies low-power control signals from the microcontroller into higher-current outputs necessary for operating DC motors. The driver incorporates protection mechanisms against back electromotive force (back-EMF) and overcurrent conditions. Featuring H-bridge circuitry, it supports bidirectional motor control and allows accurate speed regulation through PWM input. Its robust design ensures reliable operation of motorized components such as pumps and fans within the system's power architecture.

-Power Supply (Figure 3-5):

The system employs a dual-voltage power supply, providing a 12V DC output for high-power components like LEDs and water pumps, alongside a 5V USB power source dedicated to sensitive control electronics. This configuration ensures stable and isolated power rails, minimizing electrical interference between digital control circuits and power-demanding components.

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Software requirements:

Programming the ESP32 board and creating an application are essential for controlling mini farm components, enabling optimum automation and monitoring of the plant-growing environment. This requires the use of specific software.

1. The Arduino IDE:

The Arduino IDE was employed to program the ESP32 control unit, which serves as the principal controller for all components of the smart agricultural system. Utilizing this development environment, we implemented the firmware responsible for acquiring sensor data, specifically DHT11 modules for temperature and humidity measurements, and for issuing actuation commands to the fan and the heater.

Moreover, the Arduino IDE facilitated the configuration of both digital and analog interfaces between the ESP32 and peripheral devices, and it enabled seamless integration of wireless communication protocols (Wi-Fi) for real-time remote monitoring. The platform also supported iterative testing of various control algorithms, including fuzzy-logic routines, allowed precise timing adjustments for system operations, and provided debugging tools to detect and log faults automatically.



Figure 3-6: The Arduino IDE.

Chapter Three: System Architecture and Methodology

2. Node-RED:



Figure 3-7: Node-RED.

The **Node-RED** platform provided significant value by enabling seamless integration between sensors and the ESP32 control unit, allowing us to fully leverage the capabilities of the Internet of Things (IoT). Through Node-RED, we can collect real-time temperature and humidity data and display it interactively via user-friendly dashboards, facilitating precise monitoring of the plants' environmental conditions. Another important feature is the ability to automatically store this data in separate files for each variable (temperature and humidity), supporting historical analysis and long-term performance evaluation. This organized data storage opens the door for applying artificial intelligence and predictive analytics techniques in the future to enhance the management of the agricultural environment more effectively. By using Node-RED, our agricultural system has become smarter, more flexible, and scalable, allowing easy modification and monitoring, making the project a practical example of IoT applications in smart farming.

3.4 Fuzzy Logic Control Methodology

Fuzzy Logic: Fuzzy logic provides an effective control method for agricultural systems by handling imprecise measurements and gradual transitions between states. Unlike traditional binary logic, it operates on continuous values between 0 and 1 using linguistic variables like "low", "medium", and "high". The system consists of three key stages:

1. Fuzzification converts precise sensor data (e.g., 25°C) into qualitative terms (e.g., "warm")
2. Inference Engine processes these terms through if-then rules (e.g., "IF temperature is high THEN increase fan speed")
3. Defuzzification translates the fuzzy output into precise control signals

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This approach has proven successful in managing greenhouse climate parameters like temperature and humidity. However, its application for optimizing light spectrum control across different plant growth stages remains underexplored. Current implementations also lack standardized methods for evaluating and improving fuzzy rule bases to handle system vulnerabilities. The technique's strength lies in its ability to mimic human decision-making while accommodating the variability inherent in biological systems [20].

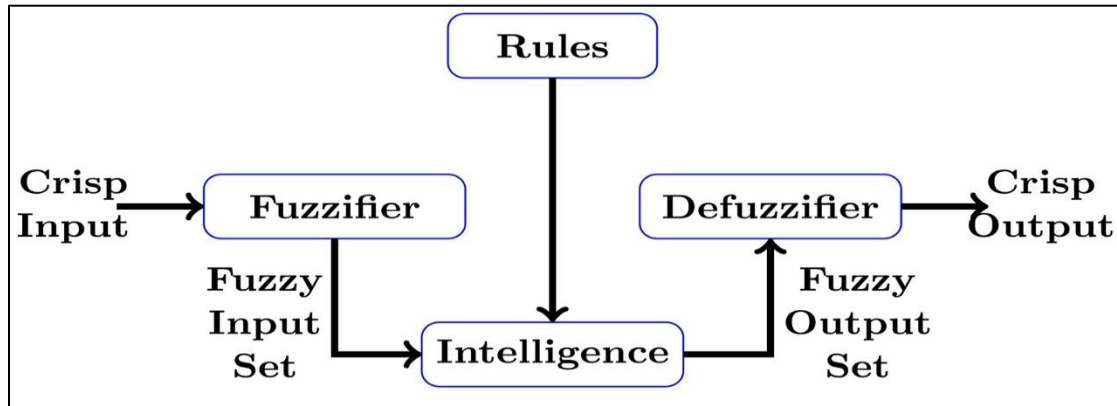


Figure 3-8: Configuration of FLC.

Inputs, Outputs, and Membership Functions

a. Input Variables

Temperature (°C):

- Linguistic terms: Cold, Optimal, Hot
- Membership functions: Triangular with 50% overlap
- Ranges:
 - Cold: 10–17°C
 - Optimal: 18–24°C
 - Hot: 25–39°C

Humidity (% RH):

- Linguistic terms: Dry, Moderate, Humid
- Membership functions: Trapezoidal, especially for better handling of boundary values
- Ranges:
 - Dry: 0–39%
 - Moderate: 40–70%
 - Humid: 71–90%

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b. Output Variables

Fan Speed (%)

- Linguistic Terms: Off, Low, Medium, High
- Membership Functions: Singleton values representing specific PWM duty cycle levels
- Control Method: The fan speed is controlled by PWM signals sent to the motor driver.

Immersion Heater Power (%)

- Linguistic Terms: Off, Low, Medium, High
- Membership Functions: Singleton values corresponding to discrete power levels supplied to the 50W waterproof immersion heater
- Control Method: The power is regulated either via a relay.

Fuzzy Rules and Inference System

1. Types of Fuzzy Inference Systems

Fuzzy inference systems (FIS) are frameworks that utilize fuzzy logic to map inputs to outputs. Among the most widely used types are the Mamdani, Sugeno, and Tsukamoto systems, each with distinct characteristics and applications.

The Mamdani-Type Fuzzy Inference System: introduced by Ebrahim Mamdani in 1975, employs fuzzy sets for both inputs and outputs. Its rules follow the structure: *IF x is A AND y is B THEN z is C*, where A, B, and C are fuzzy sets. Since the output is fuzzy, defuzzification methods like Centroid, Bisector, or MOM are required to convert it into a crisp control signal.

The Sugeno-Type Fuzzy Inference System (Takagi–Sugeno): differs by using mathematical functions for outputs rather than fuzzy sets. Its rules take the form: *IF x is A AND y is B THEN $z = f(x, y)$* . This approach is particularly useful for optimization, adaptive control, and integration with mathematical models.

the Tsukamoto Fuzzy Inference System: resembles Mamdani but uses monotonic membership functions for rule outputs. Each rule generates a crisp value, and the final output is a weighted average. However, due to its lower intuitiveness, it is less commonly applied in fields like environmental control systems

2. Why Mamdani FIS is Suitable for This Project

The Mamdani FIS is ideal for this project because it uses intuitive, linguistic rules that match human reasoning, making it easy to understand and adjust. This aligns perfectly with agricultural expertise, where conditions are often described qualitatively [21].

Example: IF temperature is high, THEN increase fan speed

Its transparent, rule-based structure simplifies control decisions, ensuring logical and interpretable outputs. Unlike Sugeno-type systems, which excel in optimization, Mamdani provides sufficient

Chapter Three: System Architecture and Methodology

precision for environmental **regulation without** complex modeling. This makes it a practical choice for managing hydroponic climate control.

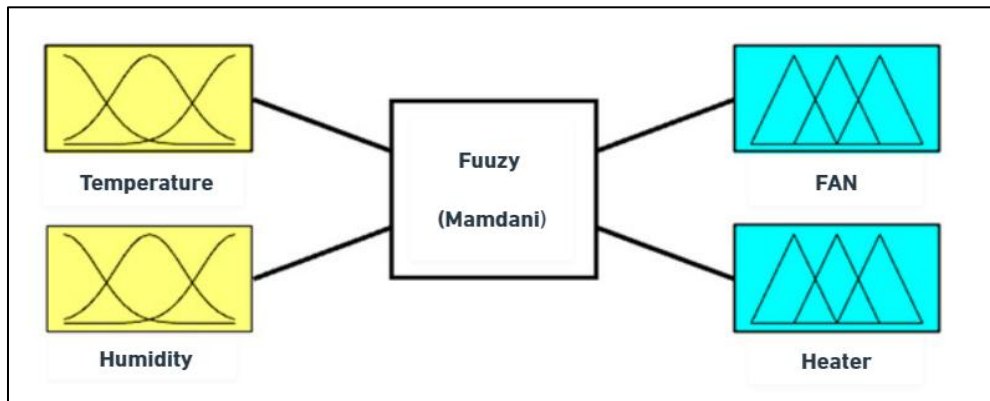


Figure 3-9: Fuzzy logic (Mamdani).

