

IoT-Based Leaf Disease Detection in Vertical Gardens Using Weighted Box Fusion

by

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requirements for the degree of*

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Under the supervision of

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DECLARATION

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We declare that this capstone project entitled *IoT-Based Leaf Disease Detection in Vertical Gardens Using Weighted Box Fusion* is the result of our own work except as cited in the references. The capstone project has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Sameen Rayan Pahlowan, Samia Khandoker, Afsana Akter

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To my beloved parents,
maternal uncles, friends
and teachers
my guardian angels

– Sameen Rayan Pahlowan

To my beloved parents,
and my brother
the source of my inspiration

– Samia Khandoker

To my beloved parents,
siblings and my friends
my strength and inspiration

– Afsana Akter

ABSTRACT

Ensuring healthy plant growth in agriculture is challenging, especially in Bangladesh, where climate change, plant diseases, and inefficient irrigation impact crop yields. Traditional disease detection methods are often slow, inaccurate, and labor-intensive, leading to reduced productivity and food insecurity. This research focuses on improving plant health monitoring in vertical gardening systems using an IoT-based leaf disease detection system using weighted box fusion. The system combines IoT technology with an advanced machine learning approach, particularly the Weighted Box Fusion (WBF) technique, to enhance detection accuracy. Key components include DHT11 sensors, soil moisture sensors, and LDR modules, which collect real-time environmental data. Automated actuators control irrigation and lighting based on predefined thresholds, optimizing plant growth. For disease detection, four deep learning models—YOLOv11, RetinaNet ResNet50, EfficientDet, and WBF—were tested. The ensemble model combining YOLOv11 and RetinaNet ResNet50 with WBF achieved a higher performance score, obtaining mAP of 0.93 at 50% IoU, 0.93 at 75%, and 0.89 across 50-95%. An edge device captures and uploads photos to an inference server, which calculates and post processes predictions and stores results in Firebase and Supabase databases. The users are able to access data using a mobile application, Phyto Sense, that tracks environmental conditions and disease trends, making plant health management more efficient. This automated system supports precision agriculture by reducing manual effort, improving disease detection, and optimizing resource use, particularly in urban vertical gardening in Bangladesh.

Keywords: Precision agriculture, Vertical Garden, IoT, Weighted Box Fusion, Smart Agriculture, leaf Disease Detection

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Chapter 1

Introduction

1.1 Background Study

The growing need for sustainable agriculture has resulted in the rise of vertical gardening systems as innovative solutions for urban challenges. These systems efficiently utilize limited spaces like balconies and rooftops, enhancing food security while boosting urban biodiversity and air quality. However, the urban environment also faces difficulties in maintaining such systems especially when it comes to maintaining optimal plant health.

Effective plant monitoring and management are crucial because factors like light availability and irrigation systems directly affect plant growth. IoT-enabled systems have also been a way to help mitigate agricultural challenges, achieving growth rates up to 90.38% for leafy greens have been shown over plain agricultural approaches [Dim and Guillermo \(2022\)](#). Yet, maintaining plant health remains an issue, specifically in terms of early detection of diseases in leaves.

Traditional diagnosis of plant disease is heavily reliant on manual inspection and observation, which generally are subjective and extremely tedious. This reliance can cause problems in spotting plant health issues, leading to delays that harm agricultural productivity [Khakimov et al. \(2022\)](#). On top of that, manual inspection are prone to human error. Recent studies have demonstrated that various deep learning and machine learning techniques have the potential to revolutionize the process of plant disease detection. For example, a study done by [Sujatha et al. \(2021a\)](#) assessed and compared the performances of deep learning models and traditional machine learning algorithms such as SVM and Random based on citrus leaf disease detection where they concluded that deep learning models are better

performing models. However, most of these studies overlooked the localization of specific infected parts of disease remains largely unexplored. Moreover, multiple classes of diseases against complex backgrounds and overlapping leaves complicate detection further.

Emerging technologies are revolutionizing agriculture through IoT and deep learning, driving higher productivity, sustainability, and better disease management. Real-time environmental monitoring, combined with deep learning and computer vision, enables accurate and robust plant disease detection and localization, enabling farmers and gardeners valuable insights for easier management. As innovation accelerates, IoT-based vertical gardens present a promising solution for maximizing efficiency and ensuring food sustainability.

1.2 Problem Statement

Rapid urbanization in Bangladesh has reduced available horizontal land for agriculture, making vertical gardening essential for maximizing space. However, effective disease monitoring remains a challenge due to the heavy reliance of manual inspection, which is tedious, laborious, and error-prone. Identifying specific infected areas and managing multiple plant species further complicates detection, especially with overlapping leaves and complex backgrounds.

To address these challenges, this system integrates IoT-based leaf disease detection combining deep learning models through weighted box fusion with real-time environmental monitoring. It aims to optimize plant health management and support sustainable, high-yield urban agriculture by enhancing detection precision, robust generalization of detections and automating disease assessment.

1.3 Aims, objectives and Motivation

1.3.1 Aims of The Study

This study seeks to design and develop an advanced leaf diseases detection system using Weighted box fusion (WBF) method suitable for IoT architecture based Vertical Gardens. The system will be able to surveil the environment and keep track of the parameters that includes humidity, soil moisture, temperature, and

photoperiod real-time, and a threshold based resource management, an ensemble of multiple deep learning object detection models using WBF for better localization and generalization. The implementation of the IoT based Vertical Garden will solve the challenges of limited space in urban areas.

1.3.2 Objectives

- Design an IoT system for leaf disease detection and real-time monitoring of vertical garden parameters (soil moisture, humidity, temperature)
- Implement an ensemble of advanced deep learning models (YOLOv11 + RetinaNet with WBF) for precise leaf disease detection
- Develop a user-friendly mobile app for plant health monitoring, real-time environmental logs

1.3.3 Motivation

The decreasing volume of agricultural land in Bangladesh, which has dropped from 190 lac acres to 186 lac acres highlights the urgent need for innovative solutions in urban gardening [Star \(2022\)](#). This reduction not only threatens food security but also emphasizes the importance of maximizing the use of available urban spaces for gardening. In today's fast-paced world, time constraints make it difficult to consistently care for plants. Many people struggle to balance busy schedules, resulting in irregular attention to their plants and poor plant health due to inadequate nutrients and care. Additionally, manual monitoring of the plant health is quite ineffective, as plants may decline before problems are identified. On the other hand, traditional disease detection methods are often slow and prone to errors, allowing diseases to severely affect plants and disrupt plant growth.

1.4 Scope

1. Enhancing Disease Detection in Vertical Gardening

This system will improve disease detection in vertical gardening, particularly in urban agriculture settings in Bangladesh, where rapid urbanization necessitates efficient plant health management. It will focus on early identification

of leaf diseases and optimizing plant growth through automated real-time monitoring.

2. Real-Time Monitoring & Automation

The system will integrate an IoT-based approach for continuous plant health assessment. An Android app will be developed to monitor environmental parameters and provide daily disease predictions for different garden levels, ensuring accessible and data-driven decision-making.

3. Analysis of Existing Detection Methods

To enhance detection accuracy, the system will analyze prevailing disease identification practices, which currently rely on visual and manual inspection. It will categorize common leaf diseases affecting urban crops, classify symptoms, and assess their severity levels.

4. Quantitative Disease Severity Measurement

Disease severity will be determined by calculating the ratio of diseased to healthy leaves as a percentage, offering an objective measure of plant health. Since overlapping leaves can interfere with precise severity estimation, the system will compensate by analyzing overall leaf distribution to provide a reliable assessment.

5. Technology & Methodology Constraints

The system will utilize the most recent technological advancements from the past four years to ensure modern and efficient disease detection while excluding outdated approaches. This focus on contemporary techniques will improve detection accuracy and adaptability.

6. Model Implementation & Fusion

To enhance localization precision, the system will combine two Single Shot MultiBox Detector (SSD) models using Weighted Box Fusion. This technique will improve detection reliability by reducing false classifications and optimizing box generation in complex vertical gardening environments.

7. Sustainability & Practical Impact

This system will contribute to sustainable urban farming by increasing the efficiency and robustness of leaf disease detection and analysis in vertical

gardens. Through automation and data-driven insights, it will reduce manual effort, enable proactive intervention, and support healthier crops for long-term agricultural sustainability.

1.5 Project Specification

The proposed system will consist of two main edge devices: ESP32 (Environment Management Unit) and ESP32-CAM (Image Processing Unit). The Environmental unit will monitor parameters such as soil moisture, humidity, and temperature in real time, logging data to a Firebase Realtime Database and controlling actuators (water pumps and lights) based on predefined thresholds. The image processing unit will capture scheduled photos and upload them to a cloud server for inference using an Ensembled Object Detection Pipeline (YOLOv11 + RetinaNet with Weighted Box Fusion) daily. The processed data, including detected diseases, infection ratio, and number of instances, will be stored in Supabase Cloud Storage and made accessible through a mobile application.

1.5.1 Functional Requirements

- **Real-Time Environmental Monitoring**

1. ESP32 will collect data on soil moisture, temperature, and humidity.
2. Store real-time sensor data in Firebase Realtime Database.
3. Automatic control of irrigation and lighting based on threshold values.

- **Leaf Disease Detection**

1. ESP32-CAM will capture images at scheduled intervals.
2. Images will be uploaded to a cloud server with device and user ID.
3. An Ensembled Object Detection Pipeline will preprocess and analyze images for disease identification.
4. Disease instances, infection ratios, and severity levels will be calculated and stored.

- **Data Storage and Access**

1. Predicted images stored in Supabase Cloud Storage.
 2. Summary data (disease type, infection ratio, instance count) stored in a structured format.
 3. Real-time and prediction log accessible via a mobile application.
- **User Interface:** Mobile application for monitoring environmental data and disease predictions.

1.5.2 Non-Functional Requirements

- **Scalability**
 1. System should support multiple devices and users without performance degradation.
 2. Cloud-based storage to handle increasing data volumes efficiently.
- **Accuracy & Efficiency**
 1. Utilize YOLOv11 + RetinaNet with WBF for high-precision disease detection.
 2. Optimize inference speed to ensure near real-time predictions.
- **Usability**
 1. A user friendly, easy to use android application for farmers.
 2. Clear visualization of environmental metrics and disease reports.

Chapter 2

Literature Review

The advent of precision agriculture has introduced innovative solutions to enhance crop production and plant health management. One area of focus is leaf disease detection, a critical component of plant health monitoring. This paper investigates the integration of IoT with an advanced model ensemble technique, Weighted Box Fusion (WBF), for disease detection in vertical gardening systems. This literature review aims to analyze existing work in vertical gardening, leaf disease detection, IoT applications, and the role of Weighted Box Fusion in object detection.

