Precision Agriculture – IoT Powered Automated Irrigation System

IT5811 Project Report

Submitted by

Sandhiya M	2020506078
Girish G	2020506028
Swetha Das R	2020506100

Under the supervision of

Dr. M. R. Sumalatha

In partial fulfilment for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

INFORMATION TECHNOLOGY

DEPARTMENT OF INFORMATION TECHNOLOGY

MADRAS INSTITUTE OF TECHNOLOGY CAMPUS

ANNA UNIVERSITY, CHENNAI – 600044

MAY 2024

ANNA UNIVERSITY: CHENNAI 600 025

BONAFIDE CERTIFICATE

Certified that this project report titled **"Precision Agriculture – IoT Powered Automated Irrigation System"** is the bonafide work of Girish G (2020506028), Sandhiya M (2020506078) and Swetha Das R (2020506100) who carried out the project work under my supervision.

Signature	**Signature**
Dr. M. R. Sumalatha	**Dr. M. R. Sumalatha**
SUPERVISOR	**HEAD OF THE DEPARTMENT**
Professor	Professor
Department of Information Technology	Department of Information Technology
MIT Campus, Anna University Chennai – 600044	MIT Campus, Anna University Chennai – 600044

ACKNOWLEDGEMENT

It is essential to mention the names of the people whose guidance and encouragement made us accomplish this project.

We express our gratitude and sincere thanks to our respected Dean of MIT Campus, **Prof. K. Ravichandran**, for providing excellent infrastructure support throughout the project.

Our sincere thanks to **Dr. M. R. Sumalatha**, Head of the Department of Information Technology, MIT Campus for catering all our needs giving out limitless support throughout the project phase.

We express our thankfulness to our project supervisor **Dr. M. R. Sumalatha**, Professor of the Department, Department of Information Technology, MIT Campus, for providing invaluable support and assistance with encouragement which aided to complete this project.

We are thankful to the panel members **Dr. Dhananjay Kumar** and **Dr. M.R. Sumalatha**, Department of Information Technology, MIT Campus for their invaluable feedback in reviews.

SANDHIYA M **2020506078**

GIRISH G **2020506028**

SWETHA DAS R **2020506100**

ABSTRACT

Precision agriculture, a paradigm integrating advanced technologies such as artificial intelligence and sensor networks, heralds a transformative approach to optimizing agricultural practices. This project, titled "Precision Agriculture – AI Enabled Automated Irrigation System," focuses on automating the irrigation process in crop cultivation, thereby minimizing human intervention. By harnessing sensor data and real-time weather information, coupled with advanced mathematical derivations, the project endeavours to predict the precise water requirements of crops. Additionally, leveraging convolutional neural network (CNN) models, the system facilitates the classification of leaf images into distinct categories, enabling targeted fertigation to address specific nutrient deficiencies. Moreover, object detection algorithms are employed for quality management, particularly for tomato crops, ensuring timely intervention to maintain optimal crop health. The culmination of this endeavor is a mobile application that enables remote control of irrigation systems, empowering farmers with real-time monitoring and management capabilities. Through the convergence of cutting-edge technologies, this project endeavors to enhance agricultural efficiency, productivity, and sustainability, ushering in a new era of precision agriculture.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADASYN	Adaptive Synthetic Sampling
AI	Artificial Intelligence
AP	Average Precision
CNN	Convoluted Neural Network
DHT	Digital Temperature and Humidity
DL	Deep Learning
FAO	Food and Agriculture Organisation
GPIO	General Purpose Input Output
IoT	Internet of Things
IPAIS	IoT Powered Automated Irrigation System
mAP	Mean Average Precision
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
PME	Penman-Monteith equation
QM	Quality Management
RPi	Raspberry Pi
SMOTE	Synthetic Minority Oversampling Technique
YOLO	You Only Look Once

CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

Modern technologies are used in precision agriculture to transform farming methods, marking a paradigm change in agricultural management. Precision agriculture primarily uses data-driven decision-making and tailored interventions to maximize resource allocation, enhance crop health, and reduce environmental impact. In this context, effective irrigation methods stand out as essential, allowing for the prudent management of water resources while guaranteeing maximum crop development and yield. Since, they depend on personal supervision or set schedules, older irrigation techniques frequently can't keep up with the changing demands of contemporary agriculture. These traditional methods usually lead to inefficiencies, such as water waste, lower crop yields, and environmental damage, highlighting the urgent need for creative alternatives in line with precision agriculture principles. Furthermore, developments in precision agriculture including the process of fertigation and quality monitoring are integrated into the same to further improve the efficacy and efficiency of agricultural techniques.

Agriculture management has advanced significantly with the practice of fertigation, which involves applying precise fertilizer solutions to crops via irrigation systems. Fertigation reduces fertilizer waste and guarantees that crops receive the right nutrients at the right time and in the right amounts by integrating irrigation and fertilization into a single process. In addition to encouraging healthy crop growth, this focused strategy lowers environmental contamination brought on by over fertilizer application.

In addition, the creation of Convolutional Neural Network (CNN) models for crop analysis has become a potent precision agriculture tool. These models identify crops according to a range of factors, such as health state and nutritional shortages, by analysing imaging data, such as leaf photos, using machine learning algorithms. CNN models enable farmers to optimize crop health and productivity by precisely diagnosing problems like late blight, leaf miner infestations, or nutrient deficits. This allows farmers to execute focused treatments like precision fertigation or pest management measures.

In summary, precision agriculture aims to transform agricultural practices by optimizing resource usage, boosting crop yields, and encouraging sustainability. It is powered by cutting-edge technologies and data-driven approaches. Effective irrigation methods are essential to this strategy because they help strike a balance between the demands of minimizing environmental damage and increasing agricultural yield. Precision agriculture incorporates innovative modern techniques to provide a comprehensive solution to the problems of contemporary farming, guaranteeing food security and environmental care for coming generations.

1.2 OBJECTIVE

The primary objective of the "Precision Agriculture - Automated Irrigation System" project is to optimize water management in piped and micro irrigation systems to automate the water supply to crops, reducing human intervention in irrigation processes and ensuring efficient resource utilization. This automation will enable precise irrigation practices, delivering water to crops at the right time and place, specifically targeting the root zone for optimal absorption and growth. Additionally, the project seeks to integrate mathematical models derived from soil data obtained from sensors and real-time weather conditions. These models will accurately predict the water needs of crops, facilitating precise irrigation scheduling and water conservation efforts. Furthermore, the project aims to enhance nutrient management by utilizing leaf image processing techniques to deliver precise amounts of nutrients to crops. This approach will optimize fertigation process, promote healthy plant growth, and minimize nutrient wastage. Moreover, the project will incorporate object detection technologies into crop quality management processes, allowing for timely interventions and improvements in overall crop quality. Through these objectives, the project aims to demonstrate the effectiveness of automated irrigation systems in enhancing crop yield, conserving water resources, and promoting sustainable agriculture practices.

1.3 SCOPE OF THE PROJECT

The scope of the project centres on optimizing water management in micro irrigation systems through the integration of advanced technologies and data-driven methodologies. The aim is to automate water supply, reduce human intervention, enable precise irrigation, and improve resource utilization. To address challenges such as water wastage, inefficient irrigation practices, and environmental impact, the project focuses on integrating mathematical models for predictive water management, leveraging image processing for precise nutrient delivery, and incorporating effective crop quality management. Additionally, the project aims to optimize crop health and minimize environmental impact by implementing targeted irrigation and nutrient management strategies based on real-time data analysis and predictive modeling, thereby achieving a balance between maximizing agricultural productivity and minimizing water utilization.

1.4 CONTRIBUTION

The "Precision Agriculture - Automated Irrigation System" project makes significant contributions to agriculture and water management by addressing its key challenges. It revolutionizes water management in agriculture by automating irrigation processes and implementing precise water delivery techniques. This innovation conserves water resources, reduces wastage, and promotes sustainable farming practices. By integrating advanced technologies like mathematical modelling and image processing the project optimizes resource utilization and enhances crop health and productivity. These contributions pave the way for efficient and environmentally conscious agricultural practices, ensuring ecosystem sustainability.

1.5 IRRIGATION METHODOLOGIES

Irrigation methodologies encompass a wide range of techniques used to supply water to crops efficiently. These methods vary in complexity, water delivery mechanisms, and suitability for different agricultural contexts. Efficiency of some commonly used irrigation methodologies is shown in Fig. 1.1.

Figure 1.1 Efficiency of Irrigation Systems

1.5.1 Surface Irrigation

Surface irrigation is an age-old and popular technique that entails flowing water directly on the soil's surface and letting gravity carry it throughout the area. Although surface irrigation is generally simple and inexpensive to implement, there are a few issues that may arise. Uneven water distribution is one of the main disadvantages, since it can lead to nutrient leaching, soil erosion, and water waste. These problems may have detrimental effects on crop growth and soil health in addition to contributing to water consumption inefficiencies. For surface irrigation systems to reduce losses and guarantee ideal water distribution across the field, meticulous management and monitoring are necessary.

