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Deep Learning-Driven Soccer Drone for Agricultural Health Monitoring System

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Abstract

Agricultural health monitoring systems are critical for guaranteeing food security and increasing crop yields by detecting plant diseases in a timely and accurate manner. Traditional monitoring approaches frequently rely on manual inspections, which are time-consuming, labour-intensive, and susceptible to human mistake, thereby delaying essential solutions. In contrast, modern monitoring systems leverage advanced technologies such as drones, sensors, and deep learning algorithms to continuously track crop health in real-time, enabling precise and targeted interventions. The main goal of this work is to integrating advanced drone technology with deep learning algorithms for real-time monitoring and disease classification in paddy and coconut trees. The drone, assembled using high-performance components, it facilitates efficient and high-resolution imaging under real-world agricultural conditions. The collected visual data is subsequently processed using deep learning techniques to identify and classify diseases affecting paddy and coconut trees. In particular, Residual Network (ResNet) architecture was employed for disease prediction and its performance was benchmarked against a conventional CNN model. Experimental results demonstrate that ResNet outperforms the CNN model, achieving higher accuracy and robustness in disease detection.

1. Introduction

The AI-Powered Alumni Portal: Connect, Learn, Global economies and food security still rely heavily on agriculture, but traditional farming methods are facing more and more difficulties as a result of resource shortages, climatic variability, and the growing need for sustainable practices. A crucial development in this regard is the use of smart agriculture, which combines cutting-edge technology like sensor networks, artificial intelligence, and unmanned aerial vehicles (UAVs) to improve crop monitoring, disease diagnosis, and farm management in general [1]. A key component of the smart agriculture trend is the incorporation of drone technology into farming operations. By leveraging drones, farmers and researchers can obtain comprehensive and accurate datasets that form the foundation for data-driven decision-making [2]. This capability is particularly important for monitoring crops like paddy and coconut trees, where early and precise disease detection can significantly reduce yield losses and improve overall productivity [3]. One of the pivotal advancements in smart agriculture is the use of drones for real-time data collection. Drones provide a unique advantage in agricultural monitoring due to their ability to rapidly survey large areas and capture high-resolution images, which are essential for assessing crop health. In particular, drones have shown significant promise in collecting detailed data from paddy fields and coconut trees. For paddy fields, drone-acquired images of paddy leaves enable the early detection of diseases and stress factors, facilitating timely intervention and precise application of treatments. Similarly, in coconut plantations, drones can efficiently gather data on the health of the trees, identifying potential issues such as nutrient deficiencies or disease symptoms that might not be immediately apparent through traditional ground-level inspections. Precision agriculture, sometimes referred to as smart agriculture, incorporates cutting-edge information and communication technologies into farming methods. Farmers may make data-driven decisions, maximise resource use, and tackle particular issues in their farms thanks to this integration. Sensor networks, geographic information systems (GIS), satellite imaging, and unmanned aerial vehicles (UAVs) or drones are essential elements of smart agriculture that enable real-time crop health and environmental condition monitoring. Maximising agricultural productivity while reducing environmental impact is the driving force behind smart agriculture [4]. Conventional monitoring techniques are frequently time-consuming, labour-intensive, and prone to human error, which can result in inefficient resource use and delayed illness identification. Smart agriculture systems, on the other hand, provide real-time data collecting and analysis, allowing for prompt interventions that can reduce crop losses and encourage environmentally friendly farming methods. For example, UAVs with high-resolution cameras and sensors can swiftly survey wide regions and provide comprehensive data on plant health that would otherwise necessitate a lot of manual labour [5].