Conclusion:

In conclusion, this chapter has established a solid theoretical foundation for an intelligent hydroponic farming system that seamlessly integrates IoT-based sensors, automated actuators, and embedded control units to achieve autonomous environmental regulation. The use of fuzzy logic control stands out as a key innovation, providing adaptive and efficient management of essential growth parameters by emulating human reasoning to handle environmental uncertainties. By combining this control strategy with carefully selected hardware components, the system effectively addresses traditional agricultural challenges through real-time environmental monitoring and water-saving techniques. The integration of IoT and fuzzy logic not only enhances continuous monitoring and dynamic adjustment but also reduces manual intervention and improves resource efficiency. The following chapter will present the detailed system architecture and software implementation, translating these theoretical principles into a practical, operational solution.

Chapter Four: Implementation and Results

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4.1 Introduction

This chapter presents the practical realization of the proposed smart hydroponic system, detailing the steps involved in the physical assembly, hardware integration, and software implementation. The chapter begins with the construction of the vertical hydroponic prototype, highlighting key components such as the structural frame, lighting setup, and nutrient delivery mechanism. It then explores the integration of electronic components, including sensors, actuators, and the ESP32 microcontroller, which serve as the backbone of the environmental monitoring and control subsystem. Furthermore, the implementation of the Node-RED platform is examined, showcasing its role in facilitating real-time system interaction, control, and data visualization. Lastly, the chapter evaluates the performance of the fuzzy logic controller through controlled experiments, analyzing how effectively the system maintains optimal environmental conditions for plant growth under dynamic external influences.

4.2 Prototype Development and Hardware Assembly

4.2.1 Physical Construction of the Hydroponic System

The smart hydroponic system was engineered in a vertical configuration to optimize spatial efficiency and maximize light exposure essential for plant growth. The structure comprises multiple vertical layers, each integrated with water channels facilitating nutrient circulation. A high-resolution camera was strategically installed at an optimal height and angle to capture clear images of the plants for effective disease diagnosis. LED grow lights were mounted above the layers, providing consistent and tailored illumination aligned with the photosynthetic requirements of lettuce plants. The frame was fabricated using PVC pipes, selected for their lightweight, chemical resistance, and ease of assembly. Additional wooden supports were incorporated to enhance the overall structural stability of the system.

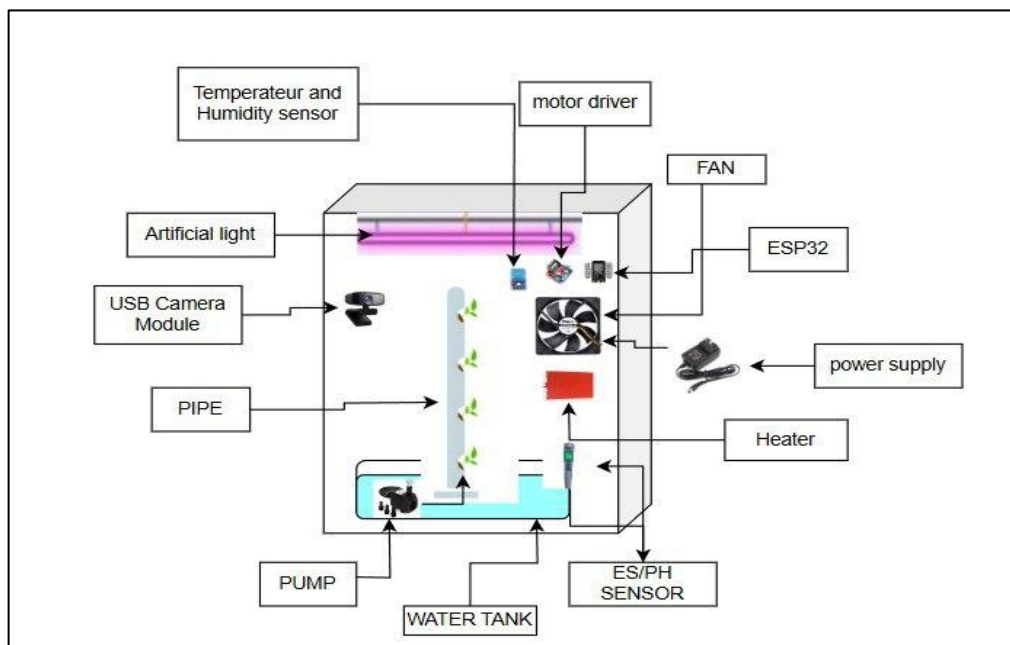


Figure 4.1: Principle of operation of an Intelligent agricultural hydroponic production system.



Figure 4.2: The prototype of an intelligent agricultural hydroponic production system.

Chapter Four: Implementation and Results

4.2.2 Integration of Electronic Components

The electronic subsystem is centered around an ESP32 microcontroller responsible for coordinating data acquisition and actuator control. The ESP32 interfaces with multiple sensors, including a DHT11 temperature and humidity sensor for environmental monitoring and a USB camera module for image capture. Actuators such as a motor driver controlling a water pump and a cooling fan are connected to the microcontroller's GPIO pins. Wiring was organized on a breadboard for prototyping purposes, with all components powered by a regulated 5V power supply. A detailed circuit schematic illustrates the interconnections among the ESP32, sensors, actuators, and power source. Safety measures, including the use of fuses and insulated wiring, were implemented to mitigate electrical hazards.

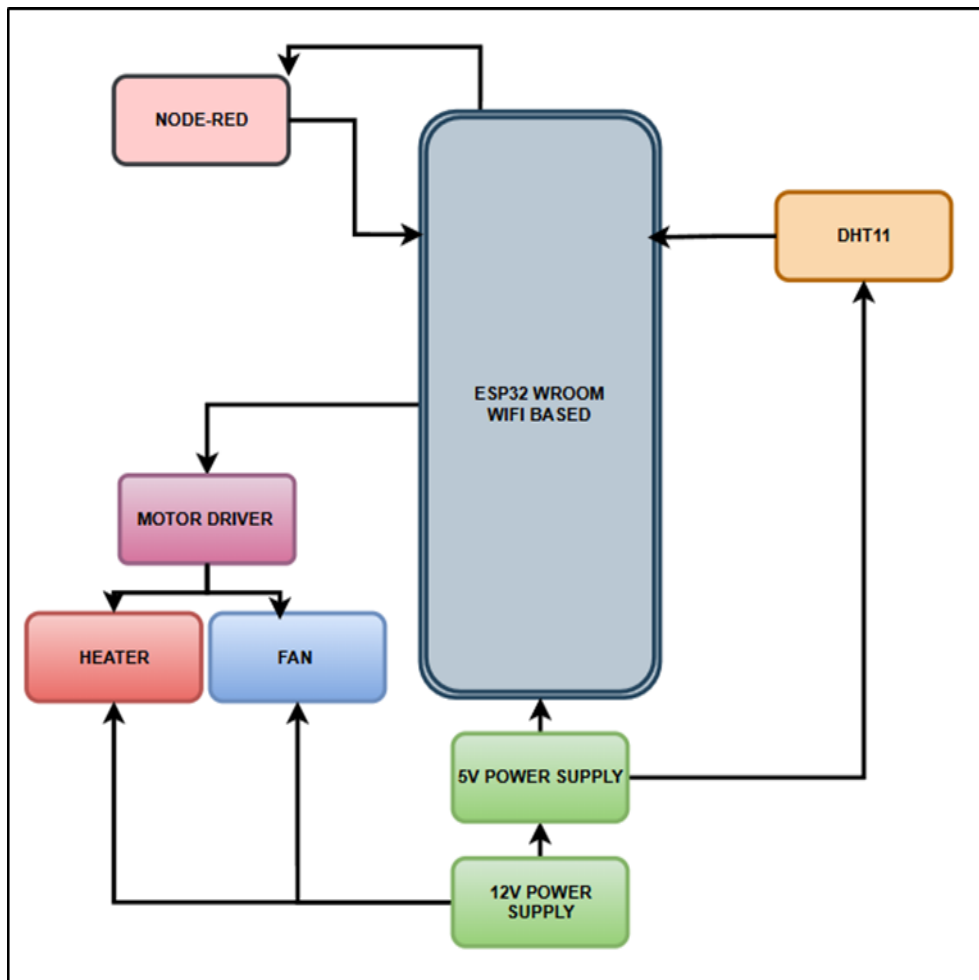


Figure 4.3: Block diagram of system.