2.1 Vertical Gardening Systems

Nowadays vertical gardening systems have gained remarkable attention for having a sustainable solution to urban agriculture challenges. However, urban areas are still highly susceptible to the disruption of food supply because of their dependency on imported food [Song et al. \(2022\)](#). In Singapore, a specific public housing apartment buildings offered an opportunity to leverage underused spaces like balconies, corridors, and rooftops where it was found that they were able to satisfy 3% of the total edible greens whereas façade gardening had the potential to fulfill 43% of the needed green concluded by [Song et al. \(2022\)](#). A recent study by [Wang et al. \(2022\)](#), introduced a that vertical gardening system provides great environmental benefits like improved air quality, and microclimate regulation by effectively absorbing and filtering the polluted air. On the other hand, the system also contributes to energy savings through shading and insulation which makes it an essential component of sustainable urban infrastructure. Another vertical farming system proposed by [Zareba et al. \(2021\)](#) discerned that it could stabilize urban biomes and improve

the quality of agricultural products as well as reduce the adverse environmental impacts of urbanization.

[Dim and Guillermo \(2022\)](#) mentioned that, despite the promising advancements in vertical gardening systems, some challenges remain in terms of maintaining plant health, such issues as limited light availability, and effective irrigation systems for plant growth. Furthermore, the research yielded that, IoT-enabled systems can significantly outperform traditional setups for crop yield and health, specifically for basil, lettuce, and spinach growth rates in IoT systems increase up to 73.13%, 84.33%, and 90.38%, respectively. A microcontroller-based vertical farming was introduced by [Alotaibi et al. \(2023\)](#) utilizing Arduino Mega and NodeMCU ESP8266 to collect real-time environmental data, which then is transmitted to an Android application that sends control signals to actuators, automating the growing process. [Ng et al. \(2023a\)](#) built a cost-effective microcontroller system that monitors and controls vertical farming parameters in real-time. However, the approach failed to utilize machine learning algorithms for optimal decision-making, limiting its effectiveness in dynamic environments. [Yusuf et al. \(2023\)](#) introduced an IoT system that monitors various environmental factors through sensors interfaced with an ESP32 microcontroller where there is a successful transmission of data to the cloud but the system lacks automated controls and analytical operations on the gathered data. IoT-based Smart Vertical Hydroponics System proposed [Chauhan et al. \(2023\)](#) utilizes a smart IoT-based hydroponics system with grow light, sensors pH sensors, and EC sensors to provide an automated system to obtain high Yield. [Kumar et al. \(2023\)](#) implemented an IoT-based irrigation management by incorporating fuzzy logic technique for vertical farming equipped with sensors and actuators to control watering quantities based on environmental data. [Bhowmik et al. \(2023\)](#) proposed an automated gardening system that incorporates smart irrigation, lighting, nutrient control, and pest management by utilizing cloud-based AI/ML/DL algorithms to enhance decision-making in environmental control . Whereas, [Obu et al. \(2021\)](#) implemented a system employing Raspberry Pi and a trained TensorFlow Lite model for crop monitoring that achieves high accuracy in detecting unhealthy crops however. [Ullah et al. \(2023\)](#) presented a prototype sensor system that integrates with any vertical farming setup. The system collects environmental information and stores it in the cloud for remote access. On the other hand, [Halgamuge et al.](#)

(2021) discussed real-times systems with cost-effective microcontrollers to monitor and control the actuators and environmental state of vertical farming.

2.2 Leaf Disease Detection Techniques

Plant pathogens has a major effect on agricultural competency and food safety, therefore early diagnosis is crucial for efficient management. According to [Khakimov et al. \(2022\)](#), traditional plant disease diagnosis methods are still useful since they are reliable and affordable. However, these approaches often involve morphological identification and other classical techniques that have many limitations to understanding plant health.

In terms of plant disease identification, recent research has shown several machine learning techniques that have transformed the field drastically. In a review by [Sujatha et al. \(2021a\)](#), the effectiveness of machine learning in plant leaf disease detection was compared using Random Forest and Support Vector Machines. Furthermore, to detect citrus leaf disease, deep learning models such as Inception-v3 and VGG-16 were implemented and tested, where the result concluded that VGG-16 produced the best results. The accuracy of SVM, K-NN, and CNN algorithms was 88%, 97%, and 99.6%, respectively, in a different study by [Harakannanavar et al. \(2022\)](#) that used these algorithms along with sophisticated feature extraction techniques. A promising accuracy of 93.40% was achieved by optimizing pre-trained CNN architectures, such as VGG-16 and Inception V3, for tomato leaf disease classification, as reported by [Ahmad et al. \(2020\)](#). In an effort to identify tip-burn stress in lettuce, [Hamidon and Ahamed \(2022\)](#) used deep learning methods to which included CenterNet, YOLOv4, and YOLOv5 algorithms where, the YOLOv5, obtained the highest accuracy, with 84.1% mAP. A study by [Verma et al. \(2020\)](#) used deep learning models like AlexNet, SqueezeNet, and Inception V3 in two modes: feature extraction and transfer learning. AlexNet achieved the highest accuracy in both, with 89.69% and 93.4%, respectively. [Mafukidze et al. \(2022\)](#) used an adaptive thresholding approach to automatically extract areas of interest (ROIs) from these heatmaps to compute the severity of the detected disease. They proposed a shallow CNN model and employed Inception V3, DenseNet, MobileNet, and VGG16. Both classification and quantification of maize leaf diseases were done using these models. A study conducted by [Hu et al. \(2021\)](#) used a VGG16 deep network to identify

and calculate severity using an enhanced Faster R-CNN model. Recent research done by [Yousuf and Khan \(2021\)](#) suggested an ensemble model based combining Random Forest and K-Nearest Neighbor, which achieved an astounding 96% accuracy in classifying plant diseases. [Jha et al. \(2023\)](#) added their notable contribution which involved an ensemble approach integrating Residual Networks, MobileNet, and Inception models, achieving an accuracy of 98.86% in classifying potato leaves . Recently [Wang et al. \(2021\)](#) implemented a model in their study where they used DBA_SSD for plant leaf disease detection, that achieved 92.20% accuracy which was higher than the popular ssd models such as the classic SSD, Yolov4, Yolov3, Faster RCNN. [Li et al. \(2023\)](#) proposed system ensemble model combines two different object detection model where the single-stage model is based on YOLO, optimized internally, while the two-stage model uses Faster-RCNN architecture that achieved accuracy of 85.4% in detecting plant diseases.

2.3 IoT-Enabled Precision Agriculture

Smart agriculture has improved productivity through improved monitoring and control techniques made feasible via IoT technology. The IoT systems developed by [Mushtaq et al. \(2023\)](#) utilized different types of sensors like temperature, and moisture of farming conditions, after sending data to a microcontroller, the system triggers alerts when threshold values are exceeded and starts automatic irrigation and necessary actions and it also automates irrigation based on humidity levels.

[Rehman et al. \(2022\)](#) emphasizes the deployment of an IoT sensor network equipped with a sensor like light sensor, moisture sensor, humidity and temperature sensor for environmental condition monitoring agriculture. The system had accurate accuracy in monitoring and controlling irrigation based on real-time data. [Waluyo et al. \(2021\)](#) proposed a system that monitors power and energy consumption using Arduino, which sends data to a NodeMCU. The NodeMCU then transmits the information to the Blynk app for real-time monitoring and analysis. Furthermore, the study used fuzzy logic methods to control farming systems. The fuzzy logic method saves more energy compared to the scheduled method. [Ng et al. \(2023b\)](#) designed a solution that includes IoT technologies with software platforms like Arduino IDE and SystemLink IoT cloud. It includes equipments such an Arduino Nano, ESP8266 module, and NI myRIO board. The system logs the

temperature, humidity, and soil moisture using sensors attached to the ESP8266 module in real-time conserving energy.

The system developed by [Karuniawati et al. \(2021\)](#) integrate sensors in IoT based architectures to improve grow light control and plant growth, whilst achieving a 90.62% classification accuracy. Another study [Ouhami et al. \(2021\)](#) used data fusion techniques to monitor plant health and detect diseases. [Orchi et al. \(2022a\)](#)'s study resulted that machine learning, deep learning, combined with hyperspectral image analysis in IoT systems can enable early disease detection, reducing disease severity and protection of crops. Another system developed by [Khan et al. \(2020\)](#) uses IoT in agricultural greenhouses. The IoT-based system effectively monitors critical parameters like temperature and humidity, providing real-time data essential for optimal plant growth. By utilizing CNN to analyze leaf images, the system accurately detects various plant diseases, enabling timely alerts for users to take necessary actions.

2.4 Weighted Box Fusion in Object Detection

Object detection plays a crucial role in machine vision since it enables classification and localization of objects within an image. Models, such as YOLO, Faster R-CNN, and SSD (Single Shot Detector), build bounding boxes around recognized objects. However, these algorithms frequently provide redundant or overlapping predictions, which may lower the detection results' reliability.

Weighted Box Fusion (WBF) is an ensemble method designed to address these challenges by combining multiple predictions from different models or runs into a single, more accurate bounding box. Unlike traditional methods such as Non-Maximum Suppression, WBF assigns weights to each bounding box depending on the probability score of the predictions, and then considers all the boxes to generate a new box resulting in a refined and precise output. Introduced by [Solovyev and Wang \(2019\)](#), their study yielded that the WBF method significantly outperforms other approaches for combining predictions, achieving superior precision score in the Open Images and COCO Detection Challenges where it score 56.1 and 56.4 mAP for the validation and test dataset respectively).

Applications of WBF extend beyond agriculture, including domains such as autonomous vehicles, where accurate object detection is crucial for safety, and

medical imaging, where precise localization of anomalies is essential. In agriculture, WBF has shown promising achievements by enhancing the robustness of disease detection by resolving overlapping bounding boxes and improving model ensemble outputs. The study by [Wang et al. \(2023\)](#), on tea leaves, utilized an embedded machine learning based pest and disease detection technique combining multiple YOLOv5 using WBF, achieving significant accuracy improvements by addressing overlapping predictions, removing redundant frames and enhancing model outputs. A study [Tiwari et al. \(2022\)](#) demonstrated the ensemble of YOLOv5 and RetinaNet-101 models using WBF, which improved the mean average precision (mAP) from individual model scores of 0.540 and 0.545 to a combined score of 0.552. This enhancement highlights WBF's ability to resolve overlapping predictions and boost model performance in diverse applications, including medical imaging. The study further established that WBF effectively reduced the difficulty of identifying COVID-19 opacities, which often resemble those caused by other viral or bacterial diseases. In another study done by [Cheng et al. \(2022\)](#), implemented target detection algorithm to detect UAVs using YOLOv4-Tiny combined with Weighted Box Fusion (WBF) technique to enhance detection accuracy. This approach replaced the traditional Non-Maximum Suppression (NMS) algorithm with WBF, addressing missed and false detections of multi-scale UAV targets. A study by [Zhao et al. \(2023\)](#) on Object Detection of Maritime UAV Images utilized WBF to fuse models and achieved 93.3 AP50 whereas the base model only achieved 87.7 previously without the fusion. Another study by [Giakoumoglou et al. \(2023\)](#) demonstrated that Weighted Box Fusion (WBF) improved the detection accuracy for *Tuta absoluta* in tomato plants, increasing mAP from 0.58 to 0.70 after applying weighted Box Fusion (WBF).