1.5.2 Sprinkler Irrigation

Sprinkler irrigation distributes water uniformly across the crop area using overhead sprinklers. Even though they can cover bigger regions than localized watering techniques, this may result in water loss due to evaporation and wind drift. To guarantee uniform water distribution and prevent problems like waterlogging or runoff, they need to be calibrated and maintained carefully. Sprinkler irrigation is nevertheless useful in some circumstances, such as protecting crops from frost or cooling crops in hot weather. When utilizing sprinkler irrigation systems, it's crucial to take the surroundings and possible water loss into account.

1.5.3 Localized Irrigation

Water distribution can be more precisely targeted with localized irrigation systems, which concentrate on supplying water to specific plant locations. This technique applies water directly to the plant root zone, minimizing water waste and optimizing water use efficiency. Localized irrigation systems come in several forms, such as drip irrigation and micro-sprinkler systems. While micro-sprinkler systems distribute water in a fine mist pattern close to the plants, drip irrigation delivers water straight to the base of plants using tubing and emitters. These systems allow for accurate nutrient distribution, minimize weed growth, and reduce water evaporation—all of which contribute to healthy plant growth. When compared to surface irrigation and sprinkler irrigation techniques, they result in increased crop yields, better resource conservation, and less environmental effect.

1.6 INTERNET OF THINGS IN AUTOMATION

Automation in a variety of industries, including agriculture, has been transformed by the incorporation of Internet of Things (IoT) technologies. Internet of Things (IoT) is a key component in improving the efficacy and efficiency of automated irrigation processes within the framework of the "Precision Agriculture - Automated Irrigation System" project. A number of Internet of Things (IoT) components are used to facilitate intelligent decision-making, data collection, and real-time monitoring, which enhances crop yields and water management.

1.6.1 Raspberry PI

The Raspberry Pi serves as the core computing unit responsible for managing and controlling various aspects of the automated irrigation system. Its compact size, low power consumption, and GPIO (General Purpose Input Output) pins, makes it an ideal choice for interfacing with sensors, executing necessary algorithms, and coordinating the irrigation process. The Raspberry Pi acts as the brain of the system, processing incoming data from sensors, analyzing environmental conditions, and triggering irrigation cycles. The Raspberry Pi 4 Model B board is shown in Fig 1.2.

Figure 1.2 Raspberry Pi 4 Model B

1.6.2 DHT Sensor

The DHT sensor is employed to monitor temperature and humidity levels in the surrounding environment. These sensors offer vital information that affects irrigation choices. For example, low humidity and high temperatures may suggest higher rates of water evaporation, which would cause the system to modify watering schedules. The DHT sensor assists in maximizing water use and guaranteeing optimal growing conditions for crops by continuously monitoring environmental factors. The DHT11 sensor is shown in Fig. 1.3.

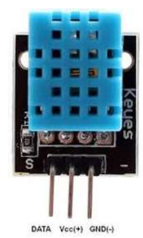

Figure 1.3 Digital Temperature and Humidity 11 Sensor

1.6.3 Soil Moisture Sensor

Soil moisture sensors play a critical role in the field of precision agriculture by offering real-time insights into soil moisture levels. The time and amount of water applied to crops are determined in large part by using this data as a foundation. By incorporating soil moisture sensors into the Internet of Things (IoT) architecture, irrigation strategies that are specifically tailored to the soil's unique moisture content are implemented. This integration greatly improves crop vitality and productivity in agricultural systems by reducing the hazards associated with either excessive or insufficient watering. It also encourages water conservation. The component soil moisture sensor is shown in the Fig.1.4.

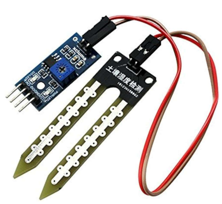

Figure 1.4 Soil Moisture Sensor

1.6.4 PC Camera (8MP)

The inclusion of a high-resolution PC camera, typically an 8MP camera, adds a visual monitoring component to the automated irrigation system. Image processing methods are utilized to examine the crop field's detailed photos that are captured by the camera. These algorithms offer important insights for crop management by identifying abnormalities like nutrient deficits, pests or insects infestations and disease symptoms.

The technology obtains a thorough picture of crop health and enables proactive actions by combining sensor and visual data. The 8MP PC camera module is shown in the Fig. 1.5.

Figure 1.5 8 Mega Pixel Camera with USB

1.6.5 Buzzer

As an auditory alert system, the inclusion of a buzzer or alarm component is vital in the Internet of Things (IoT) automation framework. This component is programmed to emit discrete sound waves in response to predetermined events or conditions. This functionality is its use to indicate low soil moisture levels, triggering an alarm when these levels descend below a predetermined threshold, indicating the need for immediate irrigation. This real-time alerting system makes it easier to react quickly to sudden changes in the environment, which helps to minimize crop stress and improve water resource management. The 5 Volt Magnetic buzzer is shown in the Fig. 1.6.

Figure 1.6 5V Magnetic Buzzer

1.7 ORGANIZATION OF THE THESIS

This thesis's framework is designed to provide the study findings from the "Precision Agriculture – IoT Powered Automated Irrigation System" project in a logical and methodical manner. The chapters are organized to provide the reader with a clear and logical flow. Chapter 1 introduces the project and lays the groundwork with an overview, objectives, scope, and contributions. Additionally, it offers a thorough analysis of irrigation methodologies and the technology used, which includes automation through the Internet of Things. Chapter 2 presents the Literature Survey, offering insights into existing research papers that inform and contextualize the project. This chapter's subsections each focus on a different facet of precision agriculture, including resource efficiency through smart irrigation systems, crop water need estimation using the Penman-Monteith Equation (PME), and fertigation. It also discusses quality monitoring and explores remote sensing applications for agriculture. Chapter 3, titled "System Architecture & Design" delves into the specifics of how the system is conceptualized and structured. Chapter 4, "Algorithm Development and Implementation" provides a detailed account of the algorithms developed for the project and the practical implementation aspects. Chapter 5, "Results and Discussions," presents the outcomes of the research, facilitating an in-depth understanding of the project's efficacy and limitations. In "Conclusion and Further Work," Chapter 6, the main conclusions are outlined, the ramifications are examined, and suggestions for additional research and development are made. The project's overall structure guarantees a thorough investigation, taking the reader step-by-step through the study process from conception to useful application and conclusions.

CHAPTER 2
LITERATURE SURVEY

The literature survey module serves as a comprehensive exploration of existing research, methodologies, and insights corresponding to precision agriculture, automated irrigation systems, and related domains. This section delves into a wide range of scholarly works, academic publications, and journals, exploring knowledge from diverse sources to aid the current study

2.1 PRECISION AGRICULTURE AND SMART IRRIGATION SYSTEMS

Recent years have seen the rise of important research fields like Precision Agriculture and Smart Irrigation Systems, which seek to transform conventional farming methods by using cutting-edge technologies. A thorough analysis of smart agriculture as proposed in the [1], with an emphasis on orchid growth inspection system for detecting the growth status of orchids in greenhouses, emphasizing the application of self-supervised learning techniques for crop monitoring and management. The [2] demonstrates an IoT-based system to automate and optimize water harvesting, moisture monitoring, and crop monitoring, further enhancing the efficiency and sustainability of precision agriculture practices. A comprehensive study on the demographic factors' influence on Precision Agriculture is shown in [3], that also assesses the influence of Agro ecological factors, behavioural factors, institutional factors, informational factors, technical factors, perception factors towards Precision Agriculture adoption. The revolutionary potential of precision agriculture and smart irrigation systems is highlighted by this study, opening the door to more sustainable agricultural methods and higher crop yields. These studies highlight the revolutionary potential of smart irrigation systems and precision agriculture together, opening the door to more productive and sustainable agricultural methods and higher crop yields.

2.2 PENMAN - MONTEITH EQUATION FOR ESTIMATING CROP WATER REQUIREMENT

Estimating evapotranspiration (ETo) is essential to managing water resources for irrigation. The study [4] focuses on modelling daily and monthly ETo using a system identification and differential evolution approach. The Penman-Monteith equation is used to estimate ETo using data on solar radiation, wind speed, relative humidity, and temperature. The study's findings show that the suggested method is suitable for accurately calculating crop water requirements because it mimics ETo dynamics sufficiently and performs similarly to the conventional Penman-Monteith method. AgTech adoption tactics could be employed in several ways to accomplish efficient use of irrigation water. In order to evaluate water loss from crop fields, the study [5] suggests using evapotranspiration as a metric. It is recommended to use the Penman-Monteith equation (PME) to calculate evapotranspiration using weather conditions. PME is regarded as a common empirical technique. By using this method, one can also determine the crop's water requirements depending on the crop coefficient of that specific crop. Additionally, models for deep learning and machine learning (ML/DL) can be used to forecast evapotranspiration.

