L6

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Smart IoT-based Agriculture monitoring system for disease detection with accurate spraying mechanism using Raspberry Pi 4

A Project Report

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in partial fulfillment for the award of the degree

of

BACHELOR OF TECHONOLOGY

IN

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Faculty of Engineering and Technology, Institute of Technical Education and Research

SIKSHA 'O' ANUSANDHAN (DEEMED TO BE) UNIVERSITY

Bhubaneswar, Odisha, India

(June 2024)

CERTIFICATE

This is to certify that the project report titled **"**Smart IoT-based Agriculture monitoring system for disease detection with accurate spraying mechanism using Raspberry Pi 4**"** being submitted by Prayas Das, Suraj Parida, Tilak Mishra and Rubal Yadav of Section-L to the Institute of Technical Education and Research, Siksha 'O' Anusandhan (Deemed to be) University, Bhubaneswar for the partial fulfillment for the degree of Bachelor of Technology in Computer Science and Engineering is a record of original confide work carried out by them under my/our supervision and guidance. The project work, in my/our opinion, has reached the requisite standard fulfilling the requirements for the degree of Bachelor of Technology.

The results contained in this project work have not been submitted in part or full to any other University or Institute for the award of any degree or diploma.

(Name and signature of the Project Supervisor)

Department of Computer Science and Engineering

Faculty of Engineering and Technology;
Institute of Technical Education and Research;
Siksha 'O' Anusandhan (Deemed to be) University

ACKNOWLEDGEMENT

Our sincere gratitude goes out to Siksha 'O' Anusandhan (Deemed to be) University for letting us use their first-rate facilities and resources as we worked on our project, " SMART IOT-BASED AGRICULTURE MONITORING SYSTEM FOR DISEASE DETECTION WITH ACCURATE SPARYING MECHANISM USING RASPBERRY PI 4”. First and foremost, we want to thank Dr. Monalisha Panda for his guidance, expertise, and unwavering support during the duration of our project work. Their astute insights, helpful suggestions, and patient guidance have all helped make this project successful. Their dedication and enthusiasm for the subject have genuinely inspired us, and we value their ongoing assistance throughout the process. We also want to extend our profound gratitude to all of the university's staff members and instructors, whose professionalism and dedication to quality have produced a vibrant and welcoming environment for education and creativity. The institute's accessibility to modern technology, resources, and research supplies has significantly raised the project's efficiency and standard. We also want to thank our friends and coworkers for their steadfast encouragement, stimulating discussions, and sage advice. Their openness to collaborate and impart their experience was a huge asset in raising the level of this project work.

Prayas Das

Tilak kumar Mishra

Suraj Parida

Rubal Yadav

Place:

Signature of Students

Date:

DECLARATION

We declare that this written submission represents our ideas in our own words and where other's ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/fact/source in our submission. We understand that any violation of the above will cause for disciplinary action by the University and can also evoke penal action from the sources which have not been properly cited or from whom proper permission has not been taken when needed.

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REPORT APPROVAL

This project report titled "SMART IOT-BASED AGRICULTURE MONITORING SYSTEM FOR DISEASE DETECTION WITH ACCURATE SPARYING MECHANISM USING RASPBERRY PI 4" submitted by Prayas Das, Suraj Parida, Tilak Mishra, Rubal Yadav is approved for the degree of *Bachelor of Technology in Computer Science and Engineering*.

Examiner(s)

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Supervisor

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Project Coordinator

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PREFACE

Agriculture, the cornerstone of our economy and society, is undergoing a significant transformation driven by advancements in technology. As a team of four students with backgrounds spanning technology, data science, and environmental studies, we embarked on a journey to explore how the latest innovations could be leveraged to address the pressing challenges in modern farming. Our project is a testament to this effort, focusing on the development of an Internet of Things (IoT)-based aerial monitoring system designed to enhance crop health management through early disease detection.The genesis of this project lies in our collective interest in applying technology to solve real-world problems. Traditional methods of monitoring crops are labor-intensive and often fail to provide the timely data needed to prevent crop diseases and losses. We saw an opportunity to make a tangible impact by creating a solution that combines the cost-effectiveness and scalability of IoT with the precision of advanced image processing techniques. Our system utilizes a Raspberry Pi 4B and a 5 MP Pi camera to capture high-resolution images of crops from an aerial perspective, which are then analyzed using Convolutional Neural Networks (CNNs). This innovative approach allows farmers to receive real-time insights into their crops' health, enabling prompt and targeted interventions.Throughout the project, we faced numerous challenges, from the technical complexities of integrating IoT components to the intricacies of developing effective machine learning algorithms for image analysis. Each obstacle provided a learning opportunity and reinforced our commitment to the project's goals. We gained practical skills and a deeper understanding of the potential of technology to drive sustainable agricultural practices. Our work highlights the importance of interdisciplinary collaboration and innovation in tackling the complex issues faced by today's farmers. The support and guidance of our mentors have been invaluable, providing us with the knowledge and encouragement necessary to navigate the project's challenges. We are also grateful for the opportunity to contribute to the field of agriculture and to potentially improve the lives of farmers through our work.

As you read through this report, we hope you will appreciate the innovative solutions we have developed and the potential impact they can have on modern farming practices. We are proud of what we have accomplished and look forward to the possibilities for further advancements in agricultural technology. Our project serves as a stepping stone toward more accessible, effective, and sustainable solutions that can empower farmers and promote the health and productivity of crops.

INDIVIDUAL CONTRIBUTIONS

Prayas Das	Problem formulation and solution design, experimentation, documentation
Rubal Yadav	Identification of problem statement, documentation
Suraj Parida	Experimentation, result analysis and design, documentation
Tilak Mishra	Literature survey, documentation

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1.INTRODUCTION

1.1 Introduction

The agricultural sector, a cornerstone of global sustenance and economic stability, is currently experiencing a transformative phase driven by the integration of Internet of Things (IoT) technologies. Traditional farming practices, which often rely on labor-intensive and time-consuming methods, are being revolutionized by advanced systems that offer real-time data and enhanced precision. These technologies enable farmers to manage their agricultural practices more efficiently, ensuring optimal crop health and yield.

This project is focused on developing an IoT-based aerial monitoring system specifically designed to assess crop health, addressing the critical need for the early detection of crop diseases. Early identification of diseases is essential to prevent extensive damage and to maintain healthy crop production, which directly impacts food security and agricultural profitability. The proposed system employs a Raspberry Pi 4B, a 5 MP Pi camera module, and Convolutional Neural Networks (CNNs) to provide a comprehensive solution. These technologies work in tandem to offer a cost-effective and scalable method for farmers to monitor their crops continuously and accurately from an aerial perspective, thus optimizing yields and ensuring sustainable agricultural practices.