Despite its promise, the application of WBF in agricultural contexts, particularly in IoT-enabled systems, remains underexplored.

2.5 Gaps in Existing Research

Although tremendous progress has been made in leaf disease diagnosis and IoT-based monitoring, some gaps yet persist:

Table 2.1: Comparative Analysis

Refs.	Monitors Environmental Parameters	IoT Based	Plant Disease Detection	Detection Type	Multi-class	Advanced Techniques	Cost Effective
Dim and Guillermo (2022)	Yes	Yes	No	N/A	No	No	N/A
Alotaibi et al. (2023)	Yes	Yes	No	N/A	No	No	N/A
Ng et al. (2023a)	Yes	Yes	No	N/A	No	No	Yes
Yusuf et al. (2023)	Yes	Yes	No	N/A	No	No	N/A
Kumar et al. (2023)	Yes	Yes	No	N/A	No	No	N/A
Sujatha et al. (2021a)	No	No	Yes	Classification	No	No	N/A
Harakannanavar et al. (2022)	No	No	Yes	Classification	Yes	No	N/A
Ahmad et al. (2020)	No	No	Yes	Classification	Yes	No	N/A
Hamidon and Ahamed (2022)	No	No	Yes	Object Detection	No	No	N/A
Verma et al. (2020)	No	No	Yes	Classification	Yes	No	N/A
Sujatha et al. (2021b)	No	No	Yes	Classification	Yes	No	Yes
Li et al. (2023)	No	No	Yes	Object Detection	Yes	Yes	N/A
Orchi et al. (2022b)	No	No	Yes	Object Detection	Yes	Yes	N/A
J. et al. (2022)	No	No	Yes	Classification	Yes	No	N/A
Khan et al. (2020)	Yes	Yes	Yes	Classification	Yes	No	N/A
Soloviyev and Wang (2019)	No	No	No	Object Detection	Yes	Yes	N/A
Wang et al. (2023)	No	No	No	Object Detection	Yes	Yes	N/A
Cheng et al. (2022)	No	No	No	Object Detection	Yes	Yes	N/A
Zhao et al. (2023)	No	No	No	Object Detection	Yes	Yes	N/A

- Current object detection models for plant health monitoring suffer from issues of accuracy due to overlapping predictions, sub-par localization, and missed classification.
- Most vertical gardening systems focus on environmental monitoring, with limited emphasis on integrating advanced disease detection algorithms.
- The application of Weighted Box Fusion in agricultural contexts, particularly for IoT-based vertical gardening systems, has not been extensively studied.
- Disease detection systems tailored to the unique challenges of vertical gardening are lacking in the existing literature.

By addressing these gaps, this research aims to develop a novel solution for leaf disease detection in vertical gardening systems, leveraging the strengths of IoT and WBF to achieve higher accuracy and efficiency.

Chapter 3

Methodology

The chapter covers the development methodology for the IoT-based leaf disease detection system in vertical gardening: dataset collection, annotation, and preprocessing; configuration of IoT devices for real-time monitoring; and implementing the fusion of the models YOLOv11, and RetinaNet ResNet50 using Weighted Box Fusion. Python is primary programming language for this study due to its extensive libraries for implementing and use transfer learning on the pre-trained models using frameworks, such as TensorFlow and PyTorch. The overall software architecture is designed to facilitate efficient data handling and model inference. The models were trained on Google Colab using a T4 GPU. Several data augmentation techniques were applied before training to enhance model generalization and performance. These augmentations included flipping, rotation, Gaussian blur, noise addition, and padding.

This flow chart represents that the process starts with data collection where necessary information like images is gathered. After that the preprocessing step is executed, which involves image augmentations to preparing it for labeling, including resizing, padding, and collaging images. The dataset is subsequently split into a test set for evaluating the performance of the model along with a train set to train the model. Following this, model selection occurs, where YOLOv11, RetinaNet Resnet50, and effientDet D0 are trained. To enhance overall accuracy, an ensemble evaluation combines the results from the trained models using techniques like Weighted Box Fusion (WBF). Models are selected for ensemble approach based on their mean average precision value. Then the model undergoes fine tuning and pipelining. Finally, the optimized model is deployed, making it ready for the project to analyze new inputs and provide predictions.

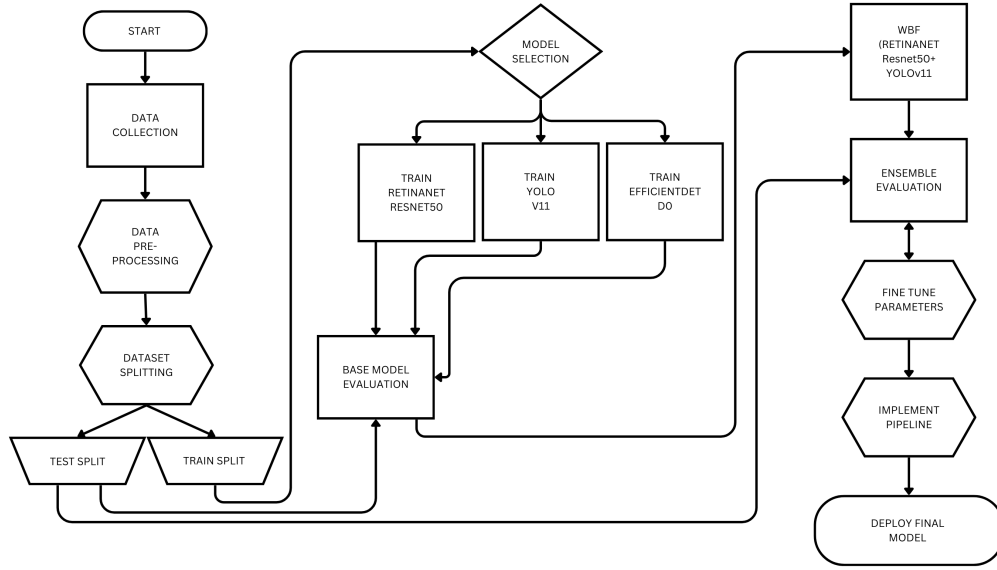


Figure 3.1: Methodology

3.1 Data Sourcing and Preparation

The dataset mostly contains photos of single potato plant leaves taken from mobile camera in Bangladesh primarily by us and from plant village dataset. The dataset initially contained large single leaves without complex backgrounds. However, real life scenarios contain complex backgrounds, multiple leaves of different sizes, orientation and overlaps. However, since diseased leaves were rare to find, the study used 2x2 collages of diseased images for the early diseased images to simulate multiple occurrences and size that is observed in **Figure: 3.2d**.

Figure: 3.2a shows a sample image from each class. **Figure: 3.2c** depicts Manual annotation of the images was performed for all affected disease regions using bounding boxes. The pre-augmented dataset consisted of around 9000 images, where around 4000 images were directly collected from plant village dataset. The post-augmented dataset was about 13,166 instances for training, 1091 instances for validation, and 1018 for testing, that included the classes: healthy leaf, early blight, and late blight. Rest of the images were collected individually using different resources. Mentioning that the percentages of training, testing and validating dataset were 72% and 14% each respectively. Image size was standardized to

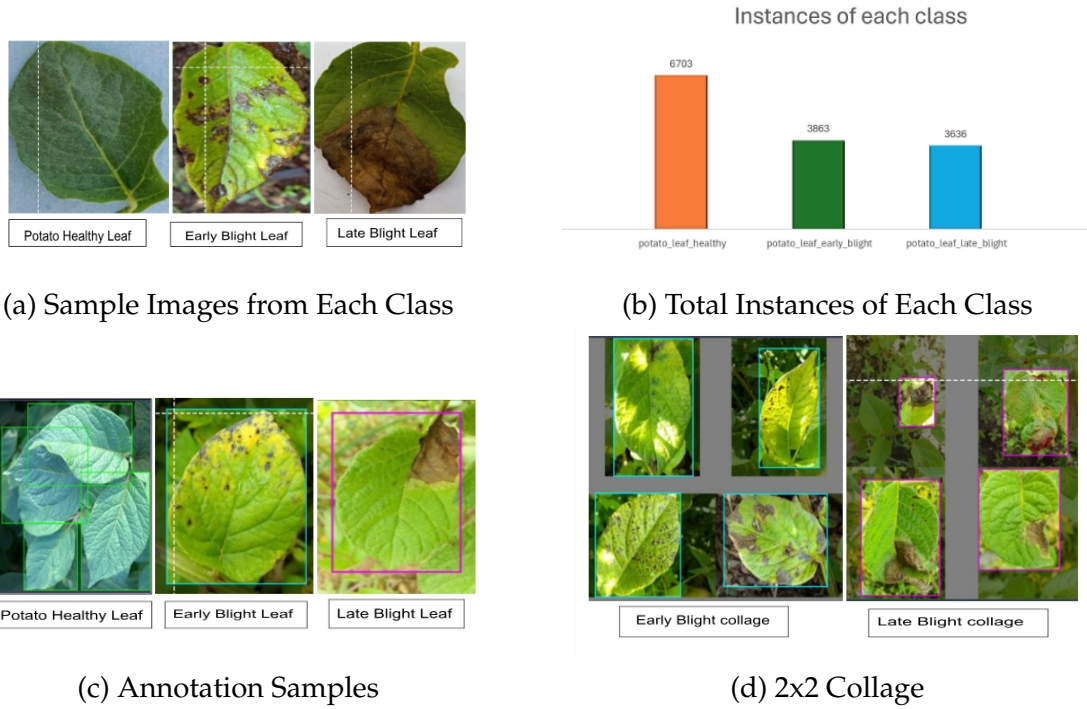


Figure 3.2: Dataset Details

512x512 pixels; this not only reduced computational complexity but also made model training feasible.

3.2 IoT Device Integration

This part describes the configuration and integration of IoT devices within the vertical garden system, further elaborating on various sensors and actuators that could form part of such a real-time surveillance and management system. The following major components comprise this system:

3.2.1 ESP32 Cam

The ESP32 Cam is a sophisticated microcontroller that includes Wi-Fi and Bluetooth. It features a camera that can take images of potato leaves and send it to cloud through the internet, which is crucial for identifying diseases.



Figure 3.3: ESP32 Camera Module

3.2.2 ESP32 microcontroller

The ESP32 is a powerful microcontroller with integrated Wi-Fi and Bluetooth, making it excellent for IoT applications. The ESP32 is appropriate since it supports a wide range of sensors and peripherals and utilize them in real-time.

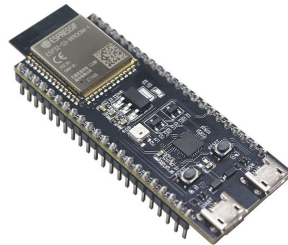


Figure 3.4: ESP32 microcontroller

for projects like environmental monitoring and automation. Its low power consumption and compact size make it perfect for portable projects.