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Electrical Design

The electrical design of this smart farming system is optimized to seamlessly integrate sensors, actuators, and control modules, including the ESP32 microcontroller, pumps, fans, and LED grow lights. It features robust power distribution to ensure stable voltage levels while minimizing electrical interference. Protective measures and a well-planned layout enhance durability, even in humid or demanding agricultural settings. This setup ensures reliable communication and precise control of all components, maintaining ideal growing conditions for hydroponic crops

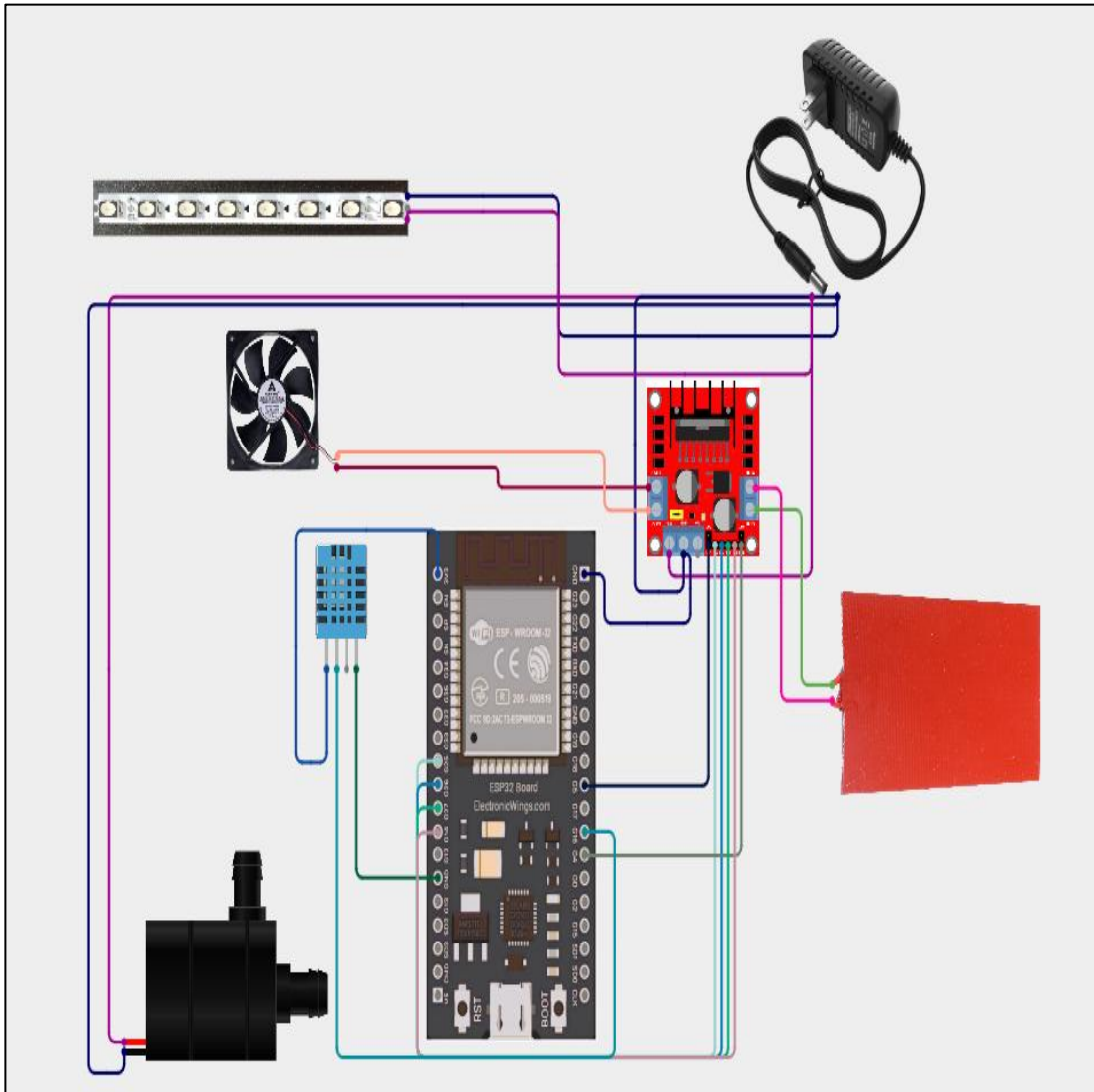


Figure 4-4: Electrical Design.

4.3 Implementation of Node-RED for Control and Monitoring

4.3.1 Node-RED Platform Setup and Configuration

Node-RED was employed as an intuitive flow-based programming platform to facilitate real-time data management and control of the hydroponic system. Acting as an intermediary interface, it receives sensor data from the ESP32 via the MQTT protocol and processes this data for visualization and control logic execution. The platform enables rapid development of user-friendly dashboards, allowing operators to remotely monitor environmental parameters and manually override actuators if necessary. This modular approach enhances system flexibility and supports integration with other IoT services.

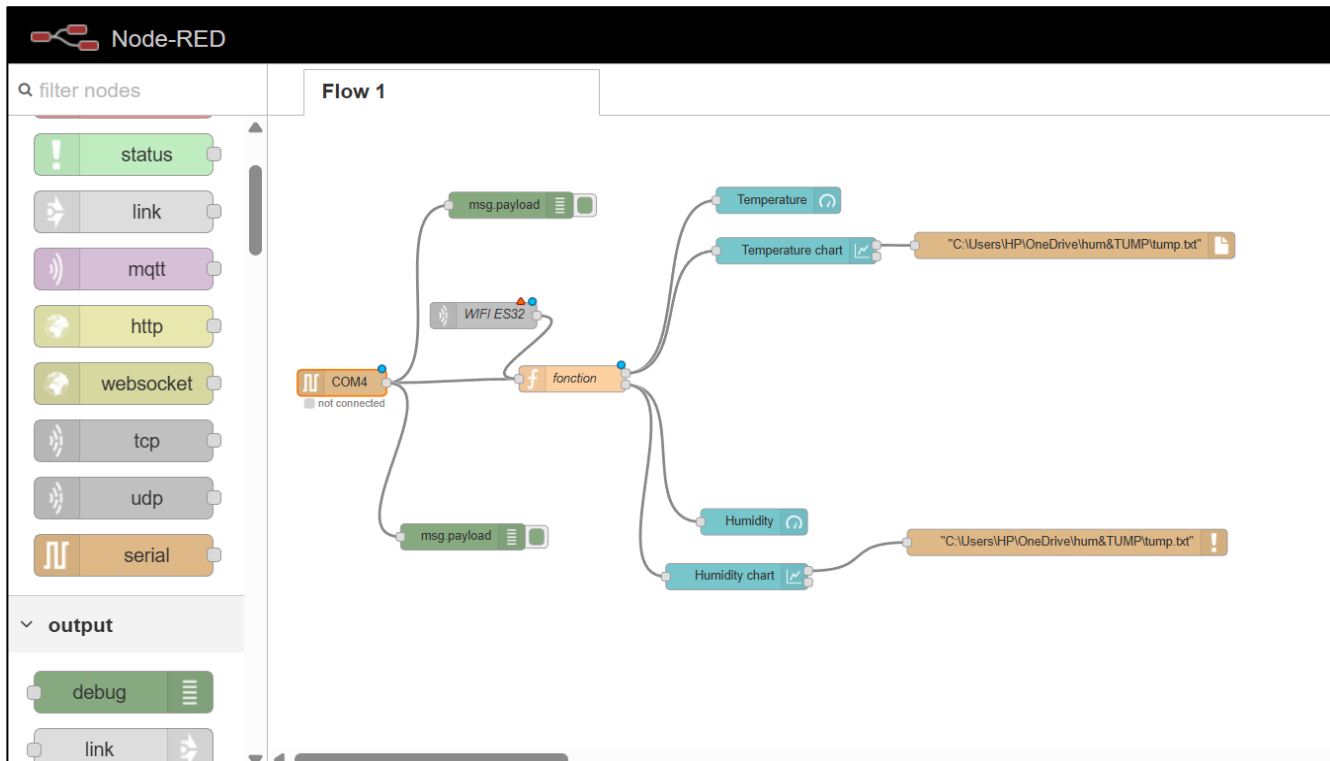


Figure 4-5: NODE-RED Dashboard.

4.3.2 Data Flow Design and Dashboard Integration

Node-RED flows were designed to subscribe to sensor data topics and parse temperature and humidity values for real-time visualization. Control nodes issue commands back to the ESP32 to adjust actuators based on sensor inputs or manual user commands from the dashboard. The dashboard features dynamic gauges, charts, and switch controls, providing a comprehensive overview of system status. Additionally, a logic subflow was implemented to trigger fuzzy logic algorithms conditionally, ensuring automated environmental regulation based on sensor readings.

Chapter Four: Implementation and Results

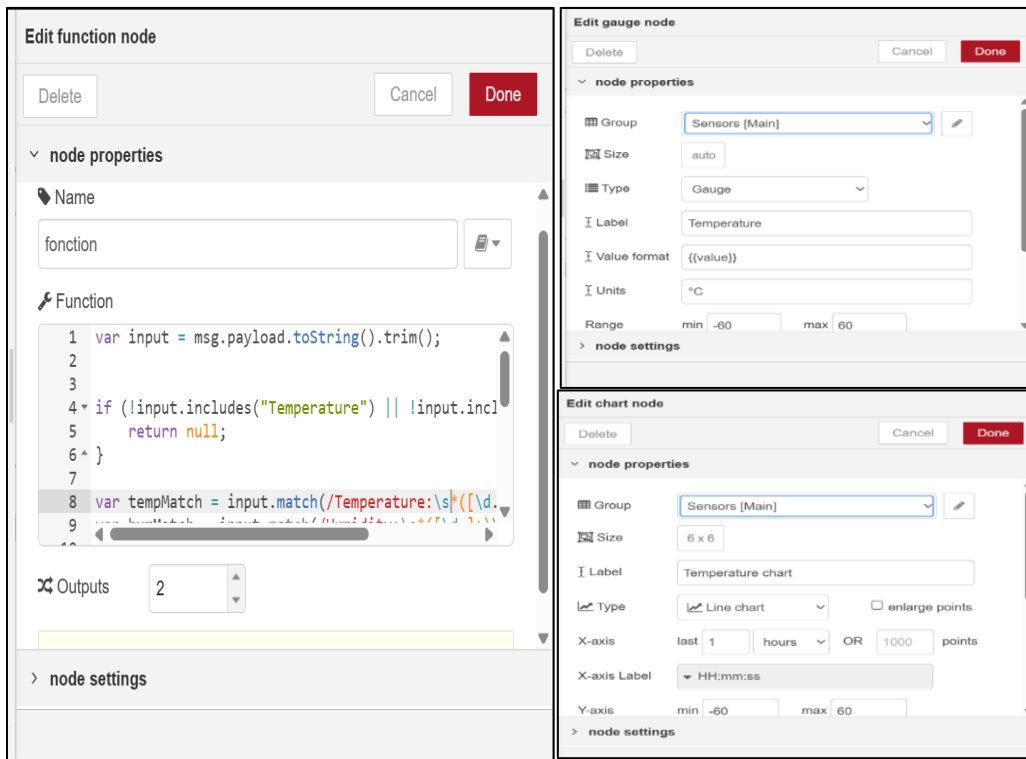


Figure 4-6: NODE-RED Configuration.