2. Literature Review

Chouhan et al. (2021) identified the lesion in a section of biofuel plants using the simple linear iterative clustering (SLIC) method. The SLIC algorithm performs through in terms of colour and pixel intensity after first choosing a range of "n" groups [6]. The subsequent cluster section of the overlapping pixel region is merged with each pixel. The super pixel clustering technique leaves few pixels, making pixel relabelling a difficult operation. Citrus leaf diseases were categorised by Ali et al. (2017) using the Delta-E colour difference technique. The Delta-E algorithm uses dependent illumination and colour differences to identify diseased regions; changes in picture lighting also have an impact on the accuracy of disease diagnosis. Zhang et al. (2017) and Zhang & Wang (2016) used sparse representation and Singular Value Decomposition (SVD) for extract lesion features from infected cucumber leaves. Each row in each column of the image contains a low-level matrix, which contains a lot of redundant information. Key attribute of SVD is its relationship with matrix rank and its ability to approximate a matrix of a given rank [7]. Digital images are usually represented by a short-distance matrix, is described by the sum of a relatively small number of original images. With this feature, SVD extracts structural information from leaf lesions. The sparse representation of image structures such as edges, corners, and textures requires the use of a large number of vector vocabularies. The logarithmic spectrum of the color histogram and the shape of the lesion feature are extracted from the cucumber leaf diseases, which can be displayed in a sparse representation for the classification of leaf diseases [8]. The sparse view model is very useful for images that change their appearance and require more memory because the array contains more zeros. Dhingra et al. (2018) use the Subtractive Pixel Adjacency Matrix (SPAM) method for extracting features from apple leaf for disease identification; where the image usually does not contain noise; identify the limited interdependence between the differences in related facial primordial, and Markov chains is used for extracting features from the leaf image. The Markov chain model extracts high-order features from the damage of apple tree leaves [9]. A total of 686 traits were extracted, and the Exponential Spider Monkey Optimization Algorithm (ESMO) was used for selecting threshold traits and SVM classifiers were used to classify apple leaf diseases. Li et al. (2020)

proposed a Convolutional Neural Network (CNN) for classifying the lesion of the infected leaf, as these networks automatically extracts the internal information from images such as edges and texture information, thereby increases the size of the deep convolutional neural network for extracting more features from the diseased leaf parts [10]. Terence et al. (2020) discussed different Internet of Things (IoT) technologies in PA conducted via sensors, gateways, communication system, user interface and experiment type, type of plant, type of disease, concludes with advantages, and disadvantages. IoT based agriculture automation does so by altering agriculture sector from static and manual to dynamic and intelligent and brings more production with less human efforts [11].

3. System Methodology

This work considers different smart agriculture system. Figure 1 depicts the Overall workflow and figure 2 illustrates the system methodology.

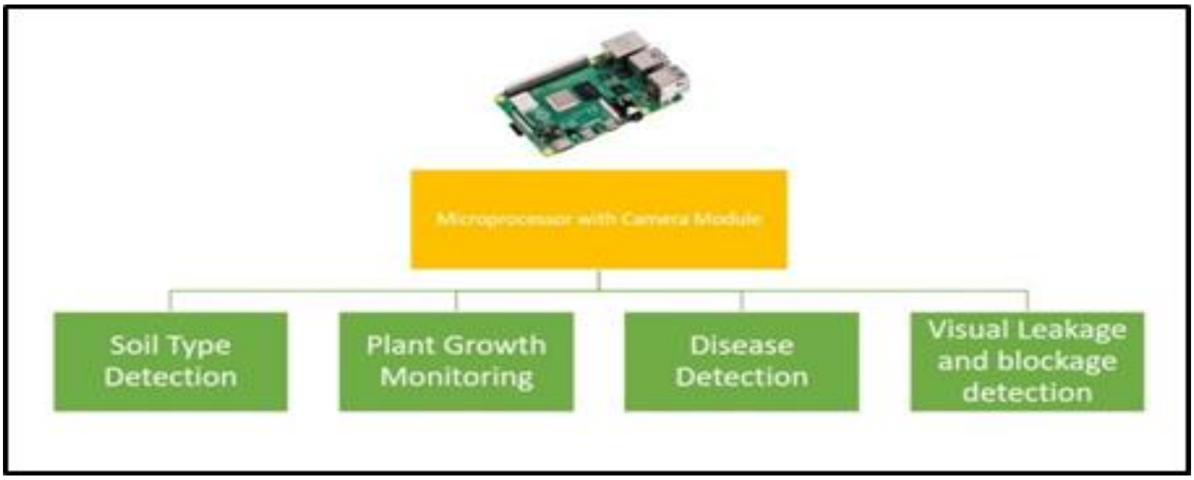

Figure 1 **Overall Workflow**

Figure 2 **System Methodology**

3.1. Data Collection

This project harvested agriculture data through two approaches, namely Soccer Drone–based Data Collection and Ground Station Components-based Data Collection. Figure 3 illustrates the mechanisms of data harvesting.