3.2.3 Digital Humidity and Temperature Sensor: DHT11

The DHT11 is an affordable digital sensor that measures temperature and humidity. It is made up of a capacitive humidity sensor and a thermistor that measures



Figure 3.5: DHT11 Humidity & Temperature Sensor

temperature. The sensor uses a single-wire communication interface to deliver calibrated digital output.

3.2.4 Soil Moisture Sensor

The Soil Moisture Sensor is used to assess the moisture content of the soil, allowing the system to determine the optimal irrigation period. Thereby, it keeps a constant check on overwatering and underwater circumstances that may promote poor plant growth by providing exactly the proper quantity of moisture.



Figure 3.6: Soil Moisture Sensor

3.2.5 LDR Sensor Module

The LDR Sensor Module measures the light intensity of the garden environment. It



Figure 3.7: LDR Sensor Module

provides data to control the operation of grow lights, which will be able to provide the required amount of light to plants for photosynthesis. It will keep the system in a watchful mode for better plant growth.

3.2.6 Ultrasonic Sensor

It will measure the distance to plants using the Ultrasonic Sensor in a vertical garden setup for proper spacing and positioning. With the use of ultrasonic waves, it detects obstacles and may monitor plant growth in time to enable changing of an arrangement if necessary.



Figure 3.8: Ultrasonic Sensor

3.2.7 The 3V Pump

The 3V Pump is the actuator used for irrigation. When the soil moisture sensor reading falls below a specified threshold, the pump can be activated to supply water to the plants. This helps maintain consistent schedules for watering and reduces manual intervention.



Figure 3.9: The 3V Pump

3.2.8 The Grow Lights

The plants require specific wavelengths of light during photosynthesis, and this is fitted on the 6.5k Temperature LED Grow Lights. They can be activated after getting the readings by the LDR sensor and then the user will set schedules for the plants to ensure that they get enough light for proper growth.



Figure 3.10: The Grow Lights

Each sensor and actuator is connected to Firebase, which can manage and communicate data in real-time. The ESP32 will upload sensor readings and pictures of leaves to Firebase, through which users will be able to check the environmental conditions remotely. There will be threshold points for the collected data to activate actuators. Users can also control actuators, such as the pump and lights, via a mobile application.

3.3 Model Selection and Training

For developing and training our machine learning models Google Colab was utilized. In the inference pipeline, user inputs are sent to the Fast API endpoint, which is accessible via a URL created by Ngrok. This setup allows external applications to communicate with the local Fast API server seamlessly. The API then invokes the trained model to generate predictions based on the received input. After generating the results, they are stored in Firebase and Supabase for easy access and further

analysis. Users can interact with the mobile application to visualize predictions and monitor environmental data. Three advanced object detection models were adopted in this paper, including YOLOv11, RetinaNet with ResNet50, and EfficientDet. Each one of these model selections is based on its strengths for real-time detection and accuracy; these are the two most important criteria for identifying diseases in potato plants. The training was done using annotated datasets of potato leaves which were classified into healthy, early blight, and late blight classes, and then divided into training (72%), validation (14%), and test (14%) splits.

3.3.1 YOLOv11

The YOLOv11 model represents remarkable advancements in terms of object detection architecture. A study found that the most recent version of the YOLO architecture, YOLOv11, improved accuracy while reducing the number of parameters. This improvement makes it ideal for various applications, such as edge computing and cloud-based analysis [Khanam and Hussain \(2024\)](#). It has enhanced feature

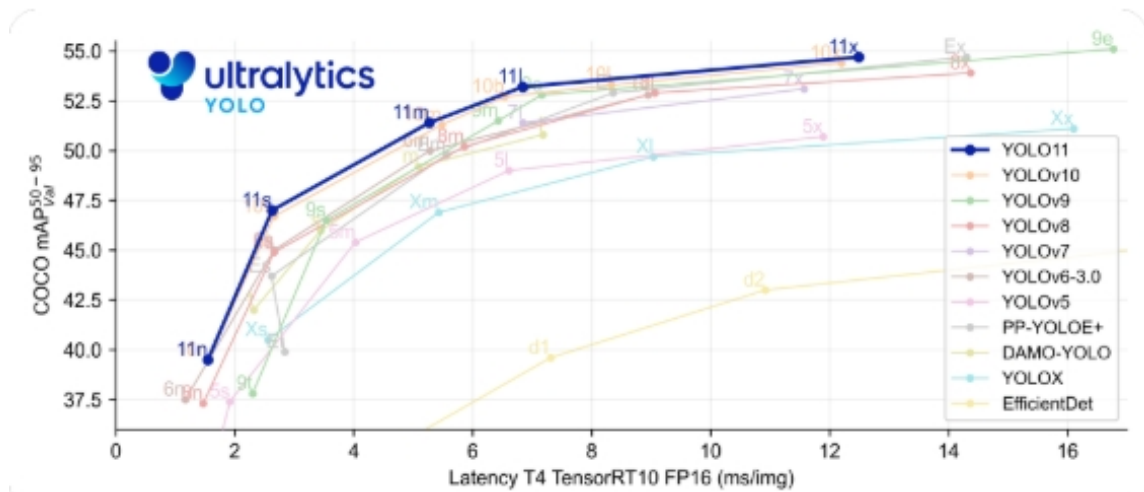


Figure 3.11: YOLO Ultralytics Performance Graph

extraction, optimized performance, and support for diverse tasks, making it a very competitive solution to complex visual recognition challenges for both research and practical scenarios [Khanam and Hussain \(2024\)](#). A comparison graph that compares the performance of various YOLO models, including YOLOv11 given in **Figure 3.11** highlights how each model balances speed and accuracy, with YOLOv11

demonstrating exceptional performance by achieving a high mAP while maintaining relatively low latency. This version of Yolo has yielded outstanding performance in numerous tasks, because of its novel architecture and training strategy [Wei et al. \(2024\)](#). The advent of YOLOv11 represents a significant advancement in existing object detection technology, laying a solid structure for our study's agenda. The

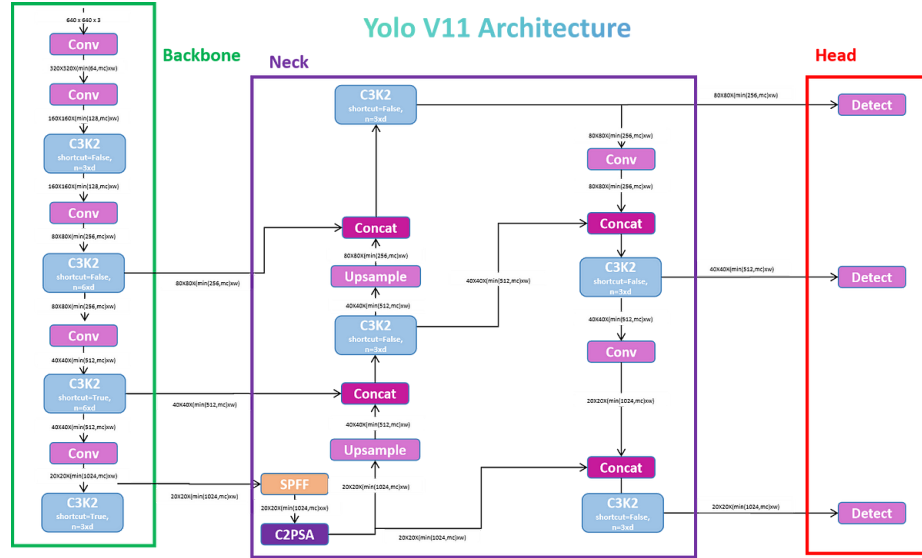


Figure 3.12: YOLOv11 model Architecture

YOLOv11 model represents remarkable advancements in terms of object detection architecture. The whole architecture is shown in **Figure 3.12**.

3.3.2 RetinaNet ResNet50 FPN

RetinaNet Resnet50 FPN is a state of the art complex object detection model that includes feature pyramid and a ResNet50 backbone. Given that this network architecture is specifically designed to perform amply on the variations in scale, it should be quite effective for a variety of applications. The ResNet50 backbone employs a residual connection technique that allows it to train deeper networks without encountering the issue of vanishing gradients, thereby increasing its ability to extract more complex features from input data and improving the model's detection accuracy. A study found that ResNet-50 obtains a mAP of 56.9 (AP of 0.5) without shared features and 57.2 with shared features [Lin et al. \(2017a\)](#). FPN in RetinaNet

can exploit multi-scale feature maps, which become pretty important for the detection of small and large objects. This is because different layer features combine the important semantic information, boosting its detection capabilities. Another

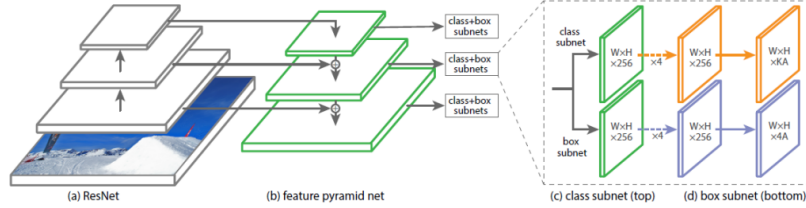


Figure 3.13: RetinaNet Resnet50 Architecture

important point, related to RetinaNet, is the use of the Focal Loss function. This addresses class imbalance in particular and puts more emphasis on hard-to-detect objects. According to [Lin et al. \(2017b\)](#), trained using Focal Loss, RetinaNet can match the speed of earlier one-stage detectors whilst outperforming the performance of all available state-of-the-art two-stage detectors. Thus, it is more capable of finding challenging examples and minimizing the influence of easy-to-detect backgrounds. Therefore, in summary, selecting RetinaNet with ResNet50 was suitable for our project to identify diseases in potato plants; it extracts powerful features, and its efficiency in class balance and real-time processing enables disease identification on location with accuracy. The architecture is shown in **Figure 3.13**.