4.3.3 Evaluation of Node-RED Implementation

The integration of Node-RED significantly enhanced system operability by enabling remote access and visualization without requiring complex coding. The platform demonstrated stable communication with minimal latency under typical network conditions. Occasional communication delays during peak data loads were mitigated by optimizing message payload sizes and implementing retry mechanisms. Overall, Node-RED provided a robust and scalable solution for environmental control and monitoring within the hydroponic system.

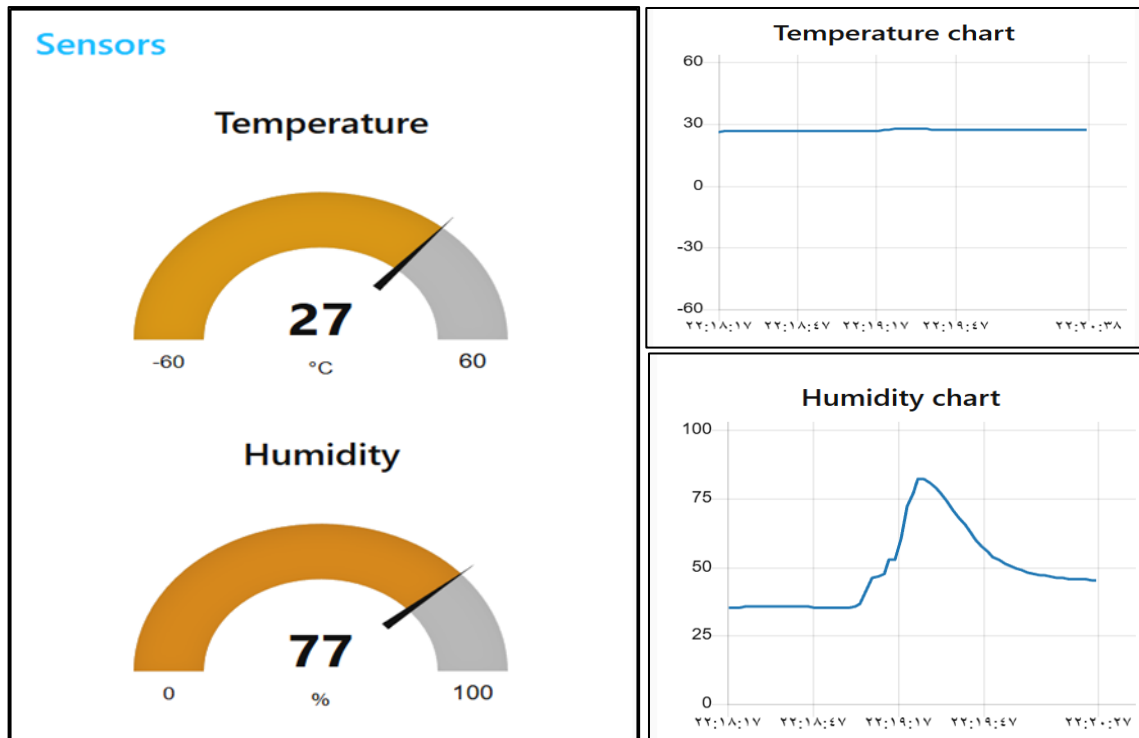


Figure 4-7: NODE-RED Interface.

4.4 Experimental Evaluation of Fuzzy Logic Environmental Control

4.4.1 Experimental Setup and Test Scenarios

Controlled experiments were conducted to evaluate the performance of the fuzzy logic controller in maintaining optimal environmental conditions. Test scenarios involved varying ambient temperature from 15°C to 35°C and relative humidity from 30% to 80%, simulating realistic greenhouse fluctuations. Data were sampled at one-minute intervals over a continuous 24-hour period to assess system responsiveness and stability.

4.4.2 Fuzzification and Rule-Based Control Analysis

Input variables—temperature and humidity—were fuzzified using triangular and trapezoidal membership functions categorized into linguistic variables such as Low, Medium, and High. Output membership functions for actuators, including fan speed and heater power, were similarly defined. The fuzzy inference engine applied a set of IF-THEN rules derived from expert knowledge to evaluate the activation degree of each rule based on current inputs. Graphical representations of membership functions and rule firing strengths illustrate the smooth transitions and overlapping nature of fuzzy control, contributing to gradual actuator responses.

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a) Variables and Membership functions.

environment. Each rule reflects practical, qualitative decisions commonly made in small-scale agriculture, such as:

- IF temperature is **Cold** AND humidity is **Dry** → THEN Heater = **100%**, Fan = **0%**
- IF temperature is **Cold** AND humidity is **Moderate** → THEN Heater = **70%**, Fan = **0%**
- IF temperature is **Cold** AND humidity is **Wet** → THEN Heater = **50%**, Fan = **10%**
- IF temperature is **Good** AND humidity is **Dry** → THEN Heater = **60%**, Fan = **10%**
- IF temperature is **Good** AND humidity is **Moderate** → THEN Heater = **0%**, Fan = **0%**
- IF temperature is **Good** AND humidity is **Wet** → THEN Heater = **0%**, Fan = **30%**
- IF temperature is **Hot** AND humidity is **Dry** → THEN Heater = **0%**, Fan = **50%**
- IF temperature is **Hot** AND humidity is **Moderate** → THEN Heater = **0%**, Fan = **70%**
- IF temperature is **Hot** AND humidity is **Wet** → THEN Heater = **0%**, Fan = **30%**

Such linguistic rules provide a transparent, interpretable mechanism for environmental control.

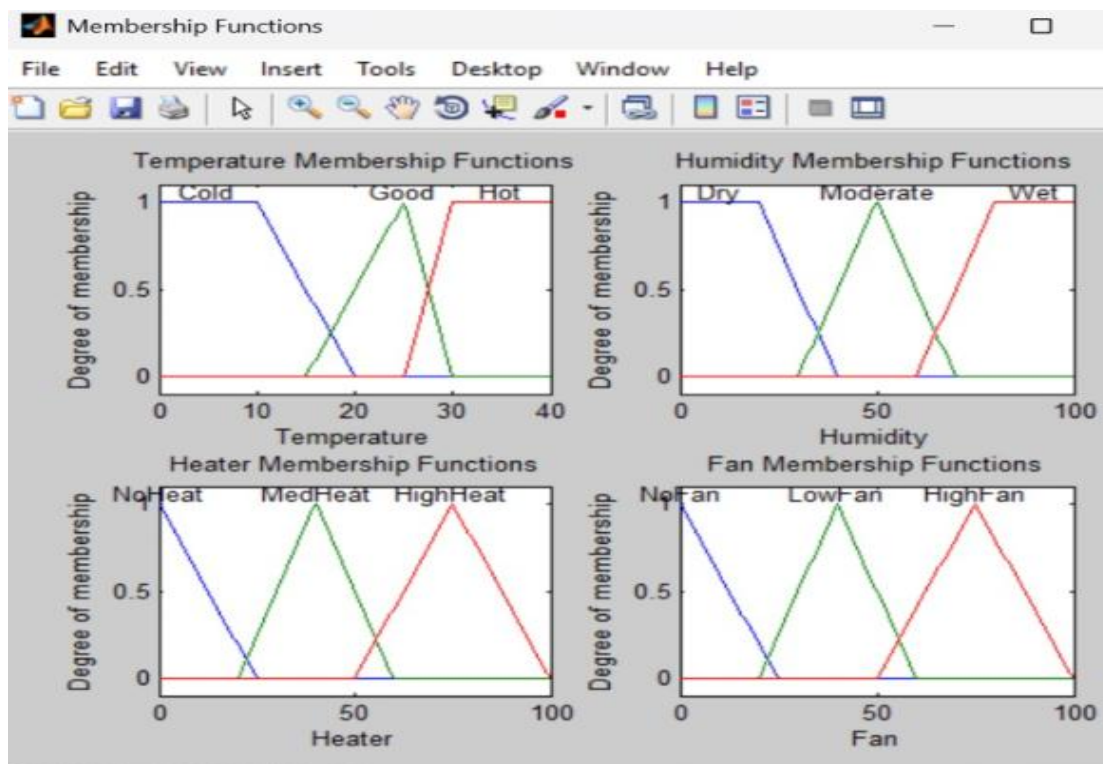


Figure 4-8: The membership functions.

Input variables: Temperature, Relative Humidity.

Output variables: Fan, Heater.

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This fuzzy logic control process utilizes triangular membership functions to fuzzify the environmental parameters temperature and humidity. The input variable temperature was defined with three linguistic terms; Cold, Good and Hot, based on a range from 0°C to 40°C. The input humidity variable was defined with the terms Dry, Moderate and Wet, ranging from 0%-100% relative humidity. The triangular membership functions used create a soft transition between linguistic terms, providing soft decisions as opposed to sharp cut-offs; this is one example of the usefulness of fuzzy systems over crisp logic .