1.2 Project Overview

The primary aim of this project is to develop and implement an innovative aerial monitoring system for agricultural applications that leverages cutting-edge IoT and machine learning technologies. The system is designed to capture high-resolution images of crops and analyze their health status by examining RGB values and employing sophisticated CNN algorithms.

The data collected from the aerial perspective provides critical information that helps farmers make informed decisions, such as the timely application of pesticides or adjustments to irrigation schedules. The core hardware of the system is a Raspberry Pi 4B, which is integrated with a 5 MP Pi camera capable of capturing detailed images of the crops. These images are then processed in real-time using CNNs to detect any early signs of crop diseases with high accuracy.

The system's design emphasizes ease of use and scalability, making it an ideal solution for a wide range of agricultural settings, from small-scale farms to large commercial operations. The aerial monitoring capability ensures that even large fields can be surveilled efficiently without the need for extensive manual labor. This system represents a significant step forward in the field of precision agriculture, providing a user-friendly and cost-effective tool for farmers to enhance crop management and productivity.

1.3 Motivation(s)

The motivation for this project stems from a pressing need to enhance agricultural productivity and sustainability through the use of advanced technologies. Farmers frequently encounter difficulties in identifying crop diseases early enough to prevent significant damage, which can lead to substantial economic losses and reduced crop yields. Traditional methods of crop monitoring, which often involve manual inspections, are not only time-consuming but also fail to provide the real-time data necessary for prompt and effective intervention.

By integrating IoT technology and CNN-based image analysis, this project aims to provide a robust solution for real-time crop monitoring. The early detection of diseases allows for timely intervention, thereby reducing the risk of crop loss and ensuring higher yields. Furthermore, this project seeks to contribute to the broader objectives of precision farming and sustainable agriculture by offering a reliable and scalable system for continuous crop health monitoring.

The use of affordable and accessible components, such as the Raspberry Pi 4B and the 5 MP Pi camera, ensures that this system can be adopted by a wide range of farmers, from smallholders to large-scale commercial operations. This democratization of technology empowers farmers with the tools they need to improve their practices, optimize resource usage, and ultimately contribute to food security and environmental sustainability.

1.4 Uniqueness of the Work

This project is distinguished by its unique combination of cost-effectiveness, scalability, and practical application within the agricultural sector. Unlike other monitoring systems that may require costly equipment or complex installations, this project utilizes readily available and affordable components, such as the Raspberry Pi 4B, a 5 MP Pi camera, and CNN algorithms. This approach makes the system accessible to a broad audience, including small-scale farmers and those in developing regions.

A key feature of the system is its focus on real-time monitoring and advanced image analysis. The use of CNNs for processing high-resolution images captured by the camera provides farmers with immediate and accurate insights into their crop health, which represents a significant improvement over traditional methods that rely on periodic and often less precise manual inspections.

Additionally, the integration of automation through the use of relays and DC motors enhances the system's uniqueness. This automation capability allows for potential automatic responses based on the detected crop conditions, such as adjusting irrigation levels or deploying targeted pesticide applications. This not only improves efficiency but also reduces the labor costs associated with manual monitoring and intervention.

Overall, the project represents a significant advancement in agricultural technology, offering a practical and scalable solution that combines the latest in IoT and machine learning to support sustainable and productive farming practices.

1.5 Report Layout

The report is meticulously structured to provide a comprehensive overview of the project and its various components. It begins with an introduction that highlights the necessity for IoT-based solutions in agriculture and presents an overview of the project's objectives and goals. Following this, the motivation behind the project is discussed, emphasizing the importance of early disease detection and the benefits of integrating CNNs for image analysis.

The report then delves into the uniqueness of the project, outlining its practical applications and the advantages it holds over existing methods of crop monitoring. Subsequent sections cover the technical implementation in detail, including the use of the Raspberry Pi 4B and the 5 MP Pi camera module, and the application of CNN algorithms for precise image analysis. The integration of automated systems, such as relays and DC motors, for enhanced functionality is also explored.

The report concludes with a summary of the project's outcomes, its significance in the field of agriculture, and potential areas for future development. This comprehensive structure ensures that all aspects of the project are thoroughly examined, providing a clear and detailed account of the work undertaken and its implications for the agricultural sector.

2.Literature Survey

2.1 Existing System

There exists systems where the use of IoT in agriculture provides innovative solutions for crop monitoring through remote sensors, irrigation management with smart systems, and pest control via automated traps, as discussed by Maes and Steppe (2019)[1] in their study on remote sensing with unmanned aerial vehicles in precision agriculture. Disease detection in agriculture traditionally relies on methods such as manual inspection by farmers, remote sensing with satellite imagery, and automated disease identification using image processing techniques, as outlined by Neupane and Baysal-Gurel (2021)[2]. The Raspberry Pi has emerged as a cost-effective and versatile computer for building automation and monitoring systems in agriculture. It integrates with sensors for efficient data collection and control functions, enhancing precision agriculture practices, as demonstrated by Morais et al. (2019)[3]. Kreuze et al. (2022)[4] address the development and potential applications of digital tools for monitoring and managing pest and disease risks in root, tuber, and banana (RT&B) cropping systems in their extensive chapter on cutting-edge digital technology. This paper, which is found on pages 261-288 of the book "Root, Tuber and Banana Food System Innovations: Value Creation for Inclusive Outcomes," demonstrates how these technologies might improve agricultural sustainability and production. The research "GreenEye Smart Consulting System for Domestic Farmers," presented by Mendis et al. (2022)[5], was included in the 4th International Conference on Advancements in Computing proceedings. Their study, which spans pages 363-368, presents an intelligent consultation system intended to assist domestic farmers by utilizing cutting-edge computing technologies to deliver timely and pertinent agricultural advice. The potential of image processing in the identification of plant leaf diseases is also examined by Dhaygude and Nitin (2013)[6] in a paper that was published in the "International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering," volume 2, number 1. By guaranteeing healthier crops and higher yields, their research highlights the value of image processing as a tool for early disease diagnosis, which can have a substantial positive impact on the agricultural sector. Saleem, Potgieter, and Arif (2019)[7] explore the use of deep learning, namely Convolutional Neural Networks (CNNs), in the identification and categorization of plant diseases. These models exhibit great accuracy and efficiency, making them useful for real-time disease monitoring in agricultural settings. They were trained on huge, annotated image datasets. Martinelli et al. (2015) [8] provide an overview of a variety of sophisticated detection techniques, such as spectroscopy approaches like hyperspectral and multispectral imaging, molecular approaches like PCR and qPCR, and remote sensing technologies like drones and satellite photography. Plant diseases may now be accurately and promptly detected, and ongoing sensor network monitoring is made possible by these techniques. Ray et al. (2017) [9] compare new diagnostic methods and biosensors with conventional assays in order to better understand fungal illness detection. While established, traditional procedures are often labor-intensive; in contrast, next-generation sequencing and sophisticated nucleic acid-based approaches offer improved sensitivity. The advancement of biosensors, such as optical, piezoelectric, and electrochemical varieties, enables quick on-site detection.