3.3.3 EfficientDet D0

EfficientDet D0 is a very lightweight efficient object detection model designed with a hybrid scaling method to methodically maintain both accuracy and computational efficiency. It uses only 2.5 billion and 3.9 million parameters, making it lightweight and suitable for resource-constrained environments. EfficientDet is developed on top of the EfficientNet backbone, combining numerous sophisticated algorithms to deliver cutting-edge performance with significantly smaller model sizes. It has an average precision of 33.8% on the Coco dataset. The architecture uses a novel compound scaling technique to uniformly scale the network's resolution, depth, and width. This helps in balancing accuracy and efficiency effectively to be appropriate for many different applications requiring real-time processing. EfficientDet incorporates BiFPN into adding improvements toward feature extraction in a multi-scale manner to enable the detector for various sizes of objects and make the model

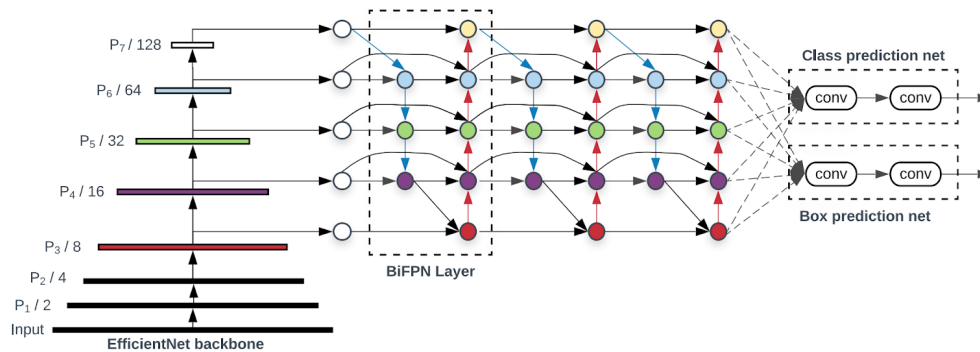


Figure 3.14: EfficientDet Architecture

amazingly capable in object detection from tiny to large objects through aggregation from features in several layers. Its effectiveness can be found through its respective metrics like mAP of 33.5% for the smallest object and 35.8% for middle object and substantial 52.2% for largest objects [Tan et al. \(2020\)](#).

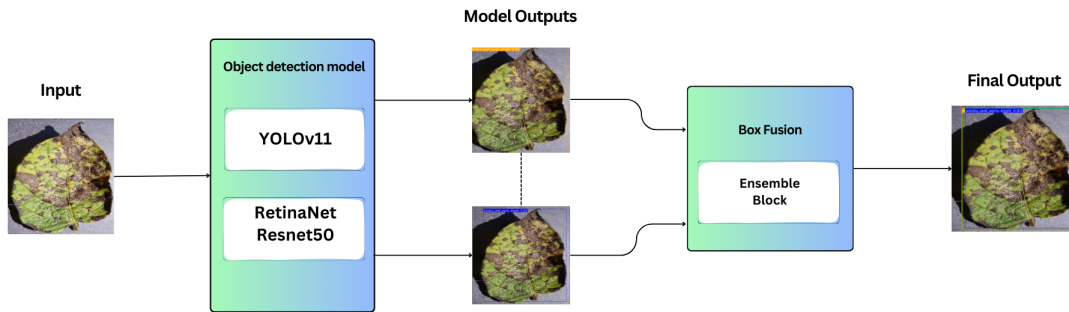
EfficientDet adds to these a focus on a reduction of computational resources without losing performance, hence it is very well-suited for utilization in edge devices with limited hardware capabilities. The architecture is shown in **Figure 3.14**.

3.3.4 Weighted Box Fusion

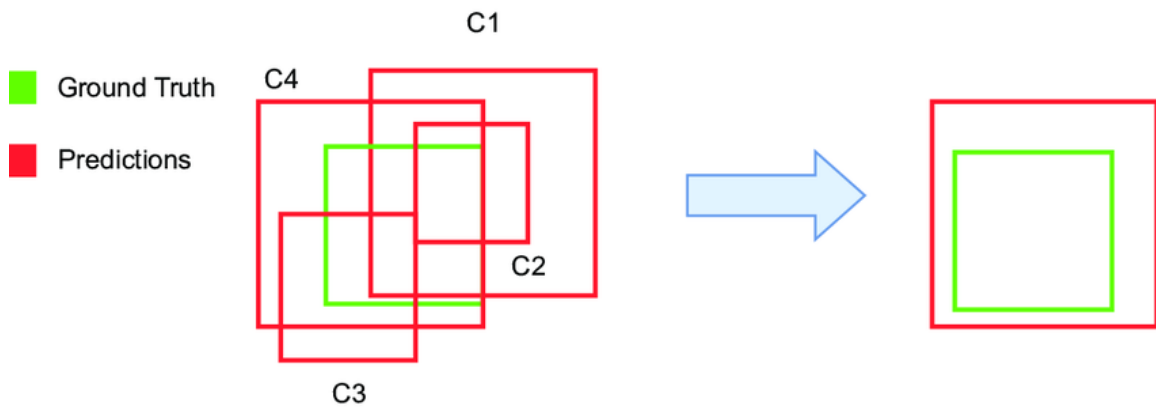
Ensemble modeling is an effective approach for improving object detection by aggregating predictions from multiple models, thereby enhancing accuracy and robustness. This approach mitigates issues such as overlapping or redundant predictions, which can lower overall detection performance. Weighted Box Fusion (WBF) was selected as the ensemble technique to refine model predictions. Unlike traditional Non-Maximum Suppression (NMS), which suppresses overlapping bounding boxes, WBF assigns weights to each bounding box based on confidence scores, generating a more precise final prediction.

Research has shown that WBF significantly outperforms other prediction combination methods, demonstrating remarkable success in competitive benchmarks Detection Challenges such as COCO and Open Image. WBF achieved a mAP of 56.1 and 56.4 training and validation set respectively in the study done by [Solovyev and Wang \(2019\)](#). This technique has broad applications beyond agriculture, including

autonomous vehicles, where accurate object detection is critical for safety, and medical imaging, where precise abnormality detection is essential. In agriculture, WBF has the potential to effectively resolves overlapping bounding boxes, improving disease detection accuracy. For this research, WBF is used to enhance the detection of leaf diseases in vertical gardening systems. The approach ensures precise disease identification by aggregating predictions from multiple models, improving detection accuracy and robustness. The system provides crucial advantages for real-time



(a) Ensemble Model Architecture



(b) WBF Method

surveillance and decision-making in agricultural applications, allowing for more

effective and efficient disease management in vertical gardening solutions.

This study implements an ensemble model fusing YOLOv11 and RetinaNet ResNet50 FPN using weighted box fusion. The goal was to combine the advantages that these advanced architectures offer in terms of enhanced detection capabilities of YOLOv11 and RetinaNet’s accuracy. Weighted Box Fusion has been used as an ensemble technique where a single, more precise bounding box is created from predictions made by both models. Contrary to standard methods like Non-Maximum Suppression, WBF weighs each bounding box based on the confidence scores of their prediction, further refining outputs. The architecture is shown **Figure 3.15a**.

WBF finds applications not only in agriculture but also in the essential sectors of autonomous vehicles, where accurate object detection is important for safety reasons, and in medical imaging, where locating abnormalities is very critical. In agriculture, this may be very useful for increasing the accuracy of disease detection by effectively resolving overlapping bounding boxes and generally improving the outputs of a model.

Various works indicate that WBF indeed works very well in diverse contexts. A study was based on the tea leaves for which an embedded deep learning-based pest and disease detection system was implemented, combining YOLOv5 with WBF to find quite good improvements in accuracy [Wang et al. \(2023\)](#).

3.3.5 Evaluation Method

The capability of object detection models was evaluated using the following essential metrics such as mean average precision (mAP), recall, and f1 score.

Precision determines a model’s ability to identify region of interests accurately. It is defined as the ratio of accurately predicted positive observations to total predicted positive observations, which includes both True Positives and False Positives. This is mathematically represented as follows:

$$Precision = \frac{TP}{TP + FP} \quad (3.1)$$

A high value of precision means most of the detected defects are correct, minimizing the false alarms when non-defect areas are mistakenly labeled as defects. Recall refers to the model’s ability to correctly identify true instances. It is determined by the number of True Positives divided by the total number of actual

positives, including both True Positives and False Negatives. The equation of recall goes like this:

$$Recall = \frac{TP}{TP + FN} \quad (3.2)$$

Recall is relevant when the aim is to identify as many real defects as possible, which means the model should have minimal missed defects. The F1-Score is also known as the harmonic average of precision and recall. It balances the differences between precision and recall, making it particularly effective in situations when the data set is very inconsistent.

$$F_1 = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (3.3)$$

F1-Score ranges from 0 to 1, where 1 is complete precision and recall. This metric would help in understanding the trade-off between false positives and false negatives of the model's predictions.

The confusion matrix provides an extensive summary of the model's projections, including how many were TP, TN, FP, or FN. This can be further honed into knowing the strengths and weaknesses the model is suffering from in identifying defects correctly or not. It also helps in highlighting where it has gone wrong.

Table 3.1: Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positives	False Negatives
Actual Negative	False Positives	True Negatives

Lastly, the precision-recall curve for all classes is condensed by the mAP, which is essential for object detection. The mAP at different recalls forms the area under the curve. Hence, the AP is averaged across all classes to produce the mAP. In object detection, mAP is usually evaluated under various IoU thresholds. Average Precision is formulated as follows:

$$AP = \int_0^1 Precision(r) dr \quad (3.4)$$

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i \quad (3.5)$$

We use several mAP metrics: mAP (50), mAP (75), and mAP (50-95) to evaluate performance.

3.3.6 Mobile Application Development

The work aimed at developing a mobile application called Phyto Sense, undertaken in Android Studio with Java. Phyto Sense is meant to be an integrated platform in agriculture for the monitoring and management of plants on real-time data visualization and control. The key Features of the application are mentioned below:

- **Sensor Data Integration:** Phyto Sense uses Firebase, which makes accessing data from multiple sensors deployed in the agricultural environment very simple. This implies that users can access real-time status of soil moisture, temperature, humidity, and any other critical parameters affecting the health of a plant.
- **Manual actuator control:** The application enables manual actuator control for irrigation system management, nutrient dispensers, and other automated devices right from their mobile device. This would allow the users to make decisions at the right time after the data receipt, optimize resource utilization, and yield the best crops.
- **Leaf Health Monitoring:** One of the major attractions that Phyto Sense has is that it assesses the health status of a plant leaf using predictions generated by our ensemble model coupled with YOLOv11 and RetinaNet using a ResNet50 backbone. It will provide insights into the present status of the health of the plant leaves and enable users to further take action regarding pest control and disease management.
- **Disease Severity Assessment:** The app also provides information on the severity level of any detected diseases. The extent of the damage that has been caused by pests or diseases can be determined by analyzing data from the ensemble model to take further action to reduce losses effectively.

Chapter 4

Design and Development

4.1 System Architecture Overview

Figure: 4.1 portrays the proposed system architecture that consists of main components like: IoT devices, Cloud, and Mobile Application, which work together to monitor plant health efficiently. The hardware section includes essential elements like microcontrollers, sensors, actuators, and cameras that collect data from plants and their environment. The edge devices are connected to the a Wi-Fi router to send data to the Cloud, where it is stored in Firebase. Collected images are sent to the ensemble model for analysis through firebase, and the predicted outputs are displayed in the mobile application for user acknowledgement. Finally, the Mobile Application serves as the user interface, featuring a dashboard for visualizing data, a user feed for updates, and controls for managing the system.

4.2 Hardware and Software Components

4.2.1 Hardware

- **ESP32-CAM:** The ESP32-CAM shall be the major microcontroller containing a camera module that captures pictures of the plant leaf, and it has Wi-Fi connectivity, allowing real-time transmission of data for monitoring and control purposes.
- **Soil Moisture Sensor:** To keep the soil moisture a constant check for irrigation purposes.