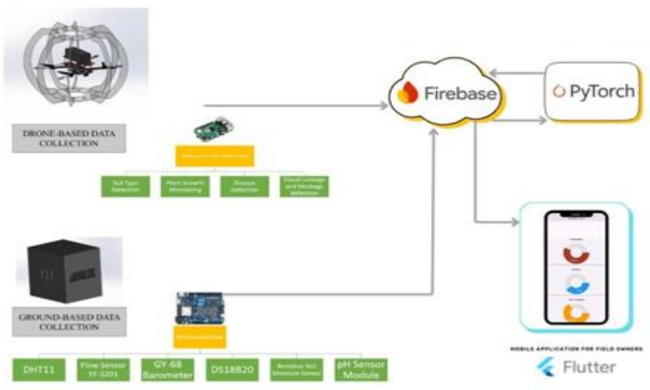

Figure 3 **Data Collection Methods**

3.1.1. Soccer Drone-based Data Collection

This work designed soccer drone for real time agricultural monitoring and data collection, which is a specialized unmanned aerial vehicle (UAV) engineered for precision tasks. It is designed to capture high-resolution images of both coconut trees and paddy leaves, enabling comprehensive data collection for agricultural monitoring. Equipped with a 5MP camera module and advanced navigation systems, the drone can fly over expansive fields and navigate between crops with precision, ensuring detailed and accurate imagery even in challenging terrains. This real-time data collection facilitates early detection of diseases and stress factors in both coconut trees and paddy crops, supporting timely interventions and enhancing crop management practices. By integrating these capabilities, the soccer drone plays a pivotal role in advancing precision agriculture and promoting sustainable farming techniques. This work designed soccer drone using integrates high-performance components to ensure agile flight and accurate data acquisition in diverse field conditions.

1. EMAX ECOII Series 2306 1700KV Motor

It is a pivotal component in the soccer drone, delivering the high power and stability required for agile flight during agricultural monitoring missions. Its high KV rating enables rapid rotor speeds, which are crucial for maneuvering through complex environments and capturing high-resolution imagery in real-time. Designed for reliability and efficient thermal management, this motor supports prolonged flight durations, ensuring continuous data collection over expansive agricultural fields. Overall, the robust performance of the EMAX ECOII Series 2306 1700KV Motor significantly enhances the drone’s capability to perform precise aerial surveillance for tasks such as disease detection in paddy and coconut trees.

2. ESC & Flight Controller: Speedybee F405 V4 BLS Stack 60A

It serving as both the ESC and flight controller, is a critical component in the soccer drone, ensuring precise control and stability during flight. This integrated unit manages the power distribution to the motors and executes complex flight algorithms, enabling rapid response to dynamic field conditions. Its high-performance design allows for smooth, stable flight, essential for capturing high-resolution images during data collection missions over agricultural fields. Moreover, the advanced control capabilities of the Speedybee F405 V4 ensure accurate maneuvering and robust safety measures, making it indispensable for maintaining optimal drone performance in precision agriculture applications.

3. 5-inch Carbon Fiber Drone Frame (160g)

The 5-inch Carbon Fiber Drone Frame (160g) plays a crucial role in the soccer drone by providing a robust yet lightweight structure that enhances both durability and flight efficiency. Its carbon fiber construction ensures that the drone remains resilient against environmental stresses and minor impacts while keeping the overall weight minimal for extended flight times and improved maneuverability. This frame's compact design facilitates agile movement and precise positioning, essential for capturing high-resolution images during agricultural data collection missions. Additionally, the high strength-to-weight ratio of the carbon fiber material contributes to the overall stability and performance of the drone, making it well-suited for the demanding requirements of precision agriculture.

4. Fly Sky i6X

It plays a pivotal role in the soccer drone by ensuring reliable, real-time communication between the operator and the drone. This control system facilitates precise command and feedback loops, enabling accurate navigation and maneuverability across complex agricultural terrains. Its robust transmission capabilities help maintain a stable link, even in environments with potential signal interference, which is critical for safe and efficient drone operation during data collection missions. Overall, the Fly Sky i6X system is essential for achieving responsive control and maintaining the operational integrity of the soccer drone in precision agriculture applications.

5. Orange HD Tri-Blade 5045 Propellers

The Orange HD tri-blade 5045 propellers are integral to the soccer drone's propulsion system, providing the necessary thrust and aerodynamic efficiency for stable flight. Their tri-blade design enhances lift and ensures smooth rotational balance, which is crucial for maintaining maneuverability and responsiveness in dynamic agricultural environments. These propellers are engineered for optimal performance, contributing to extended flight times and the precise handling needed for high-resolution data collection missions. Overall, their robust design and efficient operation play a key role in supporting the drone's ability to navigate and operate effectively in precision agriculture applications.

6. Bonka 22.2V 5200mAh 35C 6S Lithium Polymer Battery Pack

It is a critical component for the soccer drone, providing a robust and reliable power source that ensures sustained high-performance operations during agricultural data collection missions. Its high voltage and capacity allow the drone to achieve extended flight times and maintain the energy demands of rapid maneuvers and high-resolution imaging, while the 35C discharge rating guarantees efficient energy delivery even during peak power draws. This reliable power management minimizes interruptions and ensures the drone's stability and responsiveness in dynamic field conditions, making it indispensable for precision agriculture applications where consistent and prolonged operation is essential.