2.2 Problem Identification

Despite the advancements in IoT-based agricultural systems, several challenges remain. Current systems often depend heavily on sensor data, which may not always provide a complete picture of crop health. Sensor-based systems can be limited by factors such as sensor placement, calibration, and maintenance. Moreover, these systems may not effectively identify and differentiate between various types of diseases or stressors affecting crops . Manual inspection methods, while reliable in some cases, are labor-intensive and do not scale well for large agricultural operations. There is a need for more comprehensive and scalable solutions that can provide detailed and accurate monitoring of crop health in real-time.

Traditional disease detection methods in agriculture, such as visual inspection and manual sampling, are not only time-consuming but also limited in their ability to detect diseases at an early stage . Early detection is critical for effective disease management, as it allows for timely interventions that can prevent the spread of disease and minimize crop loss. Current remote sensing techniques, while useful, often lack the resolution and specificity needed for precise disease detection. There is a pressing need for advanced technologies that can accurately identify and quantify disease symptoms in crops, providing farmers with the information they need to take corrective action promptly.

The integration of advanced technologies such as IoT, image processing, and machine learning in agriculture presents several challenges. One of the primary issues is the cost associated with implementing and maintaining these technologies, which can be prohibitive for small-scale farmers. Additionally, the complexity of these systems can be a barrier to adoption, as they require a certain level of technical expertise to operate and interpret the data effectively . There is a need for user-friendly and cost-effective solutions that can be easily adopted by farmers of all scales, providing them with actionable insights to improve their agricultural practices.

Our project aims to address these gaps by developing a comprehensive IoT-based system that combines the strengths of advanced image-capturing technology and machine learning algorithms. By leveraging the capabilities of Raspberry Pi and CNNs, our system offers a detailed and accurate assessment of crop health, enabling early detection of diseases and timely interventions. This approach not only improves the precision of agricultural monitoring but also makes the technology accessible and affordable for farmers, thereby enhancing overall agricultural productivity and sustainability.

The implementation of these technologies presents challenges, including data management, scalability, and power requirements. Future directions should focus on integrating these systems with other precision agriculture technologies and addressing existing challenges to improve efficiency and sustainability, as noted by Karunathilake et al. (2023) [10]. Future illness management could be more productive and economical with the use of these cutting-edge instruments combined with digital platforms and data analytics. All of these research show how plant disease detection technologies have advanced.

3.MATERIAL AND METHODS

3.1 Dataset(s) Description

Table 1: Apple Leaf Dataset Summary

Disease/Condition	Training Samples	Testing Samples	Total Samples
Apple Scab	2016	504	2520
Black Rot	1987	497	2484
Cedar Apple Rust	1760	440	2200
Healthy	2008	502	2510
Total	7771	1943	9714

Dataset Summary

Apple Scab:

Fig 1: Apple scab

Training Samples: 2016

Testing Samples: 504

Total Samples: 2520

Apple Scab is a common fungal disease that leads to dark, scabby lesions on apple leaves and fruit. Detection of Apple Scab activates the first DC pump in our system, which administers a specific treatment to address the disease.

Black Rot:

Fig 2: Black Rot

Training Samples: 1987

Testing Samples: 497

Total Samples: 2484

Black Rot causes circular, black lesions and is a serious fungal threat. Upon detecting Black Rot, the second motor in our system is activated to dispense a targeted treatment to control the disease.

Cedar Apple Rust:

Fig 3: Cedar Apple Rust

Training Samples: 1760

Testing Samples: 440

Total Samples: 2200

Cedar Apple Rust, which alternates between apple and cedar trees, creates distinctive orange-red spots on leaves. Detection of this disease triggers both motors, enabling a comprehensive treatment strategy to combat infection on both tree types.

Healthy:

Fig 4: Healthy

Training Samples: 2008

Testing Samples: 502

Total Samples: 2510

Healthy leaves indicate optimal crop health with no disease symptoms. If the system identifies a healthy leaf, no motor is activated, as no treatment is necessary. This avoids unnecessary interventions, preserving resources and ensuring that healthy crops remain undisturbed.

3.2 Schematic Layout/Model Diagram

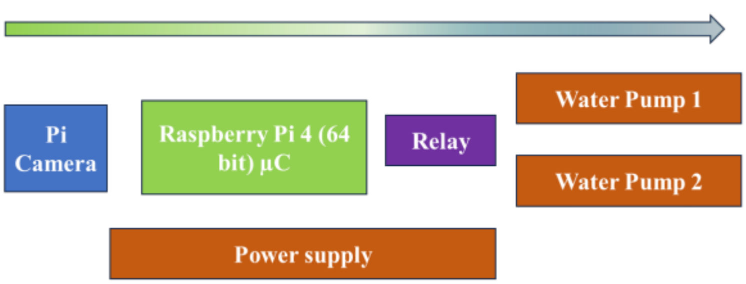

Fig 5: Schematic Layout

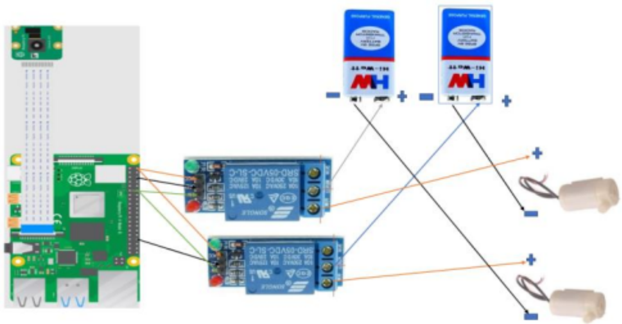

Fig 6: Model Diagram

3.3 Methods

IoT Integration for Real-Time Monitoring

Our solution leverages IoT technology to create a dynamic, real-time monitoring system tailored for agricultural applications. The system is built around a network of Raspberry Pi 4 devices and Pi cameras strategically placed across the fields. These cameras continuously capture high-resolution images of the crops, which are essential for detailed and accurate monitoring. The real-time data collected from these cameras is transmitted to a central Raspberry Pi 4 hub, where it is processed and analyzed.