2.3 FERTIGATION AND QUALITY MONITORING

Fertigation plays a crucial role in precision agriculture by delivering nutrients precisely to crops through irrigation systems. The study [6] aims to manage fertigation in precision agriculture to provide real-time control and monitoring that results in effective water and nutrient management. It also discusses how automated fertigation management may maximize plant growth and efficient use of resources in regulated agricultural environments. An IoT-based system for tracking paddy growth, made up of numerous sensors that gather information about the environment in real-time, including temperature, humidity, soil moisture, and water levels is proposed in the [7]. An agronomist must be well-versed in and aware of the precise or absolute values of temperature, precipitation, water level, rainfall patterns, and climatic variations in order to ensure good crop development, as the crop's overall success is heavily reliant on these variables. The [8] describes an automated experimental approach that uses the Internet of Things to intelligently operate systems for monitoring agriculture.

2.4 REMOTE SENSING APPLICATIONS

The integration of remote sensing technologies with precision agriculture and smart irrigation systems using the Penman-Monteith equation as shown in the [9] has further advanced the agricultural processes and are making it more efficient. The difficulties in applying decision-support remote systems in Agriculture 4.0 are examined in the study [10]. It focuses on using remote sensing applications for crop monitoring and production forecasts and assesses the advantages and disadvantages of different approaches and investigates how well they work in diverse agricultural contexts. The ultimate goal being to enhance upcoming remote sensing systems that assist in making decisions about sustainable farming methods.

2.5 SUMMARY OF LITERATURE SURVEY

The literature survey examines the automated irrigation system using the Penman-Monteith equation, fertigation, remote sensing for crop monitoring, and precision agricultural quality control techniques are all covered in this overview of the literature. Our understanding of effective irrigation, water resource management, and crop health management in contemporary farming has improved as a result of these studies taken together. Precision agriculture and smart irrigation systems are developed by them, with an emphasis on total resource efficiency, disease detection, water optimization, and quality monitoring.

CHAPTER 3
SYSTEM ARCHITECTURE AND DESIGN

The system architecture and design of the proposed Irrigation and Fertigation system includes the critical components that lay the foundation for the overall functionality, scalability, and effectiveness in optimizing crop farming practices. This chapter provides an overview of the architectural framework, hardware components, software modules, and design considerations which correspond to the development and implementation of the precision agriculture system.

3.1 SYSTEM ARCHITECTURE

The system architecture of the proposed precision agriculture framework comprises three core modules: Automated Irrigation, Image-based Fertigation System (specific to Tomato Crops), and Quality Monitoring (specific to Tomato Crops) as shown in the Fig. 3.1.

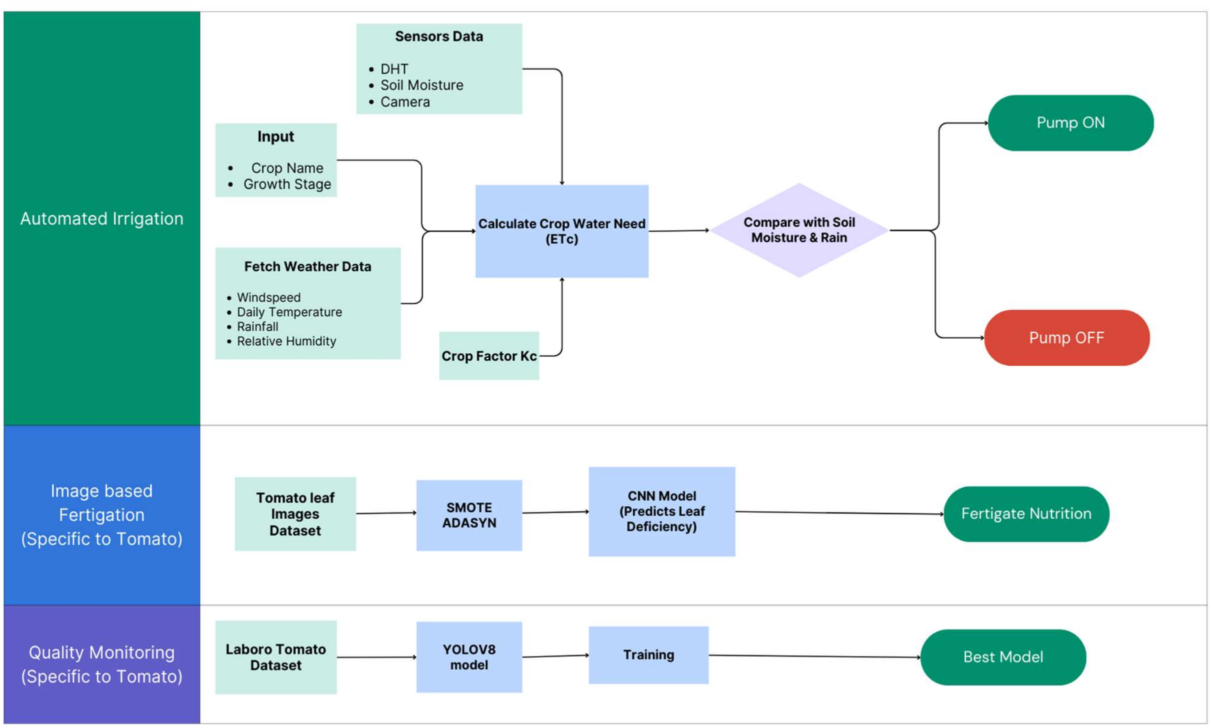

Figure 3.1 IPAIS Architecture

Each module is precisely designed to address key aspects of crop cultivation, including irrigation management, nutrient supplementation, and quality monitoring. The architecture seamlessly integrates advanced technologies such as sensor networks, image processing, and machine learning to enable efficient agricultural practices.

3.1.1 Automated Irrigation

The Automated Irrigation module serves as the keystone of the precision agriculture framework, facilitating intelligent water management tailored to the needs of individual crops. Thereby, supplying the crops with the correct amount of water to ensure optimal crop growth.

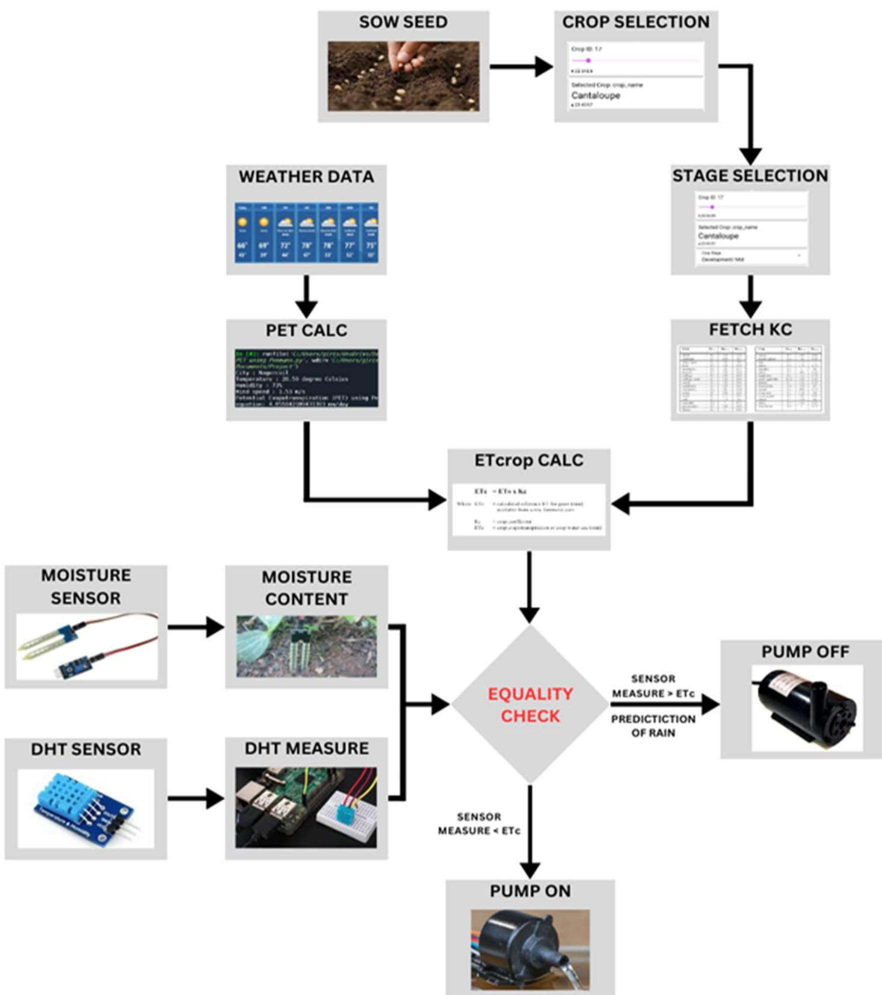

Figure 3.2 Flow of Automated Irrigation

The workflow as shown in Fig. 3.2 begins with the user(farmer) giving in the crop name and growth stage of the crop into the system through a user-friendly mobile dashboard interface. Subsequently, sensors including DHT (temperature and humidity) and soil moisture sensors capture real-time environmental data, simultaneously, the current weather information is fetched from 'openweathermap.org' using latitude and longitude of the device’s location.