7. Raspberry Pi

This work used Raspberry Pi 4 Model B serves as a powerful onboard computing platform for the soccer drone, enabling real-time processing and data management during agricultural missions. Its robust processing capabilities support complex algorithms and deep learning models necessary for tasks such as disease detection and classification in paddy and coconut trees. In addition, the Raspberry Pi facilitates seamless integration with peripheral devices, including the camera module, for high-resolution imaging and efficient data transmission. This compact yet versatile system is essential for executing advanced computational tasks on-the-fly, thereby enhancing the drone's overall functionality and operational efficiency in precision agriculture applications.

8. Raspberry Pi 5MP Camera Module

The Raspberry Pi 5MP Camera Module is vital for the soccer drone's ability to capture high-quality, detailed imagery during agricultural monitoring missions. Its 5-megapixel resolution provides the clarity needed to identify subtle signs of disease or stress in crops like paddy and coconut trees, facilitating accurate analysis and early intervention. Lightweight and compact, the camera module integrates seamlessly with the Raspberry Pi 4 Model B, enabling real-time data processing and efficient transmission of images to ground stations or cloud servers. This synergy between the camera module and onboard computing enhances the drone's overall precision and effectiveness in supporting smart agriculture initiatives.

3.1.2. Ground Station-based Data Collection

Figure 4 represents the Ground Station-based Data Collection.

Figure 4 **Ground Station-Based Data Collection**

The ground station components play a vital role in the comprehensive monitoring and data collection for coconut trees and paddy leaves by integrating a suite of advanced sensors and modules. These components continuously gather critical environmental and soil data, which provide a detailed picture of the microclimatic and agronomic conditions affecting crop health. This real-time data acquisition enables farmers to precisely monitor and analyze the growing environment, facilitating timely and targeted interventions for disease prevention and resource optimization. Ultimately, the integration of these ground station components supports sustainable farming practices and enhances the productivity of both coconut and paddy cultivation.

1. Arduino Uno R4 WiFi – 1

The Arduino Uno R4 WiFi serves as a crucial component in the ground station for agricultural monitoring, acting as a versatile interface between various sensors and the central control system. Its integrated WiFi connectivity enables seamless wireless communication, facilitating real-time data transfer from field devices and drones to the ground station. This connectivity is essential for monitoring environmental parameters, managing telemetry data, and executing remote commands during precision agriculture operations. Moreover, the Arduino Uno R4 WiFi's programmable capabilities allow for the customization of data acquisition and processing tasks, thereby enhancing the overall efficiency and responsiveness of agricultural monitoring systems.

2. DHT11

The DHT11 sensor is an essential component of the ground station in agricultural monitoring systems, providing accurate and real-time measurements of environmental temperature and humidity. This data is critical for assessing microclimatic conditions, which can directly influence crop health and productivity. By integrating the DHT11 sensor, the ground station can continuously monitor weather-related parameters, enabling farmers and agronomists to make informed decisions about irrigation, ventilation, and other vital agronomic practices. Its ease of use and reliable performance make the DHT11 an indispensable tool for maintaining optimal growing conditions and ensuring sustainable agricultural management.

3. pH Sensor

The pH sensor is a vital component in ground station systems for agriculture, providing accurate and continuous measurements of soil acidity or alkalinity. This data is crucial for assessing soil health and guiding agronomic decisions, such as the application of fertilizers or lime to optimize nutrient availability and promote robust plant growth. By integrating real-time pH monitoring into the agricultural management system, farmers can better tailor their soil treatment strategies, ultimately improving crop yield and ensuring sustainable farming practices.

4. Flow Sensor YF S201

It is a crucial component in the ground station setup for agricultural irrigation management, as it provides precise measurements of water flow speed and volume. By delivering real-time data on water distribution, this sensor enables accurate monitoring and control of irrigation systems, ensuring that crops receive the optimal amount of water. Its ability to detect variations in flow allows farmers to quickly identify and address issues such as leaks or blockages, thereby enhancing water efficiency and reducing waste. Ultimately, the YF S201 supports data-driven decision-making in irrigation practices, promoting sustainable agriculture and improved crop productivity.

5. GY - 68 Barometer

The GY-68 Barometer is an integral component of ground station systems in agriculture, providing essential measurements of atmospheric pressure and altitude. This sensor plays a pivotal role in monitoring weather conditions that directly impact crop health and field operations. By delivering real-time data on environmental pressure variations, it helps predict weather changes and supports the fine-tuning of irrigation and fertilization strategies based on altitude and atmospheric conditions. Ultimately, the GY-68 Barometer enhances the decision-making process in precision agriculture, contributing to optimized resource management and improved crop productivity.