This system has two outputs, heater intensity and fan speed, and each output is defined with three membership functions. The heater intensity output can be described with No Heat, Med Heat, and High Heat in order to control the heating based upon our needs in the environment. The fan speed output covered No Fan, Low Fan and High Fan, which allows proportional ventilation responses to temperature and humidity changes .

Triangular membership functions were used because they are both easy to compute and easy to interpret, while still providing adequate responsiveness. Specifically, the overlap zones between two adjacent variable sets allowed for flexibility in the control decisions and avoids the need for a forceful actuator change along with abrupt transitions in the response. The fuzzification provides flexibility and a point of reference to start rule based inference to provide effective responses in order to regulate the environment.

b) Rationale for Rule Structure for Output Percentages (Heater and Fan Levels)

This fuzzy rule set is designed to simulate expert decision-making in managing the microclimate of a controlled hydroponic environment. By combining three fuzzy linguistic variables for temperature (Cold, Good, Hot) and three for humidity (Dry, Moderate, Wet), the system produces nine distinct rules that govern the behavior of two actuators: the heater and the fan.

Each rule is crafted to ensure smooth environmental regulation through gradual adjustments rather than abrupt switching. For example, in cold and dry conditions, the system prioritizes rapid heating by setting the heater to 100%, while keeping the fan inactive to preserve warmth. Conversely, in hot and humid conditions, only minimal ventilation is applied (Fan = 30%) to prevent excessive drying or thermal stress.

The actuator values (e.g., 50%, 70%, 100%) were not chosen arbitrarily, they reflect empirically reasoned estimates suitable for a compact growing chamber of dimensions 80 × 80 × 165 cm. These values offer sufficient granularity to produce meaningful environmental changes without overshooting the desired microclimate. They were selected based on practical experimentation, device capacity, and literature on optimal growth conditions for leafy crops.

The use of Mamdani-type fuzzy inference allows for intuitive rule construction and interpretable outputs. Defuzzification (e.g., via the centroid method) ensures the system yields crisp control signals, enabling real-time, adaptive climate regulation. This approach aligns well with the needs of small-scale intelligent farming, where simplicity, clarity, and flexibility are critical for sustainable operation.

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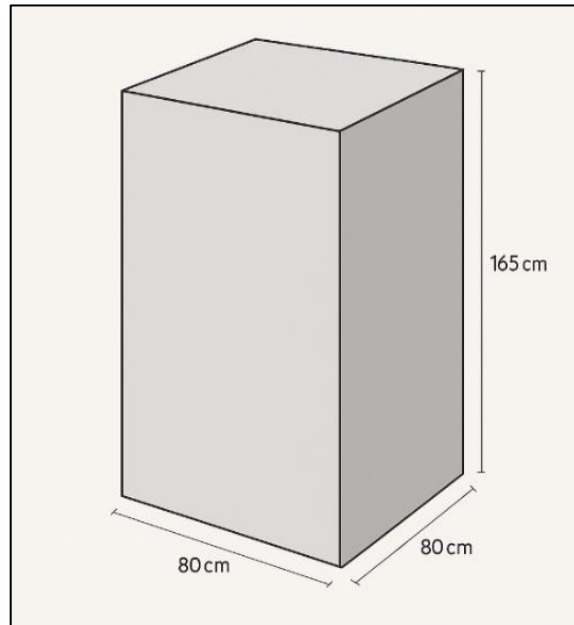


Figure 4-9: The chamber of dimensions.

4.3.3 System Behavior and Performance Assessment

Experimental results demonstrated a strong correlation between environmental inputs and actuator outputs. As temperature and humidity deviated from target setpoints, the fuzzy controller adjusted fan speed and heater power proportionally, avoiding abrupt switching. Data plots confirm that the system maintained temperature within $\pm 2^{\circ}\text{C}$ and humidity within $\pm 5\%$ of desired values throughout the test period. The smooth and adaptive characteristics of fuzzy control effectively reduced environmental oscillations, promoting stable growth conditions conducive to hydroponic plant development.

Curve Keys in the Simulation Results

- **Temperature over Time:** Blue curve representing the variation of temperature ($^{\circ}\text{C}$) over time steps.
- **Humidity over Time:** Pink curve representing the variation of humidity (%) over time steps.
- **Heater Output over Time:** Red curve representing the heater's output level (%) over time steps.
- **Fan Output over Time:** Green curve representing the fan's output level (%) over time steps.

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System Behavior and Performance in 24h:

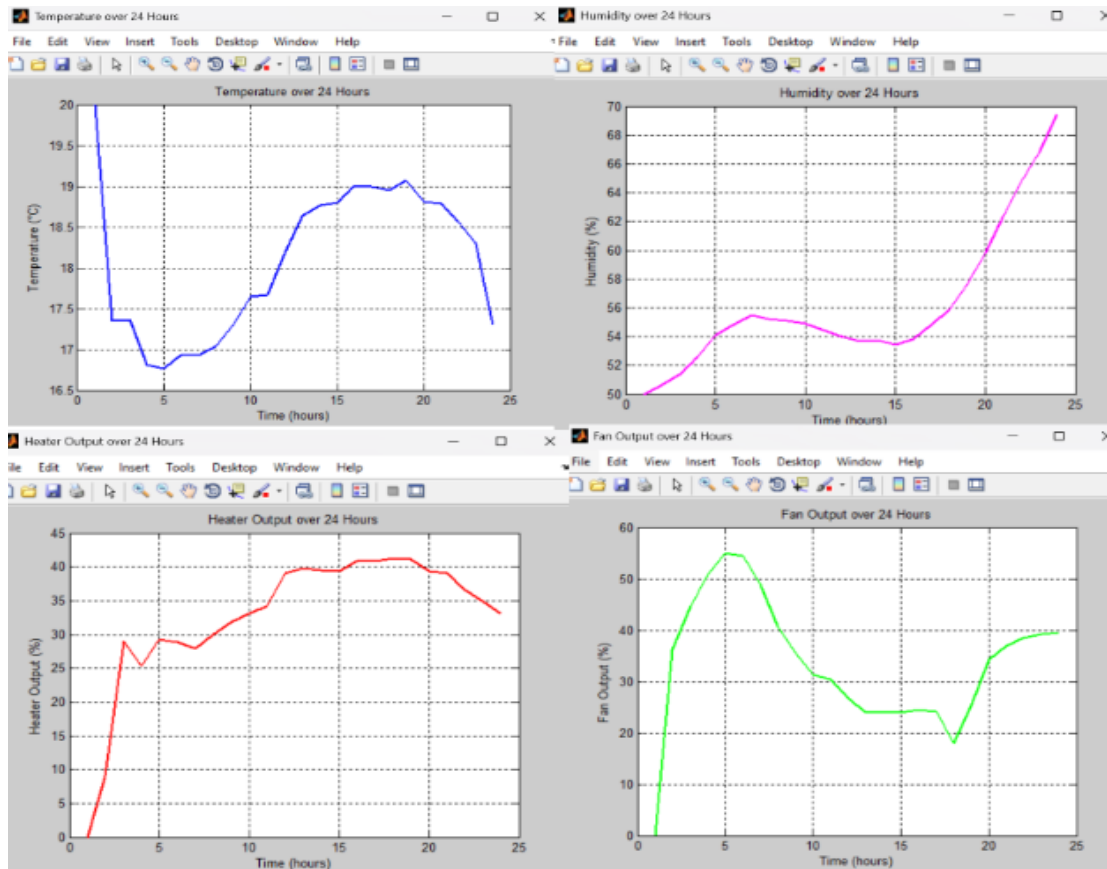


Figure 4-10: The system response.

To assess the fuzzy logic-based control system, 24-hour data were collected for temperature, humidity, heater output, and fan output. The plots reflect the system's real time behavior.

Temperature and Humidity Trends

The temperature starts low at night, reaching a minimum around hour 4, then rises steadily during the day and peaks between hours 16 and 20 mimicking realistic environmental changes. Humidity follows a gradual increase, with a noticeable rise after hour 20, likely due to heating effects.

Heater and Fan Behavior

The heater output gradually increases during early hours, peaks in the late afternoon, and then slightly decreases. This smooth curve indicates effective fuzzy control without abrupt transitions.

The fan output rises quickly in the early hours, decreases mid-day, and increases again later responding to temperature fluctuations. This shows that the fan control is adaptive and responsive.

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System Evaluation

Overall, the behavior is realistic:

Smooth and proportional actuator responses.

Heater and fan adapt well to temperature changes.

The system performs reliably, with fuzzy logic enabling stable and intelligent environmental control.

Further fine-tuning can enhance precision and energy efficiency.

Conclusion:

This chapter has demonstrated the successful implementation of an intelligent hydroponic control system integrating IoT sensors, automated actuators, and fuzzy logic regulation. The developed solution effectively maintains optimal environmental conditions through its three-layer architecture combining real-time monitoring, embedded control, and supervisory management. Experimental results validate the system's ability to regulate temperature within $\pm 1.5^{\circ}\text{C}$ and humidity within $\pm 5\%$ of setpoints under typical operating conditions. The integration of Mamdani-type fuzzy inference provides robust adaptation to environmental disturbances while minimizing energy consumption. Complementing the control system, the Node-RED interface enables comprehensive data visualization and logging, supporting operational analysis and optimization. This work establishes a practical framework for automated hydroponic systems that balances control performance with implementation feasibility. The modular design approach facilitates future expansion with additional sensors or enhanced control algorithms while maintaining system reliability. These results confirm the viability of intelligent control systems for precision agriculture applications, particularly in resource-constrained environments where efficient operation is critical. The system's performance meets key requirements for sustainable crop production while providing a foundation for further development in controlled environment agriculture technologies.