The obtained data is then utilized to calculate the water requirements, in mm/day, of the crop by leveraging the Penman-Monteith equation, which considers factors such as potential evapotranspiration and crop-specific constants. By comparing the calculated water needs with the current soil moisture levels and rainfall predictions, the system intelligently controls the water pump, turning the pump on or off as needed to maintain optimal soil moisture levels to ensure good crop growth.

The dashboard interface provides farmers with real-time access to sensor readings, weather data, and crop water needs, enabling them to make informed irrigation decisions and monitor crop health remotely. There is also an option of manual irrigation just in case the farmer wishes to change, the dashboard also provides the user a graph of the Temperature and Soil moisture levels in a day.

3.1.2 Automated Fertigation for Tomatoes through Image Processing

The Image-based Fertigation System is tailored particularly for tomato crops, aiming to optimize nutrient supplementation through Deep learning image processing techniques. The workflow depicted in Fig. 3.3 consists of several stages, beginning with data collection of tomato leaf images from diverse sources. To augment the dataset and ensure robust model performance, data preprocessing techniques such as data augmentation and class balancing are employed.

Web Scraping techniques are utilized to supplement the dataset with synthetic images, particularly for diseases with limited sample availability such as 'leaf miner’, ‘Potassium Deficiency’. There lies a custom CNN model designed to classify tomato leaf images and detect eight different types of tomato diseases (nutrition Deficiency), these deficiencies can be cured by supplying an adequate amount of fertilizers. The model architecture consists of Conv2D layers, Max Pooling layers, Dropout layers, fully connected layers, and output layers, optimized for disease detection accuracy.The detected deficiency classes are then used to determine the corresponding nutrient supplements for fertigation, ensuring optimal and precise nutrient delivery to affected crops.

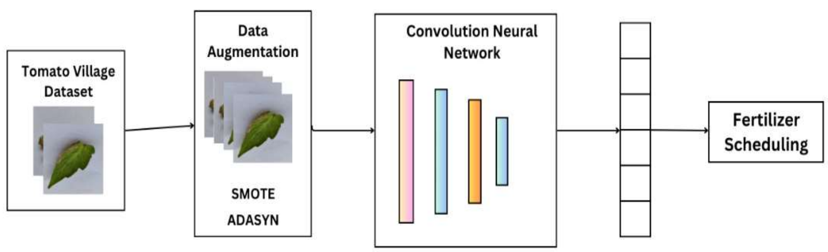

Figure 3.3 Flow of Fertigation Model

3.1.3 Quality Management of Tomatoes

The Quality Monitoring module focuses on monitoring the quality parameters of tomato crops to ensure optimal yield. Making use of the laboro-tomato dataset, an object detection model based on YOLOv8 architecture is trained to identify and classify quality attributes such as ripeness, size, colour in tomato images.

The training process involves iteratively refining the model through training and validation cycles, culminating in the selection of the best-performing model for deployment in the field. The output of the quality management module provides valuable insights to users(farmers), enabling timely interventions such as harvesting and market loading to maintain product quality and maximize profitability

CHAPTER 4

ALGORITHM DEVELOPMENT AND IMPLEMENTATION

4.1 ALGORITHM FOR AUTOMATIC IRRIGATION

Automated irrigation is the primary objective of the proposed system, enabling efficient water management tailored to the specific needs of each crop. The algorithm for automatic irrigation consists of several key components aimed at accurately determining the water requirements of crops based on weather conditions, Solar Radiation, environmental factors and crop characteristics.

4.1.1 Calculation of Water Need for a Crop

The calculation of crop water needs for a crop is the fundamental aspect of automated irrigation systems, which is essential for ensuring optimal crop growth and yield. It involves calculating the depth or amount of water required to meet the crop Transpiration needs, the calculation should also account for the water loss through evaporation in the given day. As per standard convention the crop water need is expressed in mm/day, that is the depth of the amount of water. There are several factors that influence the crop water need(ETc), these include the current climate, the crop's growth stage and the type of the crop. The effect of these factors on a crop's water requirement is discussed in this chapter

4.1.2 Evapotranspiration

Evapotranspiration or ET represents the combined loss of water through evaporation from the soil surface and transpiration from the crop's leaves. In order to accurately calculate the water needs of a crop, it is essential to know the possible water loss, or in other words, the water usage of the crops for their growth. To correctly quantify the water needs of crops, reference crop evapotranspiration (ETo) serves as a benchmark. ETo is defined as the rate of evapotranspiration from a standard reference crop, typically green grass with specific characteristics such as optimum height, coverage, and growth stage. It is expressed in millimeters per unit of time, it could be mm/day, mm/month, providing a standardized measure of evapotranspiration rates. The FAO provides methodologies for calculating ETo, which includes the Pan Evaporation Method and the Blaney-Criddle Method, which rely on only temperature to calculate evapotranspiration rates. However, these approaches have limitations in their ability to account for all relevant meteorological factors affecting ET For example, the Pan evaporation method relies only on measurements of water evaporation from a pan, which does not consider factors such as air temperature, humidity, and wind speed. Similarly, the Blaney-Criddle method estimates ET based on temperature and precipitation data alone, overlooking the influence of other weather conditions.

4.1.3 Penman-Monteith Equation

Due to the above discussed limitations, the traditional methods such as Pan Evaporation Method or the Blaney-Criddle Method may not provide accurate ET estimates under varying climatic conditions and cannot be relied upon as standalone approaches for the Potential Evapotranspiration estimation. In contrast, the Penman-Monteith equation offers a comprehensive and physically based approach for estimating potential evapotranspiration (PET) by considering a wide range of meteorological factors, including temperature, humidity, wind speed, net radiation, Vapour pressure and soil heat flux density. This makes the Penman-Monteith equation a more robust and versatile method for ET estimation, particularly in diverse climatic and environmental settings. The calculated value for ET can be considered ETo, which serves as the benchmark for crop water requirement. The equation for calculating ETo:

```
ETo = (0.408 * Δ * (Rn − G) + γ * (900 / (T + 273)) * U * (e_s − e_a)) /
(Δ + γ * (1 + 0.34 * U))
```

Where, ET is the potential evapotranspiration (mm/day), Rn is the net radiation (MJ/m²/day), G is the soil heat flux density (MJ/m²/day), δ is the slope of the saturation vapor pressure curve (kPa/°C), γ is the psychrometric constant (kPa/°C), T is the mean daily air temperature at 2 meters height (°C), U is the wind speed at 2 meters height (m/s), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa).

4.1.4 Fetching Weather Data

The process of fetching values for the parameters like temperature (T), wind speed (U), and relative humidity (RH) involves several steps as shown in Fig. 4.1, including geocoding to obtain latitude and longitude coordinates and querying the OpenWeatherMap Python API to retrieve meteorological data based on these coordinates.

Figure 4.1 Localization and Fetching Weather Data

The process can be summarized in the following steps:

1. Geocoding for Localization

Geopy Library: Geopy is a Python library that provides geocoding capabilities, which allows conversion of location names into geographic coordinates (latitude and longitude).

Geocoder: Geocoder is a module within Geopy that interfaces with various geocoding services, such as Google Maps, Bing Maps, and OpenStreetMap, to obtain geographic information.

Latitude and Longitude: Upon entering the location, Geocoder queries the chosen geocoding service to retrieve the corresponding latitude and longitude coordinates.

2. Querying OpenWeatherMap Python API

OpenWeatherMap Python API: OpenWeatherMap is a popular weather data provider that offers various APIs for accessing current and forecast weather data.

Python Integration: The OpenWeatherMap Python API provides a convenient way to access weather data within Python scripts. Other libraries such as requests to make HTTP requests to the OpenWeatherMap API can also be used to retrieve weather information.

3. Retrieving Meteorological Data

Temperature (T): The OpenWeatherMap API allows us to query for current temperature data based on geographical(latitude and longitude) coordinates. The API returns the temperature in Celsius or Fahrenheit, depending on the specified unit of measurement.

Wind Speed (U): Similarly, the current wind speed data from the OpenWeatherMap API, which provides information on wind speed in the specified unit.

Relative Humidity (RH): OpenWeatherMap also offers relative humidity data as part of its current weather data. Relative humidity is expressed as a percentage and indicates the amount of water vapor present in the air relative to the maximum possible at the current temperature.

4. Derived Parameters

In addition to the directly fetched meteorological data, several derived parameters play a crucial role in the estimation of evapotranspiration, these parameters can't be directly fetched from weather data.