6. DS18B20 Temperature Sensor

This sensor is offering precise measurements of soil temperature that are critical for monitoring and managing crop conditions. Its digital output and high accuracy allow for real-time tracking of temperature fluctuations in the soil, which directly impact seed germination, nutrient uptake, and overall plant health. By integrating this sensor into the agricultural monitoring system, farmers can make informed decisions regarding irrigation, fertilization, and other management practices to optimize growth conditions. Ultimately, the DS18B20 contributes to enhanced crop productivity and sustainable agricultural practices through its reliable and continuous soil temperature monitoring.

7. Resistive Soil Moisture Sensor

The Resistive Soil Moisture Sensor Module is an essential element in farm ground station systems, as it gives instant measurement of soil moisture levels, which are important for irrigating under optimal conditions. It helps farmers measure accurately the water level in the soil and hence identify the exact time and quantity of water to be given, avoiding both under-irrigation and over-irrigation. Its ease of integration with other monitoring devices and cost-effective nature make it an indispensable tool in precision agriculture. Ultimately, the sensor's continuous monitoring capability supports efficient water management, enhances crop health, and contributes to sustainable farming practices.

3.2. ResNet-18

This work proposed ResNet-18 for different agriculture task, such as NDVI Estimation, Leaf Disease Classification, and Visual Leakage and Blockage Detection. The ResNet-18 architecture is a deep residual network designed to reduce the vanishing gradient problem, thereby enabling efficient training of deeper neural networks. The primary innovation in ResNet (Residual Networks) is the implementation of residual connections that bypass one or more layers, allowing deeper models to be trained more efficiently (Figure 5).

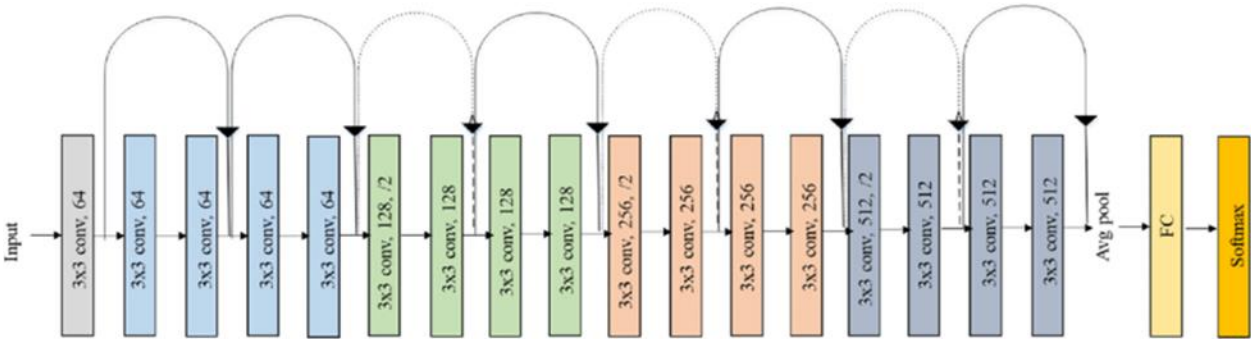

Figure 5 ResNet18

1. **Input Layer**
   - **Input Size:** The input image typically has a size of 224×224×3224 \times 224 \times 3224×224×3 (Height, Width, Channels).
2. **Initial Convolutional Layer**
   - **Convolution:** 7x7 filter with a stride of 2, followed by a Batch Normalization layer and ReLU activation.
   - **Output:** 112×112×64112 \times 112 \times 64112×112×64
   - **Max Pooling:** 3x3 max pooling with stride 2.
3. **Residual Blocks (4 stages)**

The network is divided into four stages. Each stage consists of Residual Blocks.

Stage 1 (64 filters):

- 2 Residual Blocks with 64 filters.

Each block has:

- 3x3 Convolution with padding, followed by Batch Normalization and ReLU.
- Another 3x3 Convolution with Batch Normalization.
- Shortcut connection (identity mapping) that adds the input to the output of the block.

Stage 2 (128 filters):

- 2 Residual Blocks with 128 filters.
- The first residual block of this stage uses a convolution with stride 2 to downsample the feature map.
- The blocks are similar to the previous stage but with increased filter sizes.

Stage 3 (256 filters):

- 2 Residual Blocks with 256 filters.
- The first residual block of this stage also uses a convolution with stride 2 to reduce the spatial dimensions.