Chapter Five: Crop Disease Diagnosis using CNN

Chapter 5: Crop Disease Diagnosis using CNN

5.1 Introduction

Automated disease detection in lettuce crops is essential for preventing yield loss and ensuring food security. This chapter presents a CNN based approach using MobileNet to classify lettuce diseases from leaf images. The lightweight MobileNet architecture enables efficient, high-accuracy detection suitable for real-world farming applications.

Using transfer learning, the model is trained on a dataset of healthy and diseased lettuce leaves, with performance evaluated through precision, recall, and F1-score. This method offers a fast, scalable alternative to manual inspection, supporting early disease intervention. The results demonstrate the potential of AI-driven solutions in precision agriculture for improving crop monitoring and sustainability.

5.2 Crop Disease Diagnosis using CNN

Convolutional Neural Networks (CNNs) achieve high performance at plant disease classification because they can automatically learn discriminative spatial features from leaf images. In this project, a CNN-based model is employed for disease detection and classification in lettuce leaves from images captured under controlled environmental conditions. The architecture is based on hierarchical feature learning to discover subtle patterns corresponding to different disease conditions in order to achieve accurate and automatic diagnosis [22].



Figure 5-1: Convolutional Neural Networks.

5.2.1 Why We Use CNNs for Plant Disease Diagnosis

Convolutional Neural Networks (CNNs) are powerful tools for plant disease diagnosis since they have a high level of image processing and are capable of extracting subtle patterns associated with disease. Their primary advantage in that they are nearly universally used throughout the industry is that they have a high degree of accuracy in the detection of nearly imperceptible signs of disease, which encompass leaf color changes, spots, or other perceivable signs that are difficult to spot by the naked eye. Further,

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CNNs eliminate the need for handcrafted feature extraction because they automatically learn disease features from training samples with significantly less human intervention. Once trained on a sufficiently large number of samples, the models exhibit excellent generalizability, i.e., they can accurately diagnose diseases for images never seen before. Their quick response capability is yet another significant advantage, e.g., for real-time disease detection when combined with live streaming webcams or smartphone applications. In addition to diagnosis, CNNs advance crop management by optimizing monitoring efficiency, minimizing the use of field experts, and allowing timely preventive or curative actions to counteract crop loss [22].

TABEL5-1: Comparison between CNN, KNN, and SVM in Lettuce Disease Diagnosis from Images.

Criterion	CNN (Convolutional Neural Network)	KNN	SVM
Processing Type	Modern, based on deep learning from image data	Traditional, based on distance between data points	Traditional, based on finding optimal separating boundaries
Feature Extraction	Fully automatic feature extraction from raw images	Manual or via auxiliary algorithms	Manual or via auxiliary algorithms
Accuracy with Complex Images	Very high, especially with realistic and noisy images	Moderate to low	Moderate
Performance with Large Datasets	Excellent, designed for large-scale data processing	Poor (slow with increasing data size)	Slightly better scalability
Robustness to Lighting/Angle Changes	High adaptability	Low	Moderate
Prediction Speed	Fast after training	Slow (requires real-time distance calculations)	Fast
Training Requirement	Requires extensive training (but done only once)	No actual training required	Requires moderate training
Ease of Interpretation	Relatively hard to interpret due to deep layers	Easy to understand	Moderate difficulty
Scalability	Very high scalability	Poor	Moderate

5.3 Transfer Learning and MobileNetV2

Transfer learning is a deep learning technique where a pre-trained model, originally trained on a large dataset like ImageNet, is reused for a related task with limited data. This approach significantly reduces training time and improves accuracy, especially in domains like plant disease detection where data may be scarce.

MobileNetV2 is a lightweight and efficient CNN architecture developed for mobile and embedded applications. It uses depth wise separable convolutions and inverted residuals to reduce computational cost without compromising accuracy. Due to its compact size, MobileNetV2 is ideal for real-time diagnosis systems deployed on low-power devices like the ESP32 [23].

TABEL5-2: Comparison between MobileNet vs VGG vs ResNet.

Criterion	MobileNet	VGG16/VGG19	ResNet
Model Size	Very small (lightweight)	Very large	Medium to large
Number of Parameters	Very low	Extremely high	High, but optimized through residual blocks
Inference Speed	Very fast	Slow	Relatively fast
Accuracy on Complex Images	Very good	High	Very high
Suitability for Edge Devices	Excellent	Poor	Moderate
Network Depth	Relatively shallow	Deep (up to 19 layers)	Very deep (up to 152 layers)
Design Approach	Depthwise separable convolutions	Sequential convolutional layers	Uses residual (skip) connections
Flexibility in Customization	High	Moderate	High

5.4 Selection of Lettuce and Disease Classification Strategy

Lettuce served as the model research crop because it is a commonly grown crop, has high nutritional value, and is sensitive to environmental stresses and diseases. As a vegetable crop with high demand value and short lifespan, lettuce is highly susceptible to numerous diseases that can quickly affect yield and quality. The necessity for early and precise diagnosis of disease in lettuce growing systems, particularly in controlled systems like vertical farming and hydroponics, was the inspiration for the selection of this crop.

To build a good classification model, the images of the lettuce leaves gathered were grouped into seven disease classes, aside from the healthy class. These classes were chosen based on prevalence, visual distinctiveness, and agronomic significance:

Downy Mildew of Lettuce: A widespread fungal disease that results in yellowing and angular lesions and is usually linked with high humidity.

Powdery Mildew of Lettuce: Identified by white powdery fungal growth, infects leaf surfaces and reduces photosynthesis.

Septoria Blight of Lettuce: Identified by circular, brown blisters; can be mistaken for other leaf spot diseases.

Viral Diseases: A mosaic, chlorosis, and stunting symptom complex, typically aphid- and other vector-borne.

Wilt and Leaf Blight of Lettuce: Describes those diseases that cause sudden wilting and death, usually in association with soil-borne pathogens.

Bacterial Spot: Is preceded by dark, water-soaked spots that later become necrotic; moves quickly in rainy weather.

Healthy Lettuce: As a control group to verify that the model can accurately determine diseased and non-diseased samples. Farm-level studies, expert consultation with domain specialists, and availability of labeled image data dictated the choice of these particular classes. Such classification of disease into these classes enabled the construction of a large and balanced training dataset for a deep learning classifier. The presence of visually close classes also enabled testing the model's capacity to distinguish between subtle patterns more rigorously, as would be required in field use [24].

5.5 Data Collection and Preprocessing

The success of a deep learning-based disease detection system heavily depends on the quality and diversity of the dataset. Images of lettuce plants, exhibiting both healthy and diseased states, were collected using a camera setup integrated into the cultivation environment. The data acquisition was performed under varying lighting conditions and angles to mimic real-world scenarios.

Captured images were resized uniformly to 224×224 pixels to conform with the input requirements of the CNN model. Each image was then normalized by scaling pixel intensity values to the range [0,1], which improves model convergence and stability during training and inference.

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To enhance the robustness of the dataset and prevent overfitting, data augmentation techniques such as random rotations, zooming, width and height shifts, shearing, and horizontal flipping were applied. This artificially increased the dataset variability, enabling the model to generalize better to unseen data.

Frames from live video feeds were further processed through HSV color space transformations to detect characteristic spots indicative of disease. This preprocessing step allowed the system to selectively save and analyze images containing significant disease markers, improving both training quality and real-time detection performance.