Magnus Formula for Slope of Vapor Pressure Curve (δ) and Saturation Vapor Pressure (e_s)

The Magnus formula is commonly used to calculate the slope of the vapor pressure curve (δ) and saturation vapor pressure (e_s) based on temperature. The formulas are as follows:

$$\delta = \frac{4098 \times 0.6108 \times e^{\left(\frac{17.27 \times T}{T+237.3}\right)}}{(T+237.3)^2}$$

$$e_s = 0.6108 \times e^{\left(\frac{17.27 \times T}{T+237.3}\right)}$$

These formulas provide estimates of saturation vapor pressure and the rate of change of saturation vapor pressure with temperature, respectively.

Actual Vapor Pressure (e_a)

Actual vapor pressure (e_a) represents the vapor pressure of water vapor in the air. It is influenced by factors such as relative humidity and temperature. Actual vapor pressure can be calculated using the formula:

$$e_a = \frac{RH}{100} \times e_s$$

4.1.5 Justification for Approximated Values

Apart from the above fetched weather data, there exists few other needed parameters for the estimation of Potential Evapotranspiration

Net Radiation (Rn**)**

Net radiation represents the balance between incoming and outgoing radiation at the Earth's surface. However, obtaining accurate measurements of net radiation from public weather APIs can be challenging due to the complexity of instrumentation and data availability. Therefore, a default value of 10 (MJ/m²/day) is often used as a placeholder when actual measurements are unavailable. This value provides a reasonable estimate for PET calculations in the absence of precise net radiation data.

Soil Heat Flux Density (G**)**

Soil heat flux density accounts for heat transfer into or out of the soil surface due to solar radiation and thermal gradients. Similar to net radiation, precise measurements of soil heat flux density may not be readily available from online weather APIs. Hence, a default value of 0.1 (MJ/m²/day) is commonly used as an approximation. However, this value may vary depending on soil properties and environmental conditions, it serves as a reasonable estimate for PET calculations when specific data are lacking. Fig 4.2 shows a snapshot of the process.

```
City : Chennai
Temperature : 30.2 degree Celsius
Humidity : 75%
Wind speed : 3.13 m/s
Potential Evapotranspiration (PET) using Penman-Monteith equation:
4.082929818307645 mm/day
```

Figure 4.2 Weather Data Fetched from OpenWeatherMap

Once these parameters are obtained , the reference crop's water requirement can be calculated. Nevertheless, Not all crops need the same amount of water. To account for this, there exists a crop specific constant or simply Crop factor .

4.1.6 Crop Specific Constant(Kc)

The relationship between the reference grass crop and the crop actually grown is given by the crop factor, Kc, as shown in the following formula:

$$\boxed{ET_0 \times Kc = \text{Irrigation Water Need in mm/day } (\mathbf{ET_c})}$$

The Crop factor,Kc, represents the ratio of crop evapotranspiration to reference evapotranspiration (ET crop / ETo) and accounts for variations in water usage among different crop types and growth stages. By multiplying ETo by the appropriate Kc value, the crop's water needs can be estimated accurately for each growth stage, accounting for climatic influences and crop characteristics. The determination of Kc values involves understanding the total length of the growing season, the durations of various growth stages, and the specific climatic conditions prevailing during each stage. By systematically evaluating these factors, farmers can tailor irrigation schedules to match crop water requirements, optimizing water usage and promoting sustainable agricultural practices.

Kc need not be the same value. The crop factor, Kc, is affected by several key factors:

1. **The type of crop:** For instance, fully developed maize, with its expansive leaf area, typically experiences higher transpiration rates compared to the reference grass crop. This leads to the Kc value for maize to increase to a value greater than 1. Conversely, crops like cucumber, even when fully developed, may exhibit lower transpiration rates relative to the reference grass crop, leading to a Kc value less than 1.
2. **The growth stage of the crop:** The water requirement of a crop can vary greatly depending on its growth stage. For example, a fully developed crop is likely to transpire more water compared to a crop that has just been planted.
3. **The climate:** Climate conditions also play a crucial role in shaping the duration of the growing season and the pace of crop development. In cooler climates, crops may exhibit slower growth rates compared to warmer climates, impacting their overall water usage and influencing the Kc values associated with different growth stages.

Other factors like windspeed and humidity also affect the Crop Factor. Kc value should be reduced by 0.05 if the relative humidity is high ($RH > 80\%$) and the windspeed is low ($u < 2$ m/sec) and vice versa for lower humidity values.

The Table 4.1 shows the Kc value for different conditions discussed above for Ratoon Sugarcane crop

Table 4.1 Kc Values for Ratoon Sugarcane

Climate	Little Wind		Strong wind	
Growth Stage (days)	**Dry**	**Humid**	**Dry**	**Humid**
0-1	0.4	0.5	0.5	0.6
1-2	0.8	0.8	0.8	0.85
2-4	1.1	1.0	1.2	1.1
4-10	1.25	1.05	1.3	1.15
10-11	0.95	0.8	1.05	0.85
11-12	0.7	0.6	0.75	0.65

Through the integration of climatic data, reference evapotranspiration(ETo) calculations, and crop-specific factors(Kc), the automated irrigation algorithm enables precise and efficient water management, ensuring optimal crop health and productivity in diverse agricultural settings.

4.1.7 Algorithm: Penman-Monteith Evaporation Calculation

Input: Air temperature (T) [°C], Relative humidity (RH) [%], Wind speed (u) [m/s], Solar radiation (Rs) [W/m²], Atmospheric pressure (P) [kPa], Albedo (α) [unitless]

Constants: Specific heat of air (Cp) [J/kg°C], Latent heat of vaporization (λ) [J/kg], Stefan-Boltzmann constant (σ) [W/m²K⁴], Psychrometric constant (γ) [kPa/°C], Gravitational acceleration (g) [m/s²]

Output: Evapotranspiration (ET) [mm/day]

1. Cp ←1005 // Specific heat of air [J/kg°C]
2. λ ←2.45 * 10^6 // Latent heat of vaporization [J/kg]
3. σ ← 5.67 * 10^-8 // Stefan-Boltzmann constant [W/m²K⁴]
4. γ ← 0.066 // Psychrometric constant [kPa/°C]

5. g ← 9.81 // Gravitational acceleration [m/s^2]
6. Calculate saturation vapor pressure (es)
7. es ← 0.6108 * exp ((17.27 * T) / (T + 237.3))
8. Calculate actual vapor pressure (ea)
9. ea ← (RH / 100) * es
10. Calculate slope of saturation vapor pressure curve (Δ)
11. Δ ← (4098 * es) / ((T + 237.3) ^2)
12. Δ_Term ← (Δ / (Δ + γ * (1 + 0.34 * u)))
13. Rn_Term ← ((1 - α) * Rs - σ * ((T + 273.16)^4)) * (900 / (T + 273.16))
14. Wind_Term ← (γ * (900 / (T + 273.16)) * u * (es - ea))
15. Calculate evapotranspiration (ET)
16. ET = (Δ_Term * Rn_Term + Wind_Term) / (Δ + γ * (1 + 0.34 * u))
17. return ET

4.2 IoT CIRCUIT ORGANIZATION

The organisation of the circuit of the system involves the connection between various sensors with the controller called Raspberry Pi. The data pin of the DHT sensor is connected to the RPi at the GPIO pin 26. The ground pin of the DHT sensor is connected to pin 14. The Vcc of the DHT sensor is connected to pin 4. Similarly, the Vcc, ground and analog pins are connected to pin 2, pin 20 and GPIO pin 4 respectively. The buzzer is connected to the circuit to indicate the need of water. The power and ground of the buzzer are connected to RPi in GPIO 16 and pin 34 respectively. The 8MP PC camera is connected to the board using USB cable. The digital circuit connection of the system is depicted in the Fig. 4.3

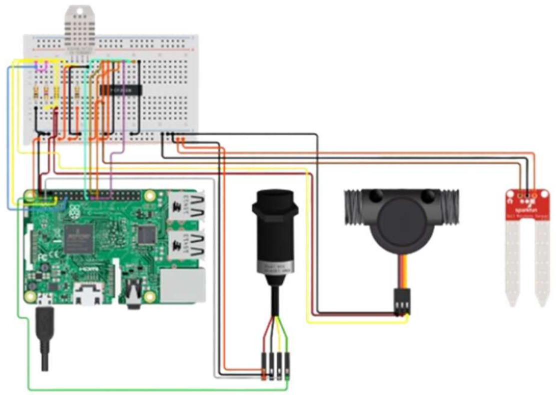

Figure 4.3 Digital Circuit connection of the IPAIS

The RPi is installed with Raspbian OS to ensure seamless interface between hardware and software. To have the interface between the sensors like DHT, Soil Moisture sensor the python packages of AdaFruit are installed in the RPi. The real-time sensor connection is shown in the Fig.4.4