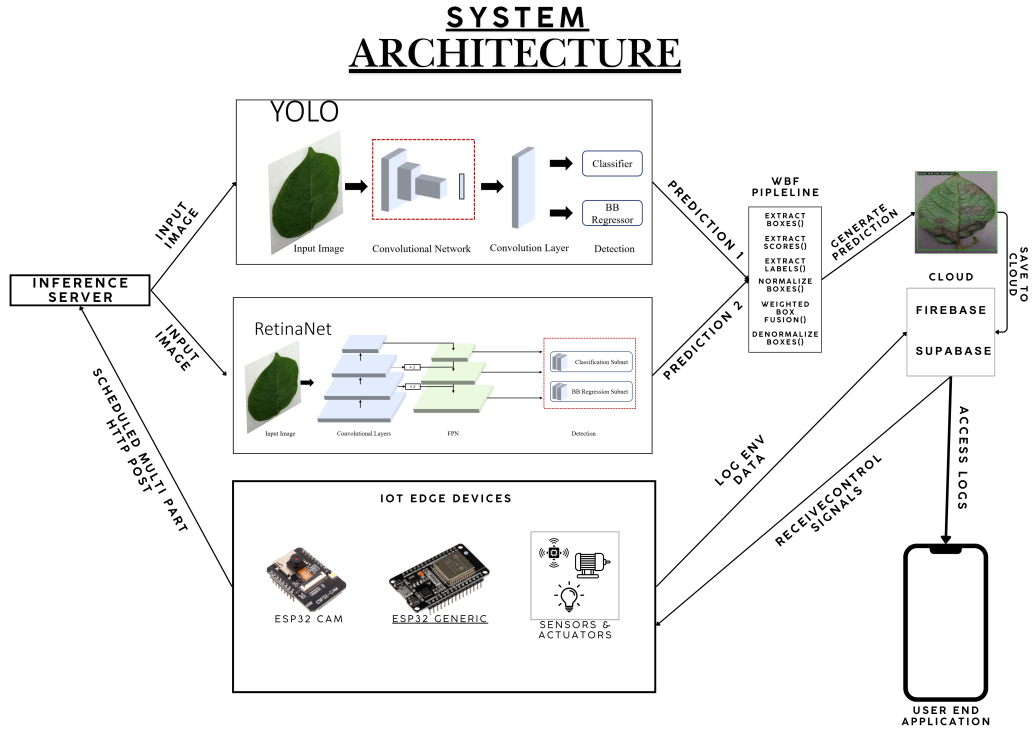


Figure 4.1: System Architecture Overview

- **Temperature and Humidity Sensors:** Track ambient temperature and humidity, ensuring ideal growing conditions for plants.
- **Light Intensity Sensors:** These measure light intensity to better control the growing environment.
- **Water Pumps:** Provide irrigation automatically, which is controlled based on the soil moisture readings.
- **Grow Light:** Provides supplemental lighting to ensure optimal growth.

4.2.2 Software

- **Google Colab:** This utilized primarily for the implementation and training of the deep learning models. Google Colab provides a collaborative platform with robust computational resources for model experimentation and implementation.

- **Firestore:** It acts as the cloud database, which can store and retrieve sensor data and images in real-time. This ensures that the latest information is always available to the users through the mobile application.
- **Android Studio:** The mobile application, developed in Android Studio, offers a user-friendly interface with up-to date libraries and support.
- **Roboflow:** Used for annotating images and pre-processing, including resizing and graying of images. Roboflow automated much of the work of preparing the data for machine learning model training.
- **Development Framework:** Python is the predominant programming language, as it has libraries for implementing and fine tuning models from frameworks such as TensorFlow or PyTorch. The overall architecture of the software is intended to enable fluent data handling and model inference.

4.3 Cost Analysis

Cost efficiency of the system will play a crucial role in its sustainability in the context of Bangladesh. Since it can be evolved and improvised as more advanced models and technologies become available, the system can be scaled for centralized cloud infrastructure or for real-time processing on edge devices. Regular updates to both the model and the dataset will ensure that it remains current with advancements in machine learning, ultimately improving its generalization over time. Although the initial setup requires a significant investment, the system reduces long-term costs by minimizing material waste and manual inspections, thereby enhancing overall efficiency and economic viability.

4.4 Challenges Faced

- The implementation of the proposed IoT-based vertical gardening system has a number of challenges that may affect its overall success. Among the major challenges, high-cost IoT hardware components are among the major deterring factors for farmers. This may reduce the adoption rate, especially for small-scale gardeners and farms that have limited budget to invest in advanced technology.

Table 4.1: Hardware Cost Analysis Table

Component	Cost(BDT)
ESP32 Cam	530
ESP32 Microcontroller	500
DHT 11(Humidity and Room Temperature Sensor)	110
Soil Moisture Sensor (Hygrow)	70
3V Pump	50
LDR sensor module	40
6.5k Temperature LED Grow Lights	300
MUX CD4051	20
Relay module (5V)	320
Ultrasonic sensor	70
Total Cost (Per Level)	1,540
Total Setup Cost (1 Level)	2,010

- establishment of such a system encompasses complex installation, calibration checks, and configuration. This may easily lead to delays in implementation that are frustrating to the users, who would like to see quick results. Scarcity may lead to delayed projects and increased costs while farmers look for alternatives.
- The scaling up of IoT infrastructure brings complexities, especially in adapting to changing environmental conditions. While adaptability is key to long-term sustainability, it also demands continuous management and investment. Large volumes of data produced by the system can be quite overwhelming to manage and analyze.
- Data collection of diseased potato leaves, especially for early blight and late blight, was not easy to find. Seasonal potato planting complicated data collection efforts further by simply restricting the time frame for gathering sufficient training data.
- One of the big challenges was to create an effective ensemble model, since these approaches are complementary to each other: YOLO performs better in predicting multiple objects on an image, while RetinaNet is optimized on those datasets it was trained on.

Chapter 5

Result Analysis & Discussion

5.1 Result Analysis

5.1.1 Efficient Det D0

Table 5.1 shows Efficient Det D0 achieved an moderate level of effectiveness on object detection tasks across classes. At 50% IoU threshold, the mAP is 0.68, reflecting average performance for objects with minor overlaps. Additionally, it achieved mAP75 of 0.61 which reflects adequate performance in detecting objects with minimal overlap.

Table 5.1: Evaluation Result of EfficientDet D0

Model	mAP50	mAP75	mAP50-95	AR50-95
EfficientDet-D0	0.68	0.61	0.53	0.80

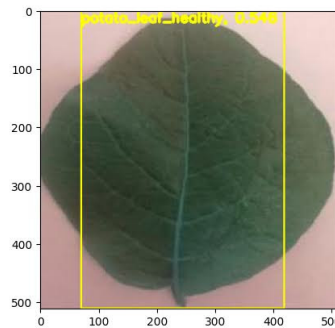


Figure 5.1: EfficientDet-D0 Prediction

The mAP50-95 is 0.53, reflecting weaker performance as the detection criteria

became more compelling. Finally, an Average Recall (AR) of 0.80 signifies that the model is capable of successfully identifying a significant instances of true positives effectively. However, **Figure 5.1** shows that even though it predicts the class properly, the box generation and the localization is average and is in need of more refinement. The performance metrics illustrate that the EfficientDet model shows potential, it needs further refinement to enhance to efficiently detect objects.

5.1.2 RetinaNet ResNet50 FPN

RetinaNet ResNet50's result portrays overall high performance of the model on object detection tasks across classes. The model was trained for 6525 steps. In **Figure 5.2**, **Figure 5.3**, and **Figure 5.4** it is seen that class loss plateaued by 6525 step achieving a 0.07 class loss whereas, the box loss and total loss where calculated at 0.11 and 0.19 respectively. On the other hand, it achieved a mAP50 of 0.90, reflecting high performance for objects with minor overlaps. Further, at mAP75 the score is 0.89, reflecting good performance of the model under a stricter IoU threshold condition.

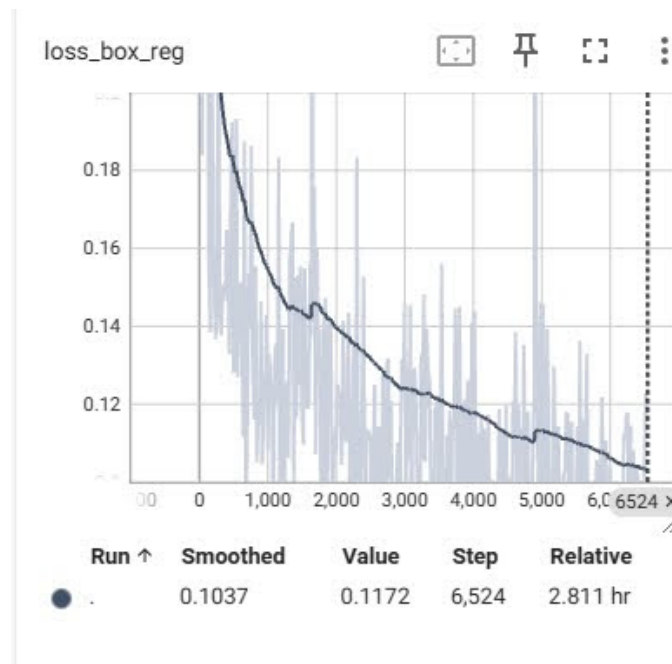


Figure 5.2: Box Loss Graph(Retinanet Resnet50 FPN)

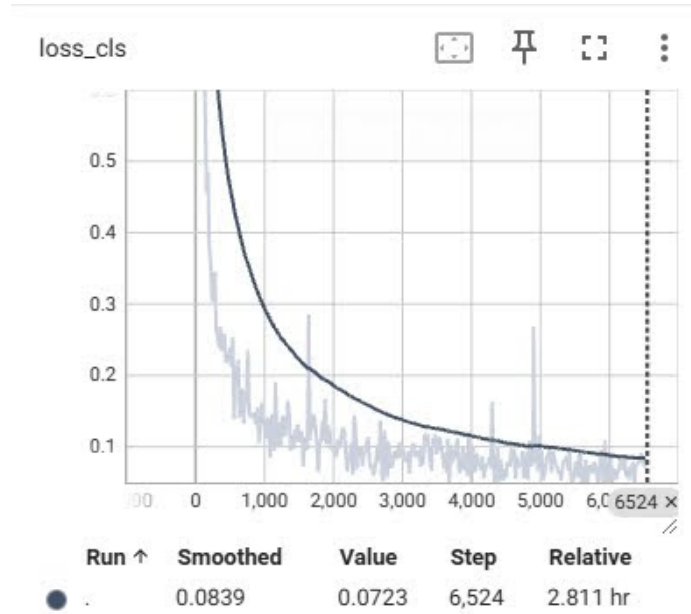


Figure 5.3: Class Loss Graph(Retinanet Resnet50 FPN)