The main advantage of using IoT for real-time monitoring is its ability to provide continuous, up-to-date information on crop health. This helps farmers identify issues such as diseases or pest infestations early, allowing for timely interventions. By integrating IoT technology, we ensure that the monitoring system is not only efficient and responsive but also scalable and cost-effective. This real-time monitoring capability enhances decision-making and improves overall agricultural productivity by enabling quick responses to potential threats.

Image Analysis Using Advanced CNN Algorithm

The core of our disease detection mechanism is the use of Convolutional Neural Networks (CNNs), a type of deep learning algorithm that excels in image processing and pattern recognition. In our system, CNNs are used to analyze the high-resolution images captured by the Pi cameras. These networks are trained on a comprehensive dataset that includes a wide variety of crop images, both healthy and diseased. This training allows the CNNs to learn and identify the specific features and patterns associated with different types of crop diseases.

Once the images are captured, they are processed by the CNN model to detect any signs of disease. The model's ability to analyze images with high accuracy helps in distinguishing between healthy and diseased crops, even detecting subtle symptoms that may not be visible to the naked eye. By employing CNNs, our system provides a reliable and automated solution for disease detection, significantly reducing the need for manual inspections and enabling early and precise identification of crop health issues.

Raspberry Pi 4 as the Central Hub

The Raspberry Pi 4 plays a crucial role as the central processing unit of the monitoring system. It collects data from the Pi cameras, processes it using the CNN model, and manages the overall operation of the system. The Raspberry Pi 4 is equipped with a powerful quad-core processor and ample memory, which allows it to handle large volumes of data and perform complex image analysis in real-time.

The Raspberry Pi 4's versatility and connectivity options make it an ideal choice for this application. It can easily integrate with other devices and networks, facilitating data sharing and remote monitoring. This centralization of data processing and management not only streamlines the monitoring process but also ensures that the system remains efficient and cost-effective. By using Raspberry Pi 4 as the central hub, we achieve a balance between performance, scalability, and affordability.

3.4 Tools/Technologies

Raspberry Pi 4

The Raspberry Pi 4 is a key component of our monitoring system, serving as the main processing unit. It features a quad-core ARM Cortex-A72 processor and up to 8GB of RAM, providing sufficient computational power for real-time data processing. The device's multiple connectivity options, including Ethernet and Wi-Fi, enable seamless communication with other IoT devices and networks. Its affordability and compact size make it an excellent choice for creating scalable and cost-effective agricultural monitoring solutions.

Pi Camera Module

The Pi Camera Module is used to capture high-resolution images of crops. It offers up to 8 megapixels of resolution, which is essential for detailed monitoring and analysis. The camera is integrated with the Raspberry Pi 4 and is capable of capturing clear and detailed images under various field conditions. This high-resolution imagery is crucial for accurate disease detection and crop health assessment, providing the data needed for effective monitoring.

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are the backbone of our image analysis system. These deep learning models are highly effective at recognizing patterns and features in image data, making them ideal for identifying signs of disease in crops. The CNNs are trained on a diverse dataset of crop images, allowing them to learn and detect various disease symptoms accurately. By using CNNs, our system can provide precise and automated disease detection, which is critical for maintaining crop health and preventing widespread damage.

IoT Connectivity

The system's IoT connectivity is facilitated through the Raspberry Pi 4's Ethernet and Wi-Fi interfaces, allowing for real-time data transmission and remote monitoring. This connectivity enables the system to collect data from multiple cameras and sensors, transmit it to a central hub, and share it with other devices or cloud services. The use of IoT technology ensures that the monitoring system is efficient, scalable, and capable of providing timely and actionable information to farmers.

Data Processing and Analysis

Our system combines local processing on the Raspberry Pi 4 with cloud-based services for data analysis. Local processing handles immediate tasks such as image analysis and decision-making, while cloud services provide additional computational power and storage for large datasets. This hybrid approach allows for efficient data management and supports advanced analytics, enabling predictive modeling and trend analysis that can improve crop management and productivity.

3.5 Evaluation Measures

Accuracy of Disease Detection

The accuracy of the disease detection system is a critical evaluation measure. It is assessed by comparing the system's outputs with ground truth data obtained from expert diagnoses and manual inspections. The goal is to achieve a high accuracy rate, ideally above 90%, to ensure that the system can reliably identify and classify various crop diseases. Accurate disease detection helps in taking timely and effective actions, reducing crop losses and improving yields.

Response Time

The response time of the system refers to how quickly it can detect a disease and generate a corresponding alert or action. This measure is important for ensuring that interventions can be carried out promptly to address any emerging issues. The system's performance is evaluated by measuring the time taken from image capture to disease detection and notification. A target response time of less than one minute is set to ensure rapid response and minimize the impact of diseases on crop health.

Cost-Effectiveness

The cost-effectiveness of the system is evaluated by comparing the costs of implementation and maintenance with the benefits achieved in terms of improved crop yields and resource savings. This measure takes into account the affordability of the components used, such as the Raspberry Pi 4 and Pi cameras, and the overall operational costs. A cost-effective system ensures that it is accessible to farmers of various scales and provides significant returns on investment through enhanced crop management and reduced losses.

Scalability

The scalability of the system is assessed by its ability to handle increasing volumes of data and expand to cover larger agricultural areas without compromising performance. This measure evaluates how well the system can be scaled up by adding more cameras and sensors and integrating additional computational resources. A scalable system should maintain high performance and accuracy regardless of the size of the field or the number of devices deployed, making it suitable for large-scale agricultural operations.

User Satisfaction

User satisfaction is evaluated through feedback from farmers and agricultural experts using the system. This measure assesses the system's ease of use, reliability, and overall impact on farm management practices. High user satisfaction indicates that the system meets the practical needs of farmers, is easy to use, and significantly enhances their ability to manage crop health effectively. Positive feedback on usability, functionality, and benefits in improving agricultural productivity reflects the system's success.