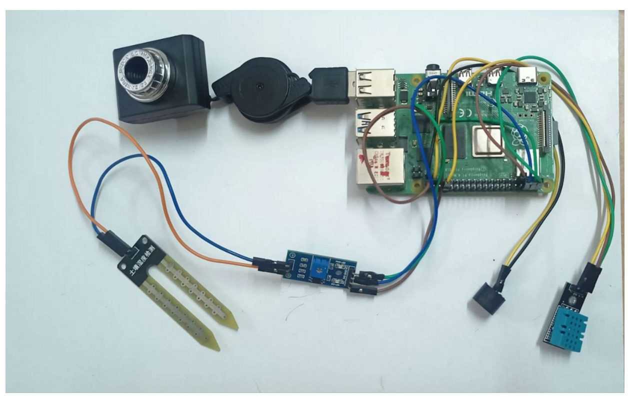

Figure 4.4 Real-time circuit connection of IPAIS

4.3 AUTOMATIC FERTIGATION

4.3.1 Data collection

Tomato Village dataset is an open source dataset available in the kaggle that contains images of tomato leaves. When attempting to predict tomato diseases, the field found that the majority of diseases are Leaf Miner, spotted wilt virus, and

Nutrition deficiency diseases, but there are no public datasets containing such categories. There is imbalance in the dataset which is depicted in the Fig.4.5

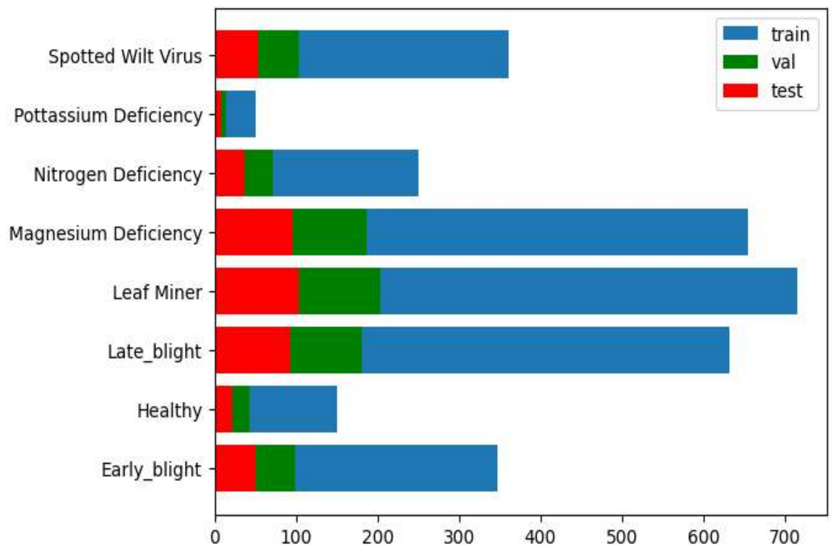

Figure 4.5 Imbalance in the dataset

4.3.2 Data Augmentation with Data Synthesis

To overcome imbalance in the dataset issue the following are the methods followed: Synthetic Minority Oversampling Technique (SMOTE) and Adaptive Synthetic Sampling (ADASYN), methods widely recognized for addressing class imbalance in machine learning datasets.SMOTE facilitated the generation of synthetic samples for minority classes, particularly focusing on the 'Potassium Deficiency' and 'healthy' leaf classes, which exhibited a notable scarcity of instances. SMOTE effectively expands the representation of minority classes, thereby balancing the class distribution and mitigating the risk of bias towards majority classes during model training. After creating the synthetic images with SMOTE all the classes have the same number of images enabling a balanced dataset. The results of the SMOTE algorithm depicted in the Fig. 4.6 ADASYN improves classification performance by balancing the dataset and reducing the bias towards the majority class. ADASYN works by generating synthetic samples for minority classes based on the feature space of the original dataset.ADASYN worked its synthesis process with the minority class i.e, 'Potassium Deficiency' and increased the number of images in the minority class leading to a lower ratio between the majority and minority classes.The results of ADASYN algorithm is depicted in the Fig. 4.7

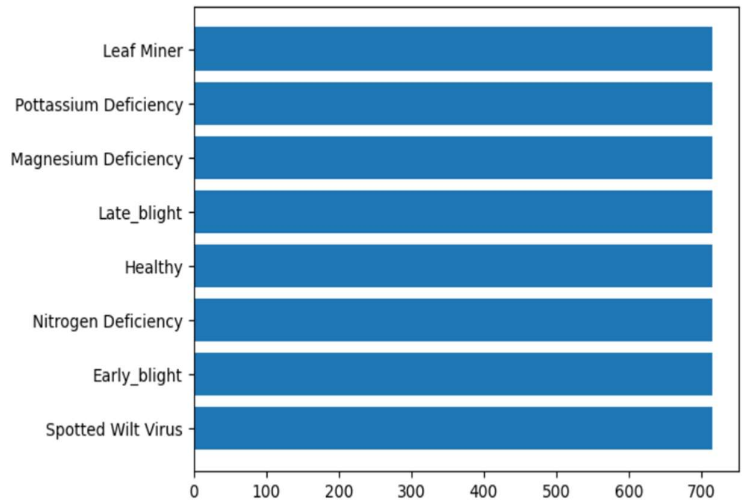

Figure 4.6 Data Synthesis by SMOTE

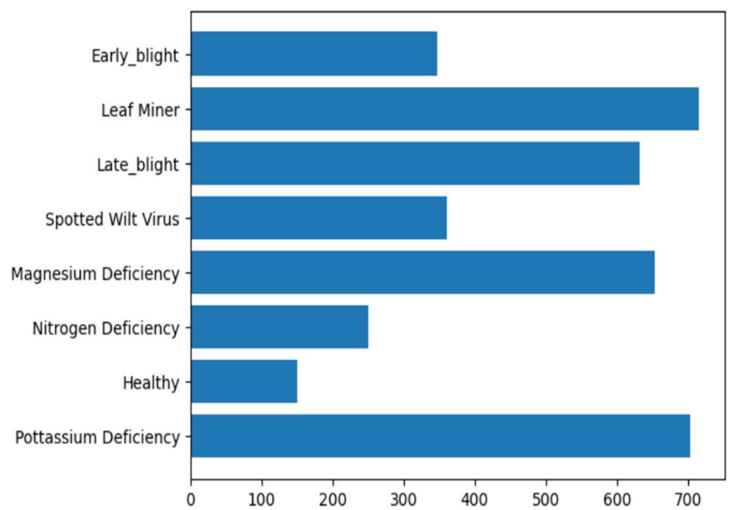

Figure 4.7 Data Synthesis by ADASYN

4.3.3 Convolutional Neural Network Model

In order to classify the image pre-processed, CNN models are developed to get trained with the data. The designed models are trained with a training dataset which has 4 classes of images of each size 224 X 224 X 3. The training of these models are compiled with various optimizers such as Adagrad, Adam, Stochastic Gradient Descent

(SGD), Root Mean Square Propagation (RMSProp). The validation dataset is used to validate the learning of the model during the training process. The trained model is tested against the test dataset and various parameters such as precision, recall, f1-score, support. The layers of the CNN model are depicted in the Fig.4.8

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 198, 198, 64)      1792
 batch_normalization         (None, 198, 198, 64)      256
 max_pooling2d               (None, 99, 99, 64)        0
 conv2d_1 (Conv2D)           (None, 97, 97, 32)        18464
 max_pooling2d_1             (None, 48, 48, 32)        0

 conv2d_2 (Conv2D)           (None, 46, 46, 32)        9248
 max_pooling2d_2             (None, 23, 23, 32)        0
 conv2d_3 (Conv2D)           (None, 21, 21, 64)        18496
 max_pooling2d_3             (None, 10, 10, 64)        0