Stage 4 (512 filters):

- 2 Residual Blocks with 512 filters.
- Similar to previous stages, with stride 2 in the first block to downsample.

4. Global Average Pooling

After passing through the 4 stages, a Global Average Pooling layer is applied to the output. This reduces each feature map to a single value by averaging over the spatial dimensions.

5. Fully Connected (FC) Layer

- A FC layer is applied after global average pooling.
- This layer has 1000 output units (for 1000 classes in ImageNet classification).
- Softmax activation is typically applied to generate class probabilities.

6. **Output**

- The final output is a vector of size 1000 (for ImageNet classification)

3.3. Normalized Difference Vegetation Index (NDVI) Estimation

NDVI estimation is a vital technique for assessing the health and vigor of paddy, coconut tree, and tomato crops by quantifying the level of healthy vegetation present. This process involves capturing high-resolution images of the crops using specialized sensors or drones and analyzing the spectral reflectance in the red and near-infrared bands to compute NDVI values. In practical applications, these NDVI values serve as a quantitative measure of chlorophyll content, which directly correlates with plant health, allowing for the detection of stress, nutrient deficiencies, or disease. By integrating NDVI estimation with deep learning models such as ResNet-18, the system can efficiently classify crop conditions into categories like chlorophyll A and chlorophyll B, thereby enabling precise, real-time monitoring and informed decision-making in crop management. In this work, ResNet-18 is employed for NDVI estimation on a real-time dataset collected from paddy, coconut tree, and tomato crops, with each crop dataset consisting of 1000 samples for each of the two classes—chlorophyll A (dark green leaves) and chlorophyll B (light green and yellow leaves). The architecture of ResNet-18, characterized by its 18-layer depth and the use of residual connections, efficiently extracts both low-level and high-level features from the images, capturing subtle variations in color and texture that are critical for distinguishing between the two chlorophyll classes. During training, the model learns to associate specific patterns in the images with corresponding NDVI values, which serve as a proxy for vegetation health. This deep feature extraction and learning process enables the network to accurately classify the images, while the residual connections help prevent gradient vanishing, ensuring robust performance even with a relatively compact architecture. The successful application of ResNet-18 in this context demonstrates its effectiveness in real-time agricultural monitoring and NDVI estimation, facilitating precise and timely decision-making in crop management.

3.4. Leaf Disease Classification

This work leverages the ResNet-18 deep CNN architecture for the task of leaf disease detection across three major crops: paddy, coconut trees, and tomatoes. The study utilizes a comprehensive, real-time dataset where each crop category comprises 14 distinct classes of leaf conditions, with 1,000 samples per class, ensuring a robust representation of both healthy and diseased states. Specifically, for paddy crops, the dataset includes disease classes such as Blight, Brown Spot, and Leaf Smut; for coconut trees, the diseases considered are Yellowing, Flaccidity, Drying, and infestations caused by Worms & Caterpillars; while for tomatoes, the focus is on Blight, Septoria, Yellow Leaf Curl, and Target Spot. The ResNet-18 architecture, comprising 18 layers and skip connections, effectively addresses the vanishing gradient issue, enabling the network to acquire profound, discriminative properties that differentiate small variations in leaf colour, texture, and shape suggestive of disease. This powerful feature extraction capacity, coupled with a balanced dataset, guarantees excellent accuracy in the real-time detection and classification of leaf diseases, facilitating prompt interventions and enhanced crop management in precision agriculture. The ResNet-18 is strategic due to its relatively shallow architecture compared to deeper networks, which makes it computationally efficient without significantly compromising accuracy. The network's design, characterized by residual connections, helps mitigate the vanishing gradient problem and enables the model to learn deep features effectively. These features are critical for distinguishing subtle differences in leaf texture, color, and patterns that indicate the presence and type of disease. During the training phase, the model learns to map the complex visual patterns from the high-resolution images to the corresponding disease classes through supervised learning. With 1,000 samples per class, the model is provided with a sufficiently large and diverse dataset that aids in generalizing well to new, unseen images. The real-time aspect of this work implies that the system is designed not only for high accuracy but also for prompt decision-making, which is essential in precision agriculture where timely interventions can prevent the spread of disease and minimize crop losses. By combining efficient feature extraction through ResNet-18 with a well-structured dataset covering a broad spectrum of leaf diseases, this work aims to deliver a robust solution for automated disease detection that can be integrated into smart agriculture systems, ultimately supporting enhanced crop management and sustainable farming practices.