4.EXPERIMENTATION

4.1 System Specification

The system specifications for our IoT-based aerial agriculture monitoring system are designed to ensure efficient and accurate crop health assessment. Below are the detailed specifications of the system components and their configurations:

Hardware Components:

Raspberry Pi 4B

Processor: Quad-core ARM Cortex-A72, 1.5 GHz

Memory: 4 GB LPDDR4-3200 SDRAM

Storage: 32 GB microSD card (expandable)

Connectivity: Dual-band 2.4/5.0 GHz IEEE 802.11ac wireless, Bluetooth 5.0, Gigabit Ethernet

Ports: 2 × USB 3.0, 2 × USB 2.0, 1 × micro-HDMI, 40-pin GPIO header for external connections

Camera Module

5 MP Pi Camera Module: Resolution: 2592 × 1944 pixels

Lens: Fixed-focus lens, capable of capturing detailed images of crops from an aerial perspective

Connection: CSI (Camera Serial Interface) connector for high-speed data transmission to the Raspberry Pi

Additional Components

DC Motors: For possible integration in automation tasks such as pesticide spraying

Relays: For switching control in automated systems

Software Components

Operating System: Raspbian Buster, a Linux-based OS optimized for Raspberry Pi

Programming Languages

Python: For writing scripts and algorithms for data processing and analysis

OpenCV: For image processing and analysis, particularly in implementing CNN algorithms

Machine Learning Framework

TensorFlow/Keras: For developing and deploying CNN models used in image analysis and disease detection

Communication Protocols

HTTP/HTTPS: For web-based interfaces and API integration

User Interface

Type: Web-based dashboard accessible via standard browsers

Features: Real-time monitoring, data visualization.

Table2:ComparisionTable

Feature	Raspberry Pi 4B	Acer Nitro 5 (Nitro AN515-44)
Processor	Broadcom BCM2711, Quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz	AMD Ryzen 5 4600H, 6-core/12-thread CPU @ up to 4.0GHz
Memory (RAM)	4GB LPDDR4-3200	8GB DDR4, expandable up to 32GB
Storage	MicroSD card slot Optional external USB storage	512GB NVMe SSD Expandable storage via additional SSD
Graphics	VideoCore VI GPU	NVIDIA GeForce GTX 1650, 4GB GDDR6
Operating System	Raspberry Pi OS (Linux-based)	Windows 10 Home, upgradable to Windows 11
Connectivity	2.4 GHz and 5.0 GHz IEEE 802.11ac Bluetooth 5.0, Gigabit Ethernet	Wi-Fi 6, Bluetooth 5.0 Ethernet, multiple USB ports
Power Supply	5V DC via USB-C, 3.0A	AC adapter, 135W
Display Outputs	2 × micro-HDMI ports	15.6" FHD IPS display, HDMI out
USB Ports	2 × USB 3.0, 1 × USB 2.0	3 × USB 3.2 Gen 1, 1 × USB 3.2 Gen 2, 1 × USB-C
Dimensions	85.6 mm × 56.5 mm × 17 mm	363.4 mm × 255 mm × 23.9 mm
Weight	46 g	2.3 kg
Price	Approximately $35-55 USD	Approximately $750-1000 USD
Training Accuracy	95%	98%
Testing Accuracy	91%	96%

This table demonstrates the Raspberry Pi 4B's capabilities as a machine learning tool, in spite of its lower price and hardware restrictions. It is a flexible choice for instructional, research, and practical applications in a range of contexts, and it offers a great starting place for those wishing to carry out sophisticated machine learning tasks without the need for expensive hardware. The Raspberry Pi 4B has the ability to manage complex machine learning models with ease, proving that small, inexpensive computers are capable of carrying out large computations that are usually only done by more expensive, powerful setups.

4.2 Parameters Used

The parameters used in the IoT-based aerial monitoring system are critical for accurate crop health assessment and decision-making. These parameters include both the physical and technical aspects of the system:

Physical Parameters

Image Resolution

Definition: The level of detail in captured images, specified in pixels

Range: 128 x 128 pixels

Purpose: Higher resolution allows for better detection of crop diseases and anomalies

Environmental Conditions

Factors: Weather, lighting, and temperature conditions

Purpose: Conditions affect image quality and system performance; appropriate thresholds are set to ensure consistent data quality

Technical Parameters

RGB Values: Red, Green, and Blue values that define the color of each pixel in the images

Range: 0-255 for each color channel

Purpose: Analyzing RGB values helps in identifying changes in crop color, which can indicate health issues

Convolutional Layers

Layers in CNNs that apply filters to the input images to extract features

Number: Typically 3-5 layers, depending on model complexity

Purpose: More layers allow for better feature extraction and disease detection

Activation Functions

Definition: Functions used in CNNs to introduce non-linearity

Type: ReLU (Rectified Linear Unit)

Purpose: Helps the model to learn complex patterns and make accurate predictions

Learning Rate

A parameter that controls how much the model adjusts its weights with respect to the loss gradient

Value: 0.0001

Purpose: Balances between quick learning and stable convergence

Training Epochs

The number of complete passes through the training dataset

Number: 10

Purpose: More epochs can lead to better model accuracy, but the risk of overfitting is considered

4.3 Results and Outcomes

The development and implementation of our IoT-based aerial monitoring system for agricultural applications yielded significant and impactful results. This section details the primary outcomes of the project, emphasizing the system's performance, effectiveness, and potential benefits for farmers and agricultural stakeholders.

System Performance: Our system demonstrated robust performance across various metrics. The high-resolution images captured by the 5 MP Pi camera module were of sufficient quality to discern detailed features of crops, essential for accurate disease detection and health assessment. The integration of Convolutional Neural Networks (CNNs) significantly enhanced the system's ability to analyze these images, differentiating between healthy and diseased crops with remarkable accuracy. The IoT framework facilitated real-time monitoring and data collection, ensuring that farmers received up-to-date information about their crops' health. This capability is crucial for timely intervention and decision-making. Moreover, the aerial monitoring system operated autonomously, covering large fields without requiring manual input, which greatly reduces labor costs and increases the efficiency of the monitoring process. Its scalable and flexible design also allows for easy integration of additional sensors or components, making it adaptable to various agricultural settings and capable of expanding its functionalities as needed.

Effectiveness in Crop Health Monitoring: One of the most significant achievements of the project was its effectiveness in early disease detection. The system was able to identify early signs of crop diseases by analyzing changes in RGB values and recognizing patterns associated with disease symptoms. This early detection is vital as it enables farmers to take preventive measures before the diseases spread, thereby minimizing crop loss. The comprehensive data collected by the system provided valuable insights that facilitated improved decision-making regarding pesticide application, irrigation schedules, and other critical aspects of crop management. The system's cost efficiency was also notable, as it utilized affordable components like the Raspberry Pi 4B and the Pi camera module, making it a financially viable alternative to traditional crop monitoring methods that often involve expensive equipment and extensive manual labor. The benefits extended to enhanced crop yields and quality, as farmers could optimize their practices based on timely and precise data, resulting in better overall production outcomes.