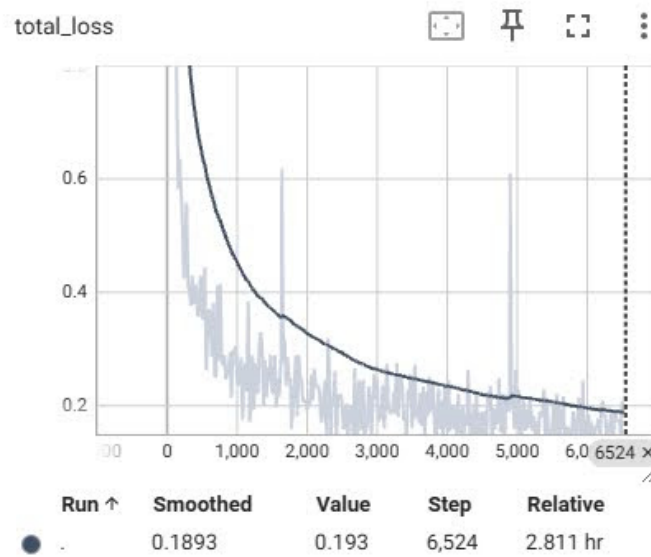


Figure 5.4: Total Loss Graph(Retinanet Resnet50 FPN)

Additionally, computed mAP50-95 is 0.85, reflecting very strong performance even as detection criteria became more conservative. Finally, an Average Recall (AR) of 0.87 reflects that the model captures a major portion of the true positive

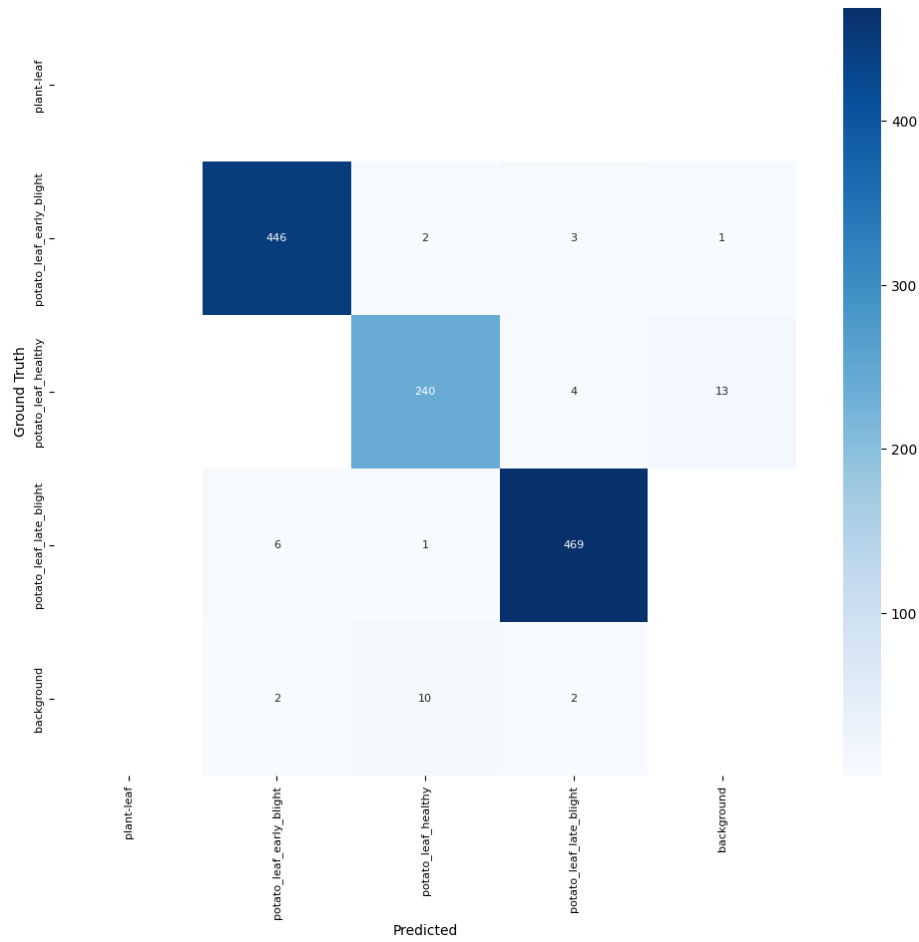


Figure 5.5: Confusion Matrix(Retinanet Resnet50 FPN)

cases effectively, which is very important to ensure timely interventions in scenarios such as disease detection in plants. The confusion matrix generated for the Retinanet Resnet50 FPN from **Figure 5.5**, where the diagonal values represent the true positives. The model correctly classified 447 instances of early blight, 236 instances of healthy leaves, and 468 instances of late blight. Off-diagonal values indicate misclassifications, where some early blight cases were predicted as healthy, late blight, background and vice versa. These overall metrics refer to the high reliability of the model while performing object detection based on RetinaNet Resnet50 FPN.

5.1.3 YOLOv11

YOLOv11 outperformed both models, achieving the highest performance. It was trained for 30 epochs, with the best checkpoint at epoch 27. At a 50% Intersection over Union (IoU) threshold, the mean Average Precision (mAP50) was 0.91. In **Figure 5.6** decreasing box loss and classification loss indicate better model performance. However, mAP50 and mAP50-95 represents a comprehensive view of the model's capability across various threshold of detection accuracy that plateaued out at the end.

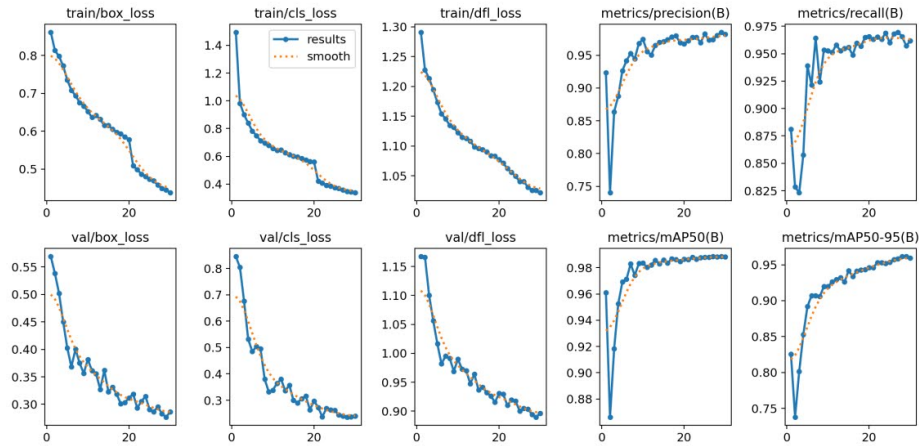


Figure 5.6: YOLOv11 Metrics

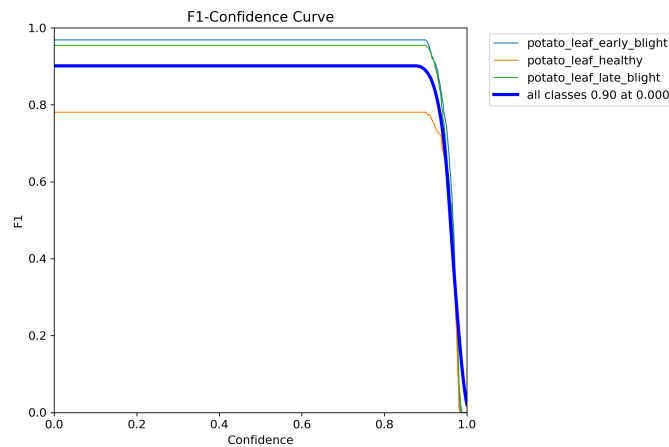


Figure 5.7: F1-Confidence Curve: YOLOv11

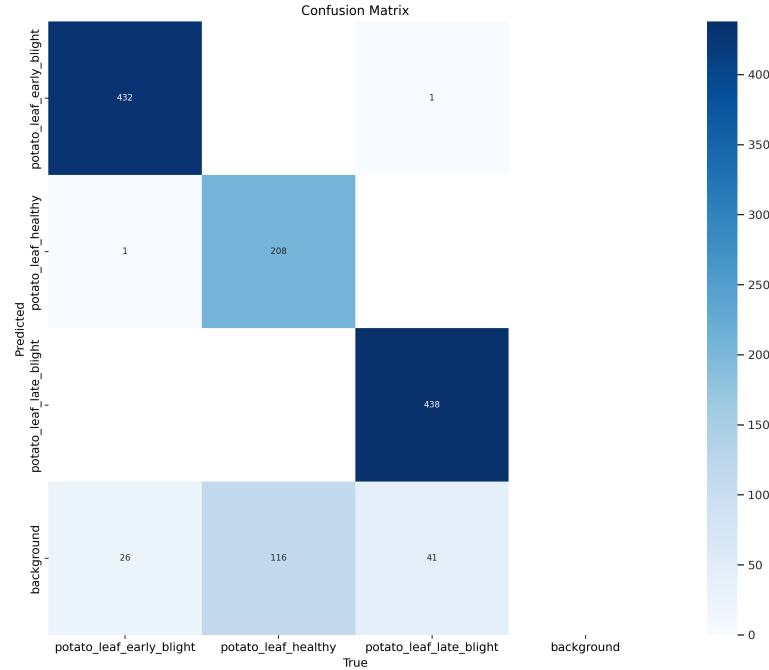


Figure 5.8: Confusion Matrix (YOLOv11)

Besides, it attained a mAP75 of 0.91, which is very strong under more stringent conditions of overlap. What’s more, the mAP over IoU thresholds from 50% to 95% was 0.90, reflecting its robust performance when the detection criteria became more stringent. Finally, an Average Recall of 0.83 signifies that the model successfully identifies a big proportion of true positive instances, which is a must in applications like plant disease management. Overall, these metrics show evidence that YOLOv11 is very efficient and reliable for object detection.

5.1.4 Weighted Box Fusion

The study’s Approach approach to ensemble utilizes the Weighted Box Fusion (WBF) method to reinforce the precision of bounding box predictions. By considering the outputs of both YOLOv11 and RetinaNet, WBF effectively aggregates the bounding boxes generated by each model, weighing them based on their confidence scores. This process helps to reduce false positives and improve the localization of detected objects, ensuring that the bounding boxes are more precise and reliable. This method combines the outputs from both the RetinaNet Resnet50 and YOLOv11 models, refining the predictions by weighing their confidence scores.