3.5. Visual Leakage and Blockage Detection

Visual leakage and blockage detection in irrigation systems is critical for maintaining efficient water distribution and ensuring the optimal performance of agricultural operations. By integrating advanced imaging technologies with deep learning models, these systems can automatically identify and classify anomalies such as pipe leakage, sprinkler leakage, or blockages that disrupt water flow. High-resolution images of the irrigation infrastructure are continuously captured and processed to detect subtle signs of wear, damage, or malfunction, enabling the system to promptly trigger maintenance alerts. This automated approach not only minimizes water wastage and reduces repair costs, ultimately enhancing crop health and overall productivity. This work used ResNet-18 approach for detecting visual leakage and blockage in irrigation systems. This work focuses on three agricultural environments—paddy fields, coconut tree plantations, and tomato farms—each represented by a real-time dataset that categorizes irrigation conditions into three classes: pipe leakage, sprinkler leakage, and perfect irrigation. For each of these classes, 104 samples are collected, providing a balanced dataset that captures the subtle visual distinctions associated with each irrigation condition. ResNet-18's architecture, with its 18 layers and skip connections, is specifically appropriate for this assignment since it keeps the vanishing gradient problem under control, enabling the network to learn deep, discriminative features even from a relatively small dataset. The remaining connections in the network enable the learning of both low-level and high-level features, which are essential for recognizing the subtle visual cues that distinguish between pipe leakage, sprinkler leakage, and well-working irrigation systems. As the model trains, it learns to map certain patterns in the images captured like water dispersion anomalies, discolorations, or structural deformations—to the respective class labels. The integration of this deep learning approach into irrigation management systems offers significant benefits for precision agriculture (Table 1 & 2). By enabling real-time detection of leaks and blockages, the system can trigger timely maintenance interventions, thereby reducing water wastage and preventing potential crop damage. Overall, the deployment of ResNet-18 in this context demonstrates a promising pathway for enhancing the efficiency and reliability of irrigation systems, ultimately supporting sustainable farming practices and improved crop productivity (Figure 6 to 12).