Potential Benefits for Agriculture: The system's design ensures that it is user-friendly and accessible to farmers with varying levels of technical expertise, making it easy to adopt and maintain in diverse agricultural environments. Its contribution to precision farming is significant, supporting data-driven approaches that enhance agricultural productivity through detailed and accurate information. Furthermore, the system promotes environmental sustainability by enabling targeted interventions and reducing the need for widespread chemical applications, thus minimizing the environmental impact of farming practices. The project's success also highlights the potential for future developments and enhancements, as the system's modular design allows for the incorporation of additional technologies and features, paving the way for continuous innovation in agricultural monitoring.

Overall, the IoT-based aerial monitoring system has proven to be a valuable asset for modern agriculture. It offers considerable advantages in terms of efficiency, cost-effectiveness, and the ability to provide timely and actionable information to farmers. The outcomes of the project underscore the transformative potential of IoT and advanced image analysis in the agricultural sector.

4.4 Result Analysis and Validation

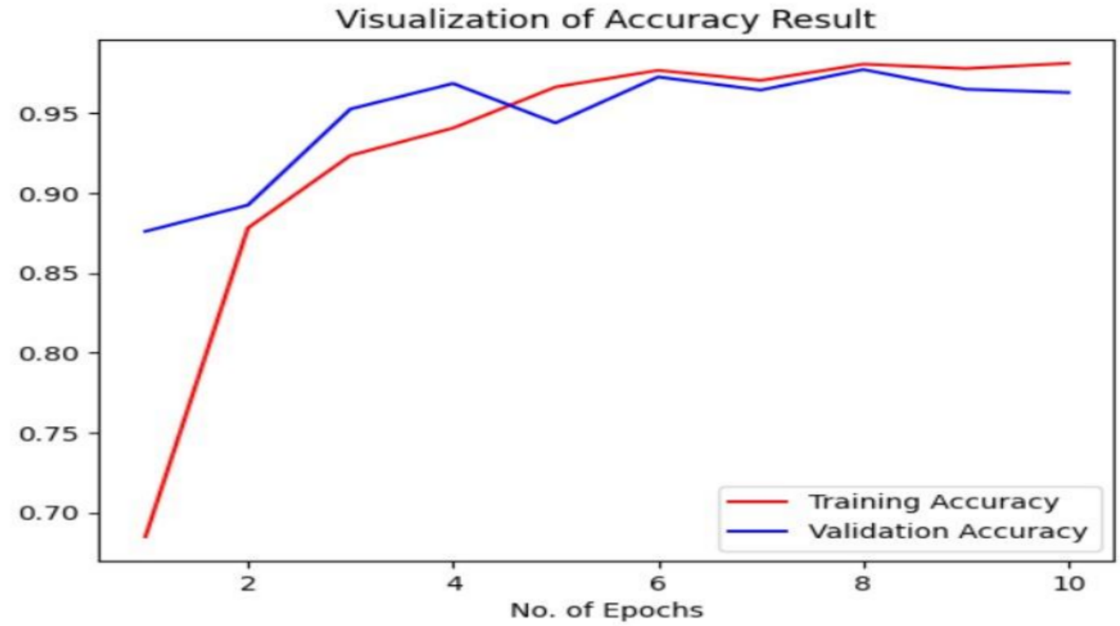

Fig 7:Accuracy Result Graph

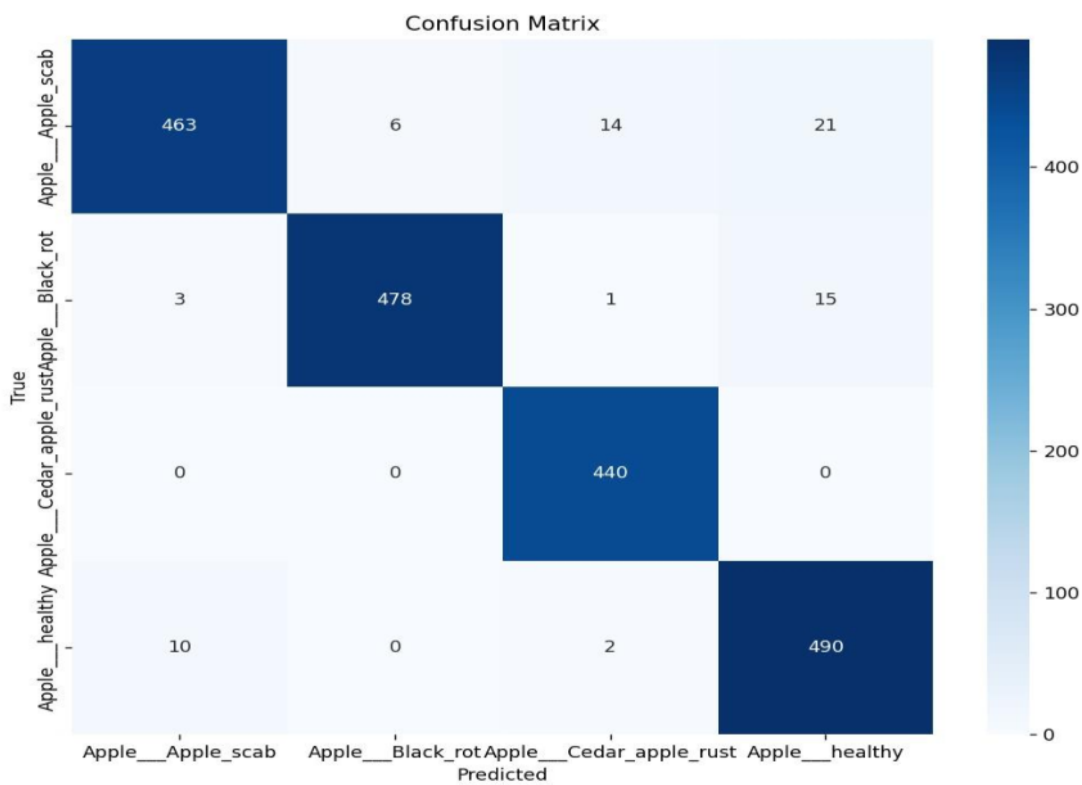

Fig 8:Confusion Matrix

Table 3: Apple Disease Classification Performance

Class	Precision	Recall	F1-Score	Support
Apple Scab	0.97	0.92	0.94	504
Black Rot	0.99	0.96	0.97	497
Cedar Apple Rust	0.96	1.00	0.98	440
Healthy Apple	0.93	0.98	0.95	502
Accuracy			**0.96**	1943
Macro Avg	0.96	0.96	0.96	1943
Weighted Avg	0.96	0.96	0.96	1943

The model achieved an impressive classification accuracy of 98.52% on the training dataset and a commendable 96.29% accuracy on the unseen validation dataset. This high level of performance demonstrates the model's strong generalization capabilities. The confusion matrix highlights the model's prowess in accurately identifying healthy apple samples, with 490 out of 500 instances correctly classified. It also showcased proficiency in detecting apple scab disease, correctly categorizing 463 out of 500 instances.