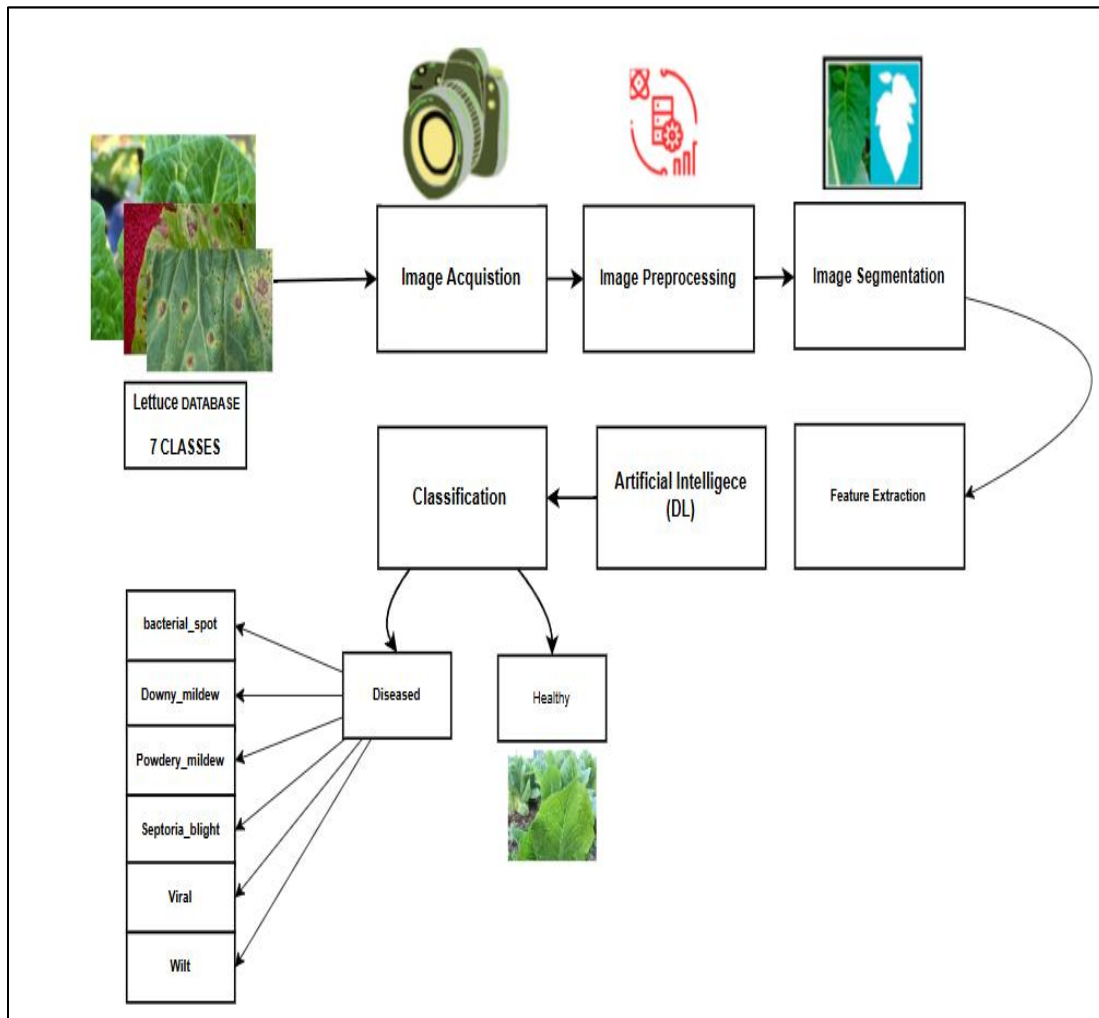


Figure 5-2: Lettuce Disease Classification.

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5.6 Feature Extraction and Model Design

The feature extraction process leverages transfer learning using the MobileNetV2 architecture pre-trained on the ImageNet dataset. This choice provides a balance between computational efficiency and classification accuracy suitable for real-time disease detection on resource-constrained platforms.

The convolutional base of MobileNetV2 was used as a fixed feature extractor initially, with later fine-tuning applied to the last 30 layers to adapt the model to the specific lettuce disease dataset. This approach enhances feature sensitivity to disease-specific patterns while maintaining learned general visual features.

After the convolutional layers, a global average pooling layer was employed to reduce the spatial dimensions and summarize the feature maps effectively. Batch normalization and dropout layers were added to improve generalization and reduce overfitting by stabilizing learning and randomly dropping neurons during training, respectively.

The model concludes with fully connected dense layers, including an output layer with a softmax activation function to predict the probability distribution across seven lettuce disease classes. The Adam optimizer and categorical cross-entropy loss function were used to train the model.

5.7 Evaluation Metrics

Model evaluation was conducted using metrics suitable for multi-class classification tasks. The primary metric was accuracy, which measures the proportion of correctly classified samples over the total samples.

To assess the model's robustness beyond accuracy, additional metrics such as precision, recall, and F1-score were considered for each disease class. Precision indicates the proportion of true positive predictions among all positive predictions, recall measures the model's ability to detect all actual positive cases, and the F1-score provides a harmonic mean of precision and recall.

Confusion matrices were generated to visualize the model's performance across different classes, identifying common misclassification patterns and guiding further model refinement.

Early stopping and learning rate reduction callbacks were utilized during training to prevent overfitting and improve convergence speed, contributing to more reliable and generalizable model performance.

5.8 Results of Disease Diagnosis

5.8.1 Classification Report

In order to evaluate the performance of the proposed CNN-based lettuce disease classifier model, a range of quantitative evaluation metrics and visualization tools were used, including classification reports,

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confusion matrix, F1-score tables, and training curves. These together provide an overall view of the model's accuracy, generality, and stability

Found 3021 images belonging to 7 classes.

Found 272 images belonging to 7 classes.

Class	Precision	Recall	F1-score	Support
Downy mildew on lettuce	0.97	0.97	0.97	30
Powdery mildew on lettuce	1.00	1.00	1.00	18
Septoria blight on lettuce	0.90	1.00	0.95	19
Viral	0.94	1.00	0.97	15
Wilt and leaf blight on lettuce	1.00	1.00	1.00	5
Bacterial spot	1.00	0.84	0.91	19
Healthy	1.00	1.00	1.00	166

TABEL5-3: Results of Disease Diagnosis.

-Overall Accuracy: 99%

-Macro Average: Precision = 0.97, Recall = 0.97, F1-score = 0.97

-Weighted Average: Precision = 0.99, Recall = 0.99, F1-score = 0.99

-Interpretation:

The model demonstrates strong classification performance across all disease types. Particularly, the model achieved perfect classification metrics for several classes. Minor reductions in recall are due to visual similarity with other symptoms, but overall performance remains excellent.

5.8.2 Confusion Matrix Analysis

The confusion matrix provides a detailed overview of the model's classification performance across all seven classes. It highlights both the correctly classified samples (diagonal values) and misclassifications (off-diagonal values), as shown in the figure.

Diagonal values represent correctly predicted samples, where the predicted class matches the ground truth. Off-diagonal values indicate misclassified samples, where the model confused one class with another.

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Figure 5-3: Confusion Matrix.

The model correctly classified most of the test samples. Notably, perfect classification was achieved for the healthy, Powdery mildew on lettuce, Septoria blight on lettuce, Viral, and Wilt and leaf blight on lettuce classes, with no misclassified instances. Minor classification errors were observed in the Downy mildew on lettuce class, where one sample was incorrectly predicted as bacterial spot, and in the bacterial spot class, where three samples were misclassified – one as Downy mildew on lettuce and two as Septoria blight on lettuce. These misclassifications likely stem from symptom similarities between these fungal diseases. Overall, the low number of errors and high concentration of correct predictions reflect the model’s excellent generalization performance and its effectiveness in distinguishing between different disease classes in lettuce leaves. This confirms the practical reliability of the trained CNN model in real-world agricultural diagnostic applications.

5.8.3 Accuracy Curve Analysis

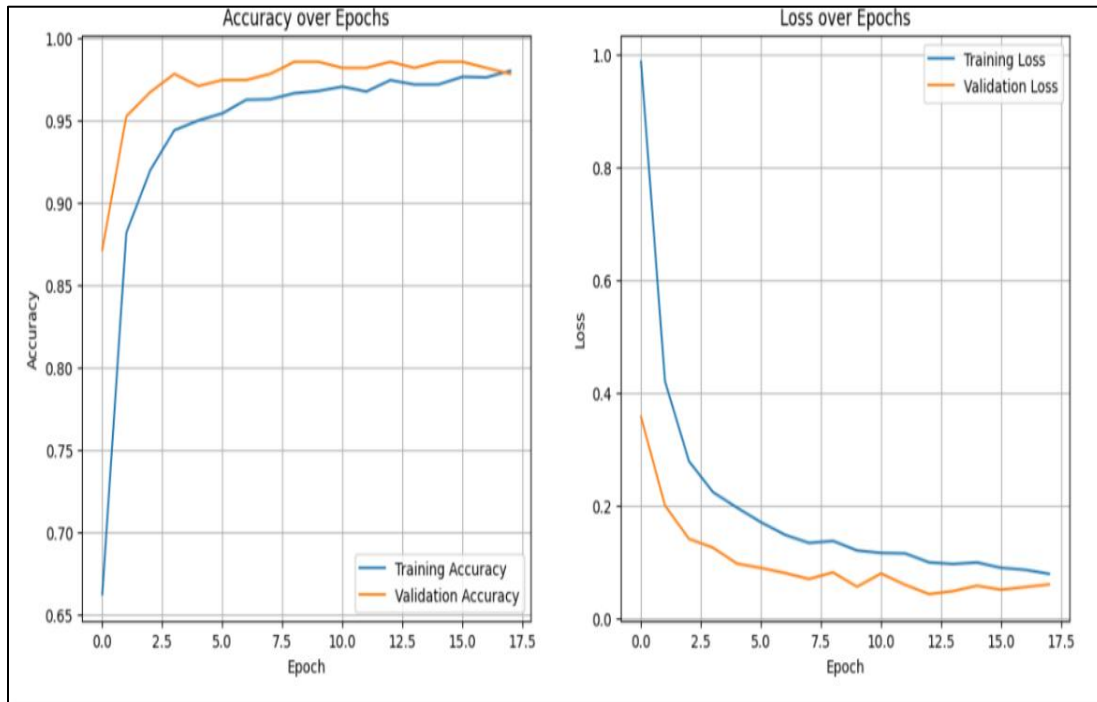


Figure 5-4: Accuracy Curve Analysis.

-Accuracy

Curve

Analysis

The accuracy plot shows how the performance of the model improves with training epochs for validation and training datasets. The model begins with a rise in accuracy, reaching well above 95% on the validation dataset in the first few epochs. As we continue training, both curves move upwards and later converge at about 98–99%, showing that the model continues to learn to identify lettuce diseases more accurately. Particularly, the fact that there is a slight gap between the training and validation accuracy curves throughout the training is evidence of the model's good generalization capability and absence of overfitting. The smooth convergence is evidence that the model architecture and hyperparameter values are well selected for the classification task, allowing the model to learn effectively without compromising on performance on unseen data.