4. Experimental Results

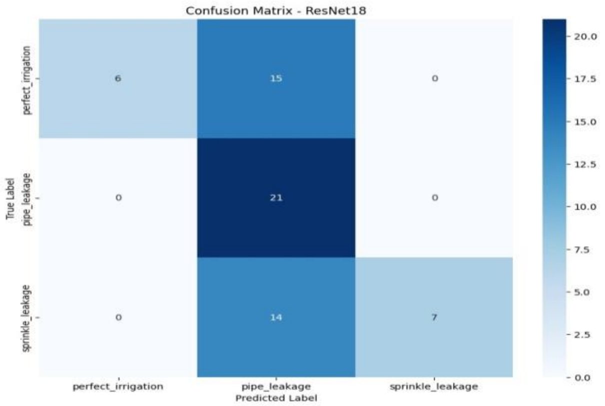

Figure 6 ResNet 18 Confusion Matrix for Visual Leakage

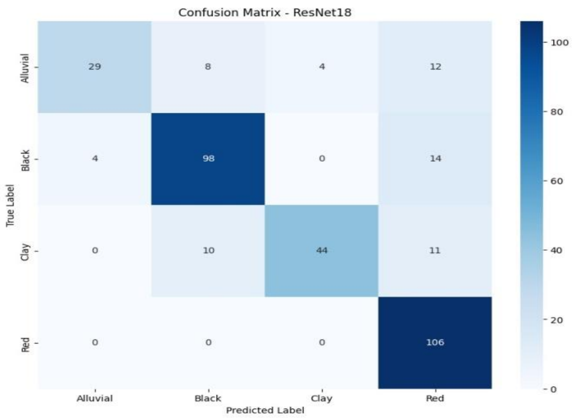

Figure 7 ResNet 18 Confusion matrix for Soil Prediction

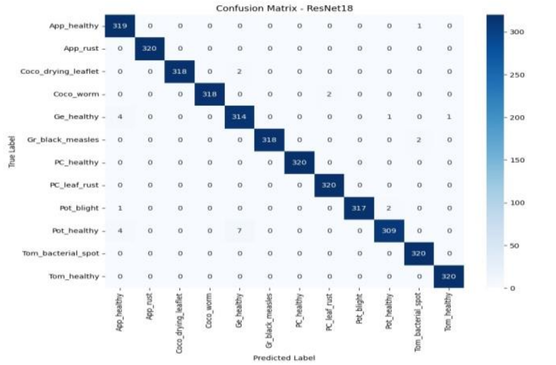

Figure 8 ResNet 18 Confusion Matrix for Leaf Disease Prediction

Table 1 Performance Analysis for ML Models

Model	Year	Parameters	Depth	Architecture	Best For	Limitations
ResNet18	2015	11.7M	18 layers	Residual learning	General-purpose image classification, object detection	Slightly heavier than MobileNet
MobileNetV1	2017	4.2M	28 layers	Depthwise separable convolutions	Mobile and edge devices	Lower accuracy compared to ResNet
LeNet-5	1998	60K	5 layers	Simple CNN with 2 convolutional and 3 fully connected layers	Handwritten digit recognition	Not suitable for complex images
VGG-16	2014	138M	16 layers	Deep CNN with multiple 3×3 convolution layers	High-quality classification, transfer learning	Very heavy, requires a lot of compute

Table 2 Performance Analysis Using ResNet18

ML Models	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Disease Detection	99.3	99.3	99.3	99.3
Irrigation Leakage Detection	53.97	80.67	53.97	51.2
Soil Type Classification	81.47	83.16	81.47	80.77

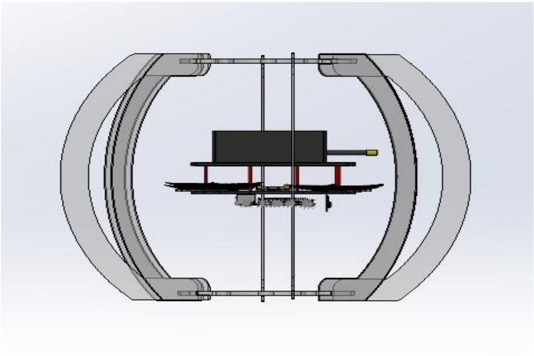

Figure 9 Soccer Drone View 1

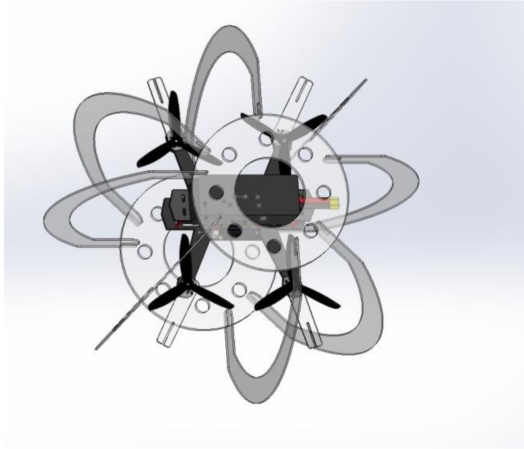

Figure 10 Soccer Drone View 2

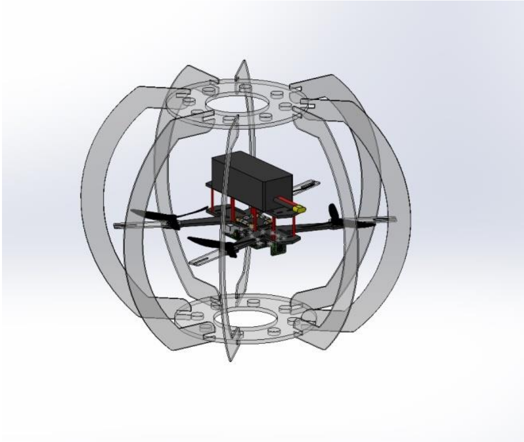

Figure 11 Soccer Drone View 3

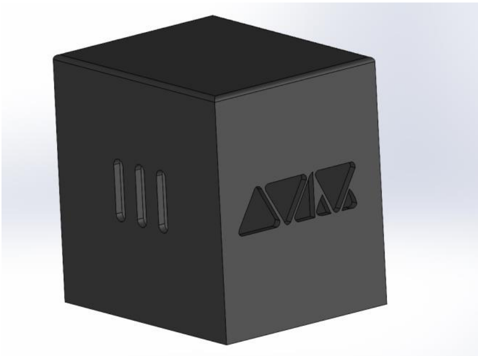

Figure 12 Ground-Based Data Collection

Conclusion

In conclusion, this work demonstrates the significant potential of integrating advanced drone technology with deep learning algorithms to revolutionize agricultural health monitoring. By leveraging high-performance components and innovative data acquisition techniques, the proposed system facilitates real-time, high-resolution imaging of paddy and coconut trees, enabling precise disease detection and classification. The application of the Residual

Network (ResNet) architecture has proven to be particularly effective, outperforming conventional CNN models in terms of accuracy and robustness. This proactive approach not only minimizes crop losses through timely interventions but also supports sustainable farming practices, ultimately contributing to enhanced food security and agricultural productivity.

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