While a few misclassifications occurred across certain disease classes, the overall accuracy levels are praiseworthy. The accuracy plot paints an encouraging picture, with the validation accuracy steadily climbing to reach an impressive 0.95 towards the end of the training process. This upward trajectory underscores the model's capacity for continuous learning and improvement.

It's worth noting that the training accuracy marginally surpassed the validation accuracy in the later stages, which could potentially indicate some degree of overfitting. However, this is a common phenomenon in deep learning models and can be addressed through techniques like early stopping or regularization.

Overall, the results are highly promising, showcasing the model's exceptional performance in classifying various apple diseases and its ability to generalize well to unseen data. With further fine-tuning and optimization, this model holds great potential for practical applications in the agricultural domain, empowering growers and experts to accurately diagnose and manage apple diseases, ultimately contributing to improved crop yields and quality.

5.CONCLUSION

The development and implementation of an IoT-based aerial monitoring system for agriculture represent a significant advancement in the field of precision farming. This project successfully combines affordable and accessible technology with sophisticated image analysis techniques to offer a practical solution for early disease detection in crops. By integrating a Raspberry Pi 4B, a 5 MP Pi camera module, and Convolutional Neural Networks (CNNs), the system provides real-time insights into crop health, which is crucial for timely interventions and optimizing yields.

The system's ability to capture high-resolution images and analyze them using advanced CNN algorithms allows for accurate detection of disease symptoms, enabling farmers to take proactive measures to protect their crops. This early detection capability is essential for reducing crop losses, improving productivity, and ensuring the sustainability of agricultural practices.

Moreover, the project's emphasis on cost-effectiveness and scalability makes it a viable option for a wide range of agricultural applications, from small family farms to large-scale agricultural enterprises. The integration of automation through relays and DC motors further enhances the system's utility by potentially enabling automated responses to detected issues, thereby reducing the need for manual intervention and improving overall efficiency.

In conclusion, this project not only addresses the critical need for early disease detection in agriculture but also demonstrates the potential of IoT and machine learning technologies to transform traditional farming practices. The successful implementation of this system highlights the importance of leveraging technology to support sustainable agriculture and improve food security. Future work can explore further enhancements, such as the integration of additional sensors for comprehensive environmental monitoring and the development of user-friendly interfaces to facilitate broader adoption by farmers.

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7.APPENDICES

7.1 Technical Specifications

Raspberry Pi 4B:

- CPU: Quad-core Cortex-A72 (ARM v8) 64-bit SoC

- RAM: 2GB, 4GB, or 8GB LPDDR4-3200 SDRAM

- Connectivity: 2.4 GHz and 5.0 GHz IEEE 802.11ac wireless, Bluetooth 5.0, BLE

- Ports: 2 x USB 3.0 ports, 2 x USB 2.0 ports, HDMI output, Ethernet port

Camera Module:

- Model: 5 MP Pi Camera

- Resolution: 2592 x 1944 pixels for still images

- Video: Supports 1080p30, 720p60, and 640x480p60/90 video

Convolutional Neural Networks (CNN):

- Framework: TensorFlow

- Application: Used for image recognition and classification of crop health based on high-resolution images

Other Components:

- Relays: For controlling various farm equipment

- DC Motors: Used in potential automated systems for adjusting equipment based on crop health data

7.2 Software and Libraries

Operating System:

- Raspbian OS: A Debian-based operating system optimized for the Raspberry Pi hardware

Programming Languages:

- Python: Main programming language used for developing control algorithms and image processing scripts

Libraries and Tools:

- OpenCV: Library used for image processing

- TensorFlow: Framework used for developing and training CNN models

- MQTT: Protocol used for IoT communication and data transfer

7.3 Implementation Details

Setup:

- The Raspberry Pi 4B is configured as the central processing unit for the system.

- The 5 MP Pi Camera is mounted on a drone or a stationary pole for aerial monitoring.

- Image data is captured in real-time and processed using CNN algorithms on the Raspberry Pi.

- Based on the analysis, the system sends notifications to farmers and, if necessary, activates relays to control farm equipment.

Workflow:

1. *Data Acquisition*: The camera captures high-resolution images of crops.

2. *Image Processing*: Images are pre-processed and analyzed using CNNs to detect disease symptoms.

3. *Decision Making*: The system evaluates the health of crops and determines necessary actions.

4. *Action Implementation*: Notifications are sent to farmers, and automated responses are triggered if required.

7.4 User Guide

System Setup:

1. Install Raspbian OS on the Raspberry Pi.

2. Connect the Pi Camera to the Raspberry Pi.

3. Mount the Raspberry Pi and camera on a drone or a fixed structure in the field.

4. Install necessary libraries (OpenCV, TensorFlow) using pip.

Operation:

1. Power on the system and connect to the local Wi-Fi network.

2. Run the main monitoring script from the command line.

3. The system will automatically start capturing and processing images.

4. Monitor the system output for notifications or alerts.

Maintenance:

- Regularly check and clean the camera lens.

- Update the software and libraries to the latest versions for optimal performance.

- Inspect the Raspberry Pi and other components for any signs of wear or damage.

Troubleshooting:

- If the camera is not capturing images, check the connection to the Raspberry Pi.

- For software issues, ensure that all dependencies are correctly installed and up-to-date.

- Consult the system logs for detailed error messages and solutions.