 flatten (Flatten)           (None, 6400)              0
 dense (Dense)               (None, 128)               819328
 dropout (Dropout)           (None, 128)               0
 dense_1 (Dense)             (None, 64)                8256
 dropout_1 (Dropout)         (None, 64)                0
 dense_2 (Dense)             (None, 32)                2080
 dense_3 (Dense)             (None, 16)                528
 dense_4 (Dense)             (None, 8)                 136
=================================================================
Total params: 878584 (3.35 MB)
Trainable params: 878456 (3.35 MB)
Non-trainable params: 128 (512.00 Byte)
_________________________________________________________________
```

Figure 4.8 Layers of CNN Model for Fertigation

4.4 QUALITY MANAGEMENT

The quality management is implemented with the help of an object detection algorithm that detects the object from the image and classifies the detected object. In the proposed system in order to monitor the quality of tomato YOLOv8 model is developed.

4.4.1 Dataset for Quality Management

The LaboroTomato dataset is an open source dataset which contains the images that contain various stages of tomato at different locations as well as the boundary box coordinates of the tomato and the labels for the respective classes. The dataset includes 804 images and six classes. The detailed information about the dataset is Tabulated in the Table 4.2

Table 4.2 LaboroTomato Dataset Description

Number of images	643 train, 161 test
Number of classes	6
Class names	b_fully_ripened, b_half_ripened, b_green, l_fully_ripened, l_half_ripened, l_green
Total Boundary Boxes	train[7781], test[1,996]
Boundary Boxes per Class	**Train**: b_fully_ripened[348], b_half_ripened[520], b_green[1467], l_fully_ripened[982], l_half_ripened[797], l_green[3667] **Test**: b_fully_ripened[72], b_half_ripened[116], b_green[387],l_fully_ripened[269], l_half_ripened[223], l_green[929]
Image Resolution	3024x4032, 3120 x 4160

4.4.2 YOLOv8 for Object Detection

YOLOv8 from Ultralytics is the latest version of object detection model which has more flexible features compared to the previous versions of YOLO models. This latest version could support detection, segmentation, pose estimation, tracking and classification. The model is loaded from the Ultralytics package and trained with the dataset mentioned in Section 4.5.2. The train dataset is used to train the model and the model is tested against the dataset.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 IMPLEMENTATION ENVIRONMENT

The smart irrigation system is made to be controlled remotely from the phone by the user. The user had full control over the irrigation pipeline to open/close manually as well as enabling the automation of the irrigation with real-time weather data and soil moisture value. The mobile application is designed in such a way that it automatically connects with Raspberry Pi and communicates with the application using Message Queuing Telemetry Transport (MQTT).

5.2 MOBILE APPLICATION FOR REMOTE ACCESS

The mobile application is created to enable farmers to control and monitor the land remotely. The application helps in monitoring the temperature, humidity and soil moisture level from the mobile phone and can either take action to automate the irrigation by the system itself or can open/close the pipeline. The application contains two dashboards namely Smart Irrigation Dashboard and Performance dashboard. The snapshots of the mobile application is shown in the Fig. 5.1.

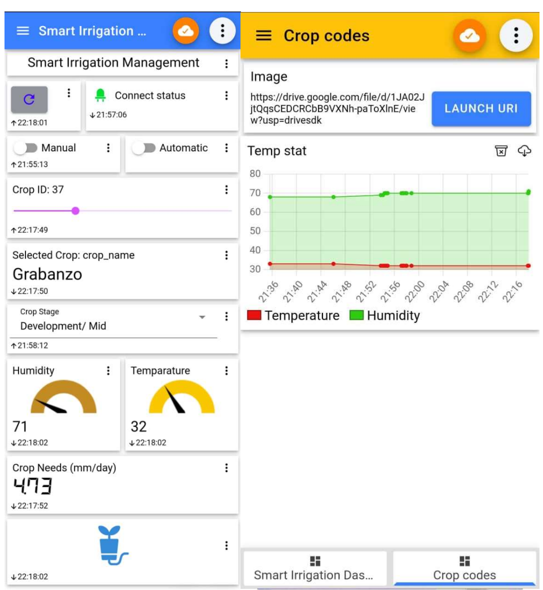

Figure 5.1 Dashboards in Mobile Application

5.2.1 MQTT Protocol for Communication

The MQTT protocol is a messaging protocol which is lightweight that helps in communication between various clients to send/receive the data. This protocol is based on the publish-subscribe model. The publish-subscribe model will be a broker in between the client and server to send the data to the respective topic. The topic is a logical name which can be subscribed by one or more clients so that any information that is published to this topic can be read by the client. MQTT protocols are mainly used in Machine-to-Machine communication (M2M). The working of MQTT with the system is depicted in Fig. 5.2.

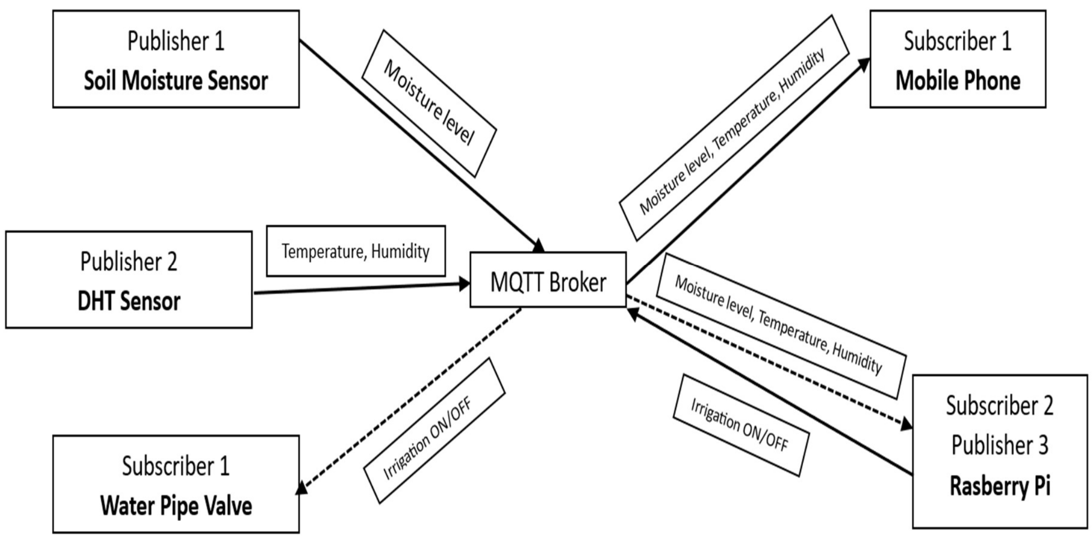

Figure 5.2 Role of MQTT in IoT Automation

5.2.2 Smart Irrigation Dashboard

The Smart Irrigation Dashboard provides the control over the pipeline as well as to monitor the temperature, humidity and moisture level in the soil. This dashboard also allows users to select the crop and the stage of that crop to estimate the water needed by that crop for that day. The amount of water required by the crop for the day is also displayed to the user. The switch manual is used to ON/OFF the water flow of the pipeline from the phone. The switch automatic is used to enable the system to irrigate on its own.

5.2.3 Performance Dashboard

The performance dashboard contains the crop code sheet which is used to represent the unique codes for each crop that will be given as input in the smart irrigation dashboard. The level of the crop is chosen to select the appropriate crop specific constant from the sheet. This dashboard also shows the user about the trend in the temperature and humidity in a day.

5.3 FERTIGATION MODEL RESULTS

The convolutional neural network is used to classify the image to various classes and the model is trained with the dataset mentioned in Chapter 4. The dataset is split into train, validation and test dataset. The train dataset is used for training the model and the validation dataset is used to tune the model during the training process. The test dataset is used to test the model that is trained. The model classifies the image and the evaluation metric for the test data is shown in Fig.5.3.

	precision	recall	f1-score	support
0	0.75	0.89	0.81	95
1	0.76	0.76	0.76	92
2	0.75	0.38	0.50	8
3	0.77	0.46	0.57	50
4	0.56	0.42	0.48	53
5	0.10	0.05	0.06	22
6	0.73	0.65	0.69	37
7	0.60	0.81	0.69	104
accuracy			0.68	461
macro avg	0.63	0.55	0.57	461
weighted avg	0.67	0.68	0.66	461

Figure 5.3 Evaluation Metrics of Fertigation Model

The trend in training and testing accuracy of the model during each epoch shows the learning rate adjustment of the model during training which leads to higher accuracy of the model. The graph shown in the Fig. 5.4 represents the trend in the training and validation accuracy.

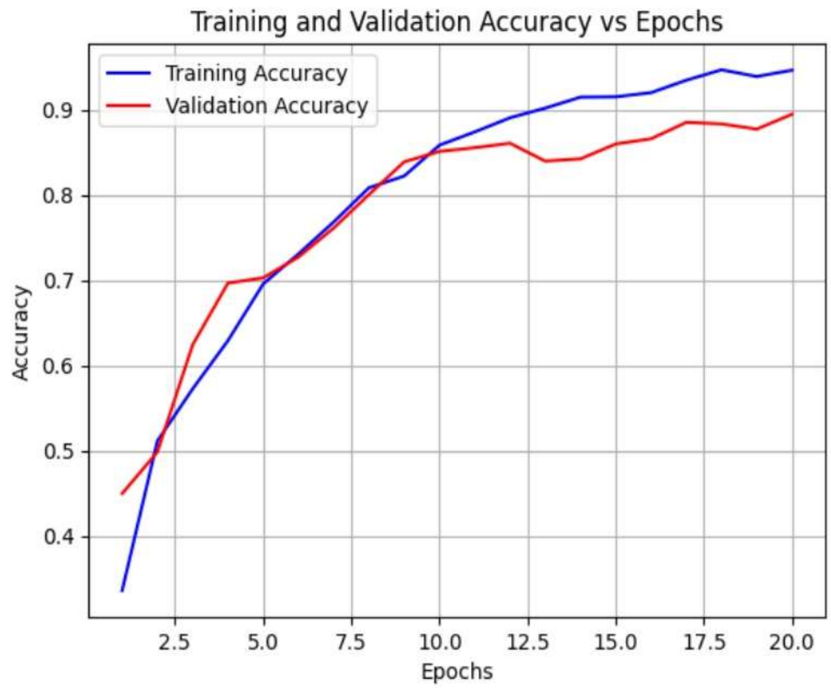

Figure 5.4 Graphical representation of trend in training and validation accuracy

5.4 QUALITY MANAGEMENT RESULTS

The YOLOv8 model is used for the quality management for the tomato plants. The YOLOv8 model is imported from Ultralytics and trained with the dataset mentioned in Chapter 3. The model is evaluated with the following evaluation measures

5.4.1 Average Precision (AP)

AP calculates the region under the precision-recall curve, which yields one statistic that summarizes the model's accurateness and recall performance.

5.4.2 Mean Average Precision (mAP)

mAP builds on the principle of AP by formulating the average AP values across multiple object classes. This is useful in multi-class object detection scenarios to provide a thorough evaluation of the model's performance. The following is the formula to calculate the mAP values given the class and its average precision.