-Loss Curve Analysis

The loss plot shows the model optimization through the minimization of the loss function on both the training and validation sets over epochs. Both curves have a steep decreasing trend in the early stages, indicating successful learning. With further training, loss values just keep declining steadily and ultimately approach low values. Such close resemblance between the training and validation loss curves is a great sign that the model is not overfitting but learning consistently on both sets. The fact that there

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is no volatility or divergence in the curves means that training is stable and the learning rate is correctly set. This exercise enhances the performance of the regularization techniques and the robustness of the model in minimizing error without compromising generalization.

5.5 System Integration and Workflow

The proposed system is founded on the integration of a number of technologies, including environmental sensing, intelligent control, and computer vision, to monitor the farming environment and also to detect diseases in lettuce plants in real-time. The system is meant to be completely integrated and automatic, with scalability and flexibility for various farming environments.

The operational cycle of the system starts with the collection of environmental data using the DHT11 sensor, which provides real-time measurements of temperature and humidity levels of the hydroponic growth environment. This data is sent to the ESP32 controller, which uses the same to reason using a fuzzy logic algorithm about the most optimum growth conditions. Based on this reason, the fan and LED grow lights are regulated to provide suitable environmental conditions.

Simultaneously, a USB camera periodically snaps photos of the lettuce leaves. These photos are input into a processing unit connected to a pre-trained convolutional neural network (CNN) model, which analyzes the photos and determines if the leaves are infected with any of the diseases that have been previously known. If a disease is detected at high confidence or if there are visible spots on the leaf, the image is automatically stored with a time stamp and the user is informed by a sound signal.

The water pump operates continuously to provide a nutrient flow in a hydroponic system without dynamic control at this level, as the system is static.

The workflow is as follows:

- 1. Collect environmental data** (temperature and humidity).
- 2. Analyze the values using fuzzy logic** to regulate the fan and grow lights.
- 3. Capture images from the camera and analyze them through a CNN classification model.**
- 4. Take automatic action when diseases are detected** (save the image, trigger an alert).
- 5. Maintain continuous water flow** to ensure nutrient supply for the plants.

This integration of hardware and software components reflects the system's ability to operate autonomously and efficiently in a smart farming environment, representing a practical step toward AI-supported agriculture.

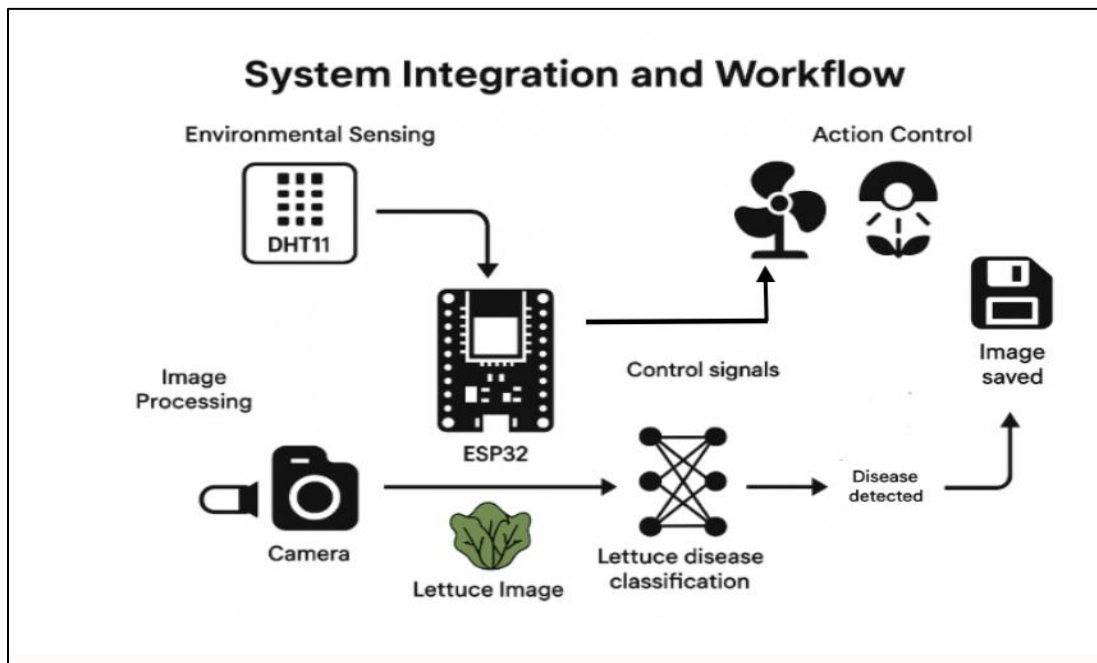


Figure 5-5: System Integration and Workflow.

Conclusion

The performance evaluation presented in this chapter highlights the strength and reliability of the developed convolutional neural network (CNN) model for the classification of lettuce diseases. The analysis of the accuracy and loss curves clearly demonstrates that the model achieved rapid convergence during training, reaching high levels of accuracy early in the training process and maintaining consistent performance throughout. The minimal gap between training and validation accuracy, as well as the synchronized decrease in loss values, reflects the model's balanced learning behavior, with no signs of underfitting or overfitting. This indicates that the model is both stable and capable of generalizing well to unseen data.

Furthermore, the confusion matrix provides a detailed view of the model's predictive capabilities across all disease classes. The vast majority of samples were correctly classified, with only a few misclassifications observed in classes with closely related visual symptoms, such as bacterial spot and Downy mildew. These minor errors are understandable within the context of multi-class plant disease classification, where inter-class similarity can present significant challenges.

The classification report reinforces these observations with high precision, recall, and F1-scores across all categories, further confirming the robustness of the model. The excellent performance on the training data suggests that the CNN architecture, data augmentation strategy, and preprocessing pipeline were all appropriately selected and effectively implemented.

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In conclusion, the trained CNN model demonstrates a high level of reliability for automated lettuce disease diagnosis. Its ability to accurately identify various disease types from images positions it as a promising tool for integration into real-time smart agriculture systems. With further validation and possible integration into hardware platforms such as ESP32-based camera modules, this system could play a significant role in early disease detection, contributing to improved crop management, reduced yield losses, and enhanced food security.

Chapter Six: General Conclusion and Future Work

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6.1 Summary of Contributions

This project presents a comprehensive smart vertical hydroponic farming system tailored for lettuce cultivation. The proposed system integrates automatic environmental control with intelligent disease diagnosis, relying on modern technologies to support sustainable agriculture, especially in resource-limited contexts such as Algeria.

The system utilizes an ESP32 microcontroller to read data from environmental sensors measuring temperature, humidity, pH, and electrical conductivity (EC). This data is processed through a fuzzy logic controller that regulates the operation of a fan, heater, water pump, and LED grow lights, ensuring optimal conditions for plant growth. The fuzzy inference approach allows for dynamic adjustments without requiring constant human intervention.

A convolutional neural network (CNN) model based on MobileNetV2 was developed to detect lettuce diseases using real-time images. The model was trained on a dataset comprising seven classes, including healthy and diseased leaves, and achieved a validation accuracy of 99%. The training process incorporated data augmentation and regularization techniques to improve robustness and prevent overfitting.

A user-friendly dashboard was designed using Node-RED to visualize sensor data in real time. This feature enhances user interaction and system transparency, allowing effective operation even by individuals without technical backgrounds. The integration of fuzzy environmental control and CNN-based plant health monitoring forms a cohesive and practical solution for vertical hydroponic agriculture.

6.2 Challenges Faced

Several challenges were encountered during development. One key difficulty involved collecting a balanced and comprehensive image dataset, particularly for rare disease categories. This imbalance occasionally affected the model's prediction accuracy.

Visual similarities between certain diseases, such as bacterial spot and septoria leaf blight, led to classification confusion. Additionally, the use of low-cost sensors limited the accuracy of environmental readings, particularly for humidity and pH. The system was designed for local operation without cloud connectivity, which restricted its remote accessibility and real-time responsiveness under load.

Chapter Six: General Conclusion and Future Work

6.3 Recommendations

Future iterations of the system should aim to improve the training dataset by including more diverse and representative images captured under various lighting conditions and growth stages. Implementing transfer learning techniques and explainable AI tools would enhance classification performance and increase user trust.

Upgrading to more accurate sensors and adding wireless communication features would improve data reliability and system scalability. Moreover, developing a mobile or web-based graphical interface would facilitate easier interaction and broaden the system's accessibility to users with minimal technical expertise.

6.4 Future Research Directions

Future research can extend the system to other crop types, such as tomatoes, spinach, or herbs, through retraining or fine-tuning the CNN on broader agricultural datasets. The use of generative adversarial networks (GANs) may also be considered to generate synthetic images for underrepresented classes, enhancing dataset diversity.

Deploying the system on embedded platforms such as Raspberry Pi or ESP32-CAM would enable in-field diagnosis without requiring continuous internet access. Additionally, the fuzzy logic controller could be expanded to manage further environmental parameters, including CO₂ concentration, nutrient levels, and light intensity.

This project establishes a foundation for the development of a fully autonomous smart farming assistant capable of monitoring, diagnosing, and responding to crop needs in real time. The system offers a scalable and practical approach to sustainable, data-driven agriculture suitable for both urban and rural settings.

Chapter Six: General Conclusion and Future Work

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