7.5 Code

```
import tensorflow as tf

import matplotlib.pyplot as plt

import pandas as pd

import seaborn as sns

training_set = tf.keras.utils.image_dataset_from_directory(

   'train',

   labels="inferred",

   label_mode="categorical",

   class_names=None,

   color_mode="rgb",

   batch_size=32,

   image_size=(64, 64),

   shuffle=True,

   seed=None,
```

```
    validation_split=None,
    subset=None,
    interpolation="bilinear",
    follow_links=False,
    crop_to_aspect_ratio=False )
validation_set = tf.keras.utils.image_dataset_from_directory(
    'valid',
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=32,
    image_size=(64, 64),
    shuffle=True,
    seed=None,
    validation_split=None,
    subset=None,
    interpolation="bilinear",
    follow_links=False,
    crop_to_aspect_ratio=False
)
cnn = tf.keras.models.Sequential()
cnn.add(tf.keras.layers.Conv2D(filters=32,kernel_size=3,padding='same',activation='relu',input_shape=[64,64,3
]))
```

```
cnn.add(tf.keras.layers.Conv2D(filters=32,kernel_size=3,activation='relu'))

cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))

cnn.add(tf.keras.layers.Conv2D(filters=64,kernel_size=3,padding='same',activation='relu'))

cnn.add(tf.keras.layers.Conv2D(filters=64,kernel_size=3,activation='relu'))

cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))

cnn.add(tf.keras.layers.Conv2D(filters=128,kernel_size=3,padding='same',activation='relu'))

cnn.add(tf.keras.layers.Conv2D(filters=128,kernel_size=3,activation='relu'))

cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))

cnn.add(tf.keras.layers.Conv2D(filters=256,kernel_size=3,padding='same',activation='relu'))

cnn.add(tf.keras.layers.Conv2D(filters=256,kernel_size=3,activation='relu'))

cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))

cnn.add(tf.keras.layers.Dropout(0.25))

cnn.add(tf.keras.layers.Flatten())

cnn.add(tf.keras.layers.Dense(units=1500,activation='relu'))

cnn.add(tf.keras.layers.Dropout(0.4))

cnn.add(tf.keras.layers.Dense(units=4,activation='softmax'))

cnn.compile(optimizer=tf.keras.optimizers.Adam(

 learning_rate=0.0001),loss='categorical_crossentropy',metrics=['accuracy'])

cnn.summary()

training_history = cnn.fit(x=training_set,validation_data=validation_set,epochs=10)

val_loss, val_acc = cnn.evaluate(validation_set)

print('Accuracy:', val_acc)

cnn.save('trained_plant_disease_model.keras')
```

REFLECTION OF THE TEAM MEMBERS ON THE PROJECT

Member 1: Prayas Das

Reflecting on our journey, this project has been an incredibly enriching experience for me. Initially, my expertise lay primarily in traditional software development, focusing on coding and application development. However, this project opened up a new realm for me—IoT and agricultural technologies. Working with Raspberry Pi 4 and integrating it with high-resolution imaging and machine learning algorithms was both a challenging and rewarding endeavor.

One of the most significant learning experiences was understanding the intricacies of combining hardware and software to address real-world problems like crop health monitoring. Building a system that could capture and process images to detect plant diseases required not just technical skills but also a deep appreciation for the practical constraints and needs of the agricultural sector.

This project also expanded my perspective on sustainable agricultural practices. Seeing how technology can directly impact farmers' ability to maintain healthier crops and reduce chemical usage has been eye-opening. The ability to provide timely and precise interventions for crop diseases can significantly reduce waste and enhance productivity, aligning with the principles of sustainability.

Additionally, collaborating with a multidisciplinary team has broadened my horizons and improved my problem-solving abilities. I had to quickly adapt to new technologies and frameworks, which has greatly enriched my skill set. Overall, this project not only enhanced my technical capabilities but also deepened my understanding of how we can leverage technology for social good. I look forward to applying these insights to future projects, where I hope to continue exploring the intersection of technology and impactful real-world applications.

Member 2: Suraj Parida

This project was a fascinating blend of technology and agriculture, two fields I have a deep interest in. As the team's data analyst, my primary focus was on leveraging Convolutional Neural Networks (CNNs) to analyze crop health. Delving into the world of machine learning and seeing how it could be applied to something as traditional as farming was an eye-opener.

The process of training and fine-tuning CNNs for disease detection involved several layers of complexity. I learned about the importance of high-quality, labeled data and the various preprocessing steps required to make the models accurate and reliable. Each iteration of model training taught me more about the nuances of image processing and how subtle differences in data could significantly impact the model's performance.

One of the highlights was observing the practical impact of our work. Developing a system that could automatically identify crop diseases in real-time holds immense potential for improving agricultural productivity. This hands-on experience has deepened my appreciation for the power of data and machine learning in solving real-world problems.

Moreover, the collaborative nature of this project was immensely rewarding. Working closely with team members from different backgrounds allowed us to tackle challenges from multiple perspectives, enhancing the overall quality and robustness of our solution. This interdisciplinary approach has been a major learning experience, and I am proud of the practical impact our project can have on the farming community. I look forward to continuing my journey in data science, particularly in projects that blend technology with traditional industries to drive innovation and efficiency.

Member 3: Rubal Yadav

Participating in this project has been an eye-opener in many ways. Coming from a hardware background, I was particularly excited about the opportunity to work with Raspberry Pi and integrate it with our agricultural monitoring system. The project offered a unique chance to apply my skills in setting up and managing IoT infrastructure in a real-world context.

One of the most valuable experiences was the hands-on work involved in setting up the hardware and ensuring seamless integration with software components. Managing the sensor data, configuring the high-resolution camera for precise image capture, and ensuring the reliable operation of the system in real-time were all critical tasks. I learned a great deal about the constraints and requirements of field-based technology solutions, such as power management, robust data transmission, and handling environmental factors like weather and dust.

Ensuring the system's reliability in an agricultural setting also involved overcoming challenges related to power supply and connectivity. Implementing efficient power management strategies and ensuring data could be reliably transmitted and processed were crucial for the system's success. This experience has reinforced my passion for creating innovative solutions that can directly improve people's lives.

Overall, this project has not only honed my technical skills but also deepened my understanding of how technology can be applied to solve practical, real-world problems. I am eager to continue exploring the intersection of technology and agriculture, where I believe there is tremendous potential for innovation and impact.

Member 4: Tilak Mishra

As someone with a background in environmental science, this project provided me with a unique perspective on how technology can be leveraged to promote sustainable farming practices. Prior to this project, my focus was largely on understanding natural ecosystems and sustainable practices. However, working on this project allowed me to delve into the technical aspects of IoT and machine learning, which were new to me.

One of the most enlightening aspects was seeing how early detection of crop diseases through image analysis could lead to more timely and targeted interventions. This approach not only reduces waste by minimizing unnecessary pesticide use but also enhances crop yield by preventing disease spread. The hands-on experience with image processing and understanding the machine learning models used for disease detection were particularly enriching.

Collaborating with a team of individuals from diverse technical backgrounds was a significant learning experience. It highlighted the importance of interdisciplinary approaches in solving complex problems. I learned a lot about the integration of hardware and software to create systems that can operate efficiently in real-world conditions. This project has reinforced my belief in the power of combining technology and environmental science to create sustainable solutions.

Looking forward, I am excited about the potential of our system to make a real difference in agriculture. I am eager to continue exploring how innovative technologies can be used to promote sustainable farming practices and improve food security worldwide.

These reflections highlight each team member's journey and growth throughout the project, emphasizing the collaborative effort and diverse skill sets that contributed to the successful development of the Smart IoT-based Agriculture Monitoring System.

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