$$\text{Mean Average Precision} = \frac{1}{n}\sum AP_{\mathrm{k}}$$

AP_k - Average Precision of the class k

n - number of classes

k = 1 to n

5.4.3 Evaluation metrics of YOLOv8

- **Class**: This refers to the name given to the object class
- **Images**: This metric counts the total number of images in the validation set that include the object class.
- **Instances**: This returns the number of times the class appears across all images in the validation set.
- **Box (P, R, mAP50, and mAP50-95)**: This metric provides insight into the model's performance in detecting objects.
- **P (Precision)**: The detected object's accuracy, expressed as the number of correct detections.
- **R (Recall)**: The model's ability to recognize all instances of objects in the images.
- **mAP50**: Mean average precision calculated using an intersection over union (IoU) threshold of 0.50. It is a measure of the model's accuracy based only on "easy" detections.
- **mAP50–95**: The average of the mean average precision calculated at varying IoU thresholds, ranging from 0.50 to 0.95. It gives a comprehensive view of the model's performance across different levels of detection difficulty.

The mAP value found for the YOLOv8 built for tomato quality detection is tabulated in Table 5.1.

Table 5.1 Evaluation Metrics for YOLOv8 Model

Class	Images	Instances	Precision	Recall	mAP50	mAP50-95
all	161	1996	0.846	0.816	0.883	0.789
b_fully_ripened	161	72	0.819	0.819	0.837	0.777
b_half_ripened	161	116	0.825	0.772	0.868	0.776
b_green	161	387	0.914	0.876	0.946	0.85
l_fully_ripened	161	269	0.808	0.858	0.896	0.803
l_half_ripened	161	223	0.814	0.728	0.833	0.753
l_green	161	929	0.898	0.844	0.918	0.776

5.4.4 Real Time Testing of the YOLOv8

The saved best weights of the YOLOv8 model are loaded to test against an image to identify the quality of tomato projected in the image. The input image is fed into the saved model. The model identifies the object first and provides boundary boxes to identify the tomato. Then each object detected is classified into their respective classes. The Fig. 5.5 represents the output image from the model with boundary boxes and their respective class.

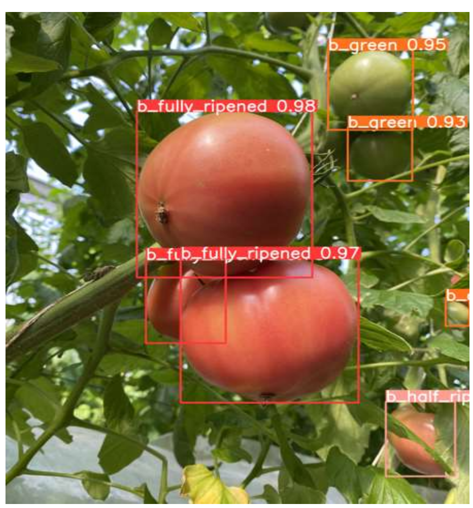

Figure 5.5 Output Image of Quality Management Model

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The smart irrigation system is able to estimate the water needed for the crop based on their stage of growth and atmospheric conditions such as temperature, humidity, and wind speed by the calculation of evapotranspiration of a plant. With the estimated water needed the pipeline is automated accordingly. The additional features of fertigation through image processing and quality management for Tomato are implemented to bring the power of Artificial Intelligence in Precision Agriculture. This intelligence helps in supplying only the required amount of fertilizer to the plants thus enabling precise usage of fertilizer that is harmful to both the environment and human kind. The entire system is made to be controlled remotely with the help of mobile application which facilitates the farmers by not visiting the land frequently. The application is portable since it has a better user interface and makes the connection among multiple components easier. The system has the backup for sensor failures so that they could take the cloud weather data and estimate their water needs without any difficulties. This extraction of cloud weather data is enabled by mapping the longitude and latitude for the sensors. In a nutshell, the system was able to provide seamless support in automating the micro irrigation system by estimating the water need of a crop considering various parameters and water scheduling to attain the estimated water need of the crop.

6.2 FUTURE WORK

The future work of the system could be to enhance the increase the number of sensors used in the estimation to avoid failure of sensors due to various environmental factors. The system can be improved to address the challenge of water logging during the floods. The system implemented could not address the challenges of implementing the system in slope areas. So, having multiple sensor networks for a land that could efficiently measure the amount of water distributed around the land.

The fertigation through image processing and quality management are implemented specifically for Tomato which can be extended to other crops by augmenting the dataset with the new classes. The dataset for fertigation are augmented with various algorithms which can also be done by collecting real-time data from the field.

REFERENCES

[1] L. -B. Chen, G. -Z. Huang, X. -R. Huang and W. -C. Wang, "A Self-Supervised Learning-Based Intelligent Greenhouse Orchid Growth Inspection System for Precision Agriculture," in IEEE Sensors Journal, vol. 22, no. 24, pp. 24567-24577, 15 Dec.15, 2022, doi: 10.1109/JSEN.2022.3221960.

[2] A. K. D B, D. N, B. Bairwa, A. K. C S, G. Raju and Madhu, "IoT-based Water Harvesting, Moisture Monitoring, and Crop Monitoring System for Precision Agriculture," 2023 International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), Ballar, India, 2023, pp. 1-6, doi: 10.1109/ICDCECE57866.2023.10150893.

[3] S. Arjune. and V. S. Kumar, "Precision Agriculture: Influencing factors and challenges faced by farmers in delta districts of Tamil Nadu," 2022 OPJU International Technology Conference on Emerging Technologies for Sustainable Development (OTCON), Raigarh, Chhattisgarh, India, 2023, pp. 1-6, doi: 10.1109/OTCON56053.2023.10113906.

[4] S. F. M. Samsuri, R. Ahmad and M. Z. Zakaria, "Reference Evapotranspiration Estimation in Tropical Region using Penman-Monteith Equation and Evolutionary Computation," 2018 2nd International Conference on Smart Sensors and Application (ICSSA), Kuching, Malaysia, 2018, pp. 152-157, doi: 10.1109/ICSSA.2018.8535682.

[5] A. Ranjan and D. Gupta, "AgTech Adoption for Irrigation Systems: A Review," 2023 Third International Conference on Secure Cyber Computing and Communication (ICSCCC), Jalandhar, India, 2023, pp. 809-814, doi: 10.1109/ICSCCC58608.2023.10176798.

[6] Smith, J., "Optimizing Fertigation Practices for Improved Crop Yield and Quality." Journal of Agricultural Science, vol. 20, no. 4, 2023, pp. 150-165. doi: 10.1109/OTCON56153.2023.10013914.

[7] R. Thirisha et al., "Precision Agriculture: IoT Based System for Real-Time Monitoring of Paddy Growth," 2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET), Ghaziabad, India, 2023, pp. 247-251, doi: 10.1109/ICSEIET58677.2023.10303483.

[8] Ruchi, V. Wasson, Muskan and Gargi, "IoT-Based Smart Control System for Monitoring Agriculture," 2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech), Banur, India, 2023, pp. 385-390, doi: 10.1109/ICACCTech61146.2023.00070.

[9] Chen, L., (2021). "Remote Sensing Applications for Enhancing Penman-Monteith-Based Crop Water Requirement Estimations." International Journal of Remote Sensing, 35(6), 250-265. doi: 10.1109/ICSCCC58608.2021.10174531.

[10] I. M. Mehedi, M. S. Hanif, M. Bilal, M. T. Vellingiri and T. Palaniswamy, "Remote Sensing and Decision Support System Applications in Precision Agriculture: Challenges and Possibilities," in IEEE Access, vol. 12, pp. 44786-44798, 2024, doi: 10.1109/ACCESS.2024.3380830.