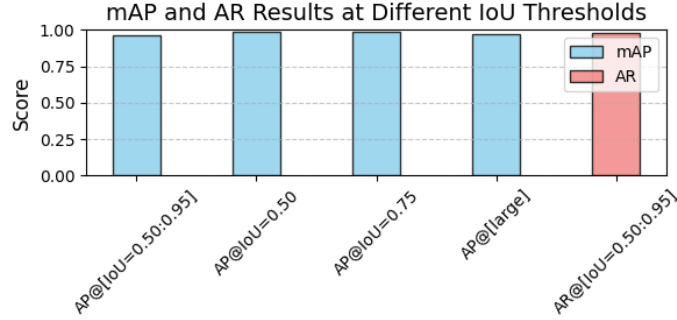


Figure 5.9: mAP and AR Graph of WBF

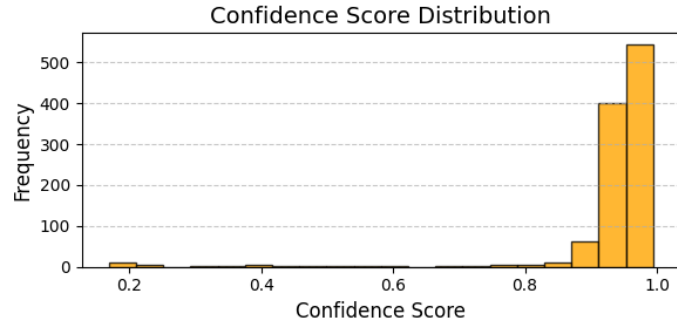


Figure 5.10: Confidence Score Distribution

The ensemble model achieved an AP score of 0.96, demonstrating exceptional object detection capabilities across different classes. The high mean Average Precision (mAP) scores—0.93 at the 50% IoU threshold and 0.93 at the 75% threshold—highlighted its ability to refine bounding boxes for improved detection accuracy. Additionally, the model maintained strong performance across various Intersection over Union threshold, where it yielded a mAP of 0.89 across the 50–95% range. These mAP scores, along with an Average Recall (AR) of 0.91, were all higher than those achieved by the individual models, YOLOv11 and RetinaNet ResNet50. This improvement demonstrated the strength of the ensemble approach in balancing precision and recall for object detection. Despite these improvements, the increase in recall also introduced some challenges. Many images in the dataset contained overlapping potato leaves that were not annotated. The WBF ensemble’s ability to generalize led to the detection of these unlabeled regions, which were mistakenly considered false positives during evaluation. This emphasizes the importance of comprehensive and accurate annotations in training datasets to

maximize the utility of advanced fusion techniques like WBF.

This results in bounding boxes that are not only accurate but also robust across different scenarios, making the ensemble model a formidable tool for monitoring plant leaf diseases in an IoT based vertical gardening system. Finally, an average Recall of 0.91 ensures that most true positive cases are captured by the system. This indubitably important in such applications.

5.2 Comparative Analysis

The result of RetinaNet ResNet50 FPN, YOLOv11, and their Weighted Box Fusion (WBF) ensemble demonstrates the effectiveness of WBF for leaf disease detection . RetinaNet ResNet50 FPN achieved mAP50 of 0.90, mAP75 of 0.89, mAP50-95 of 0.85, and AR50-90 of 0.87. While these results indicate strong detection capabilities, the model exhibited some limitations in precision, missed detections and minor misclassification. YOLOv11 outperformed RetinaNet, achieving an mAP50 of 0.91, mAP75 of 0.91, mAP50-95 of 0.90, and AR50-90 of 0.83, highlighting superior accuracy and detection consistency. On the other hand, Efficient Det D0 achieved an mAP50 of 0.68, mAP75 of 0.61, mAP50-95 of 0.53, and AR50-90 of 0.80. The result highlight its relatively lower detection performance compared to both RetinaNet and YOLOv11.

Table 5.2: Result Analysis Table

Model	mAP50	mAP75	mAP50-95	AR50-95
EfficientDet-D0	0.68	0.61	0.53	0.80
Retinanet Resnet50 FPN	0.90	0.89	0.85	0.87
YOLOv11	0.91	0.91	0.90	0.83
WBF (Retinanet+YOLOv11)	0.93	0.93	0.89	0.91

The WBF ensemble, combining predictions from YOLOv11 and RetinaNet, achieved an mAP50 of 0.93, mAP75 of 0.93, mAP50-95 of 0.89, and AR50-90 of 0.91. This approach retained the high precision of WBF while achieving the highest Average Recall (AR) of 0.91 among all models. The improvement in AR reflects WBF's ability to detect a broader range of instances, as it compensates for false negatives by leveraging complementary strengths from both YOLOv11 and RetinaNet.

Moreover, the WBF ensemble resolved missed detections effectively, integrating predictions where one model compensated for the other's limitations.

Despite these improvements in recall, the lack of an increase in mAP suggests potential penalties for false positives. Many images in the dataset contained overlapping potato leaves that were not annotated. The WBF ensemble's generalization capabilities likely led to the detection of these unlabeled regions, which were treated as false positives during evaluation. This explains why mAP did not increase, even though recall improved significantly. This observation underscores the importance of comprehensive and accurate annotations in training datasets to maximize the utility of advanced fusion techniques like WBF.

These results highlight the utility of WBF in achieving balanced precision and recall, particularly for complex datasets with challenging annotations. The ensemble model provides a robust solution for leaf disease detection, addressing false negatives while maintaining competitive precision. This validates the use of WBF for practical and efficient disease detection systems, making it an effective approach for improving the robustness of the precision and reliability of automated plant health monitoring systems.

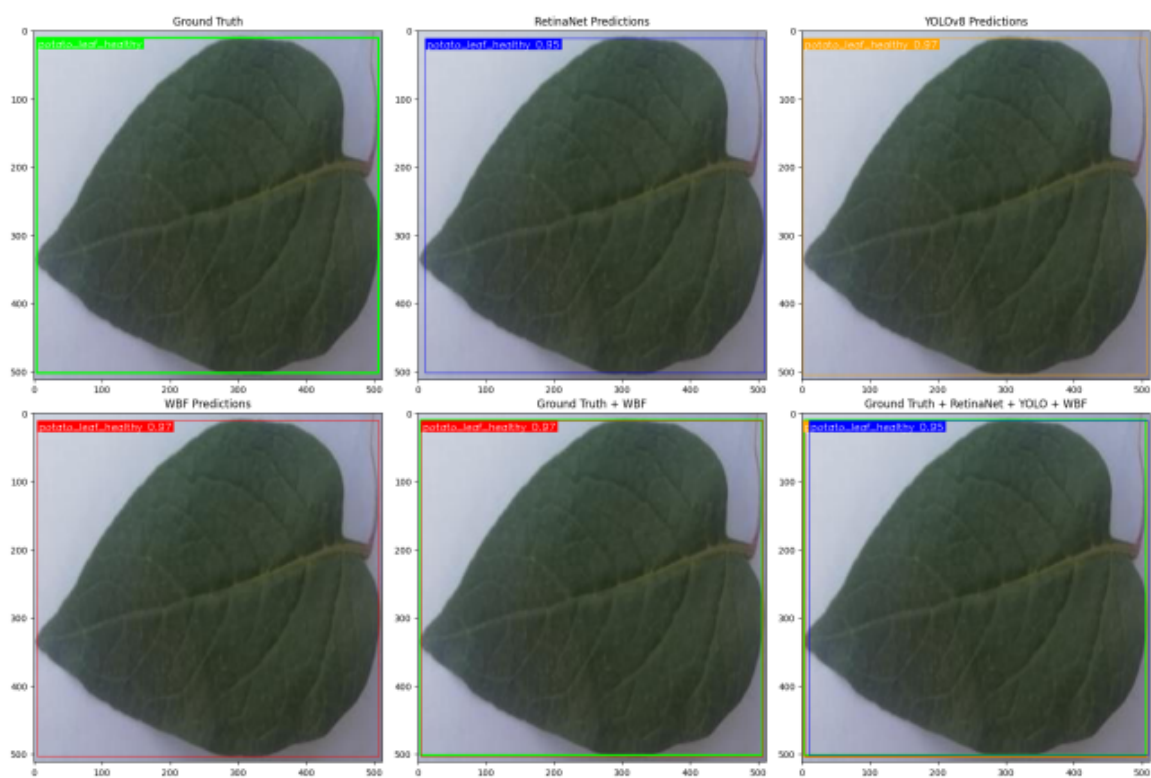


Figure 5.11: Prediction: Healthy

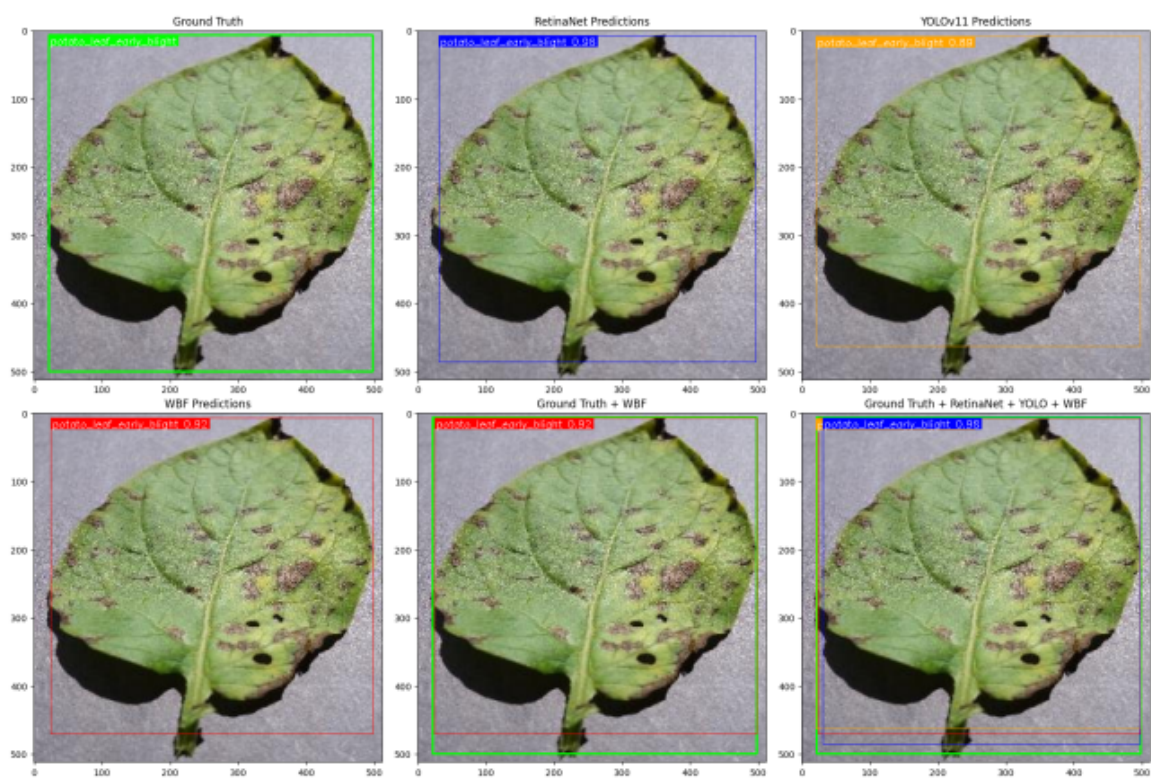


Figure 5.12: Prediction: Early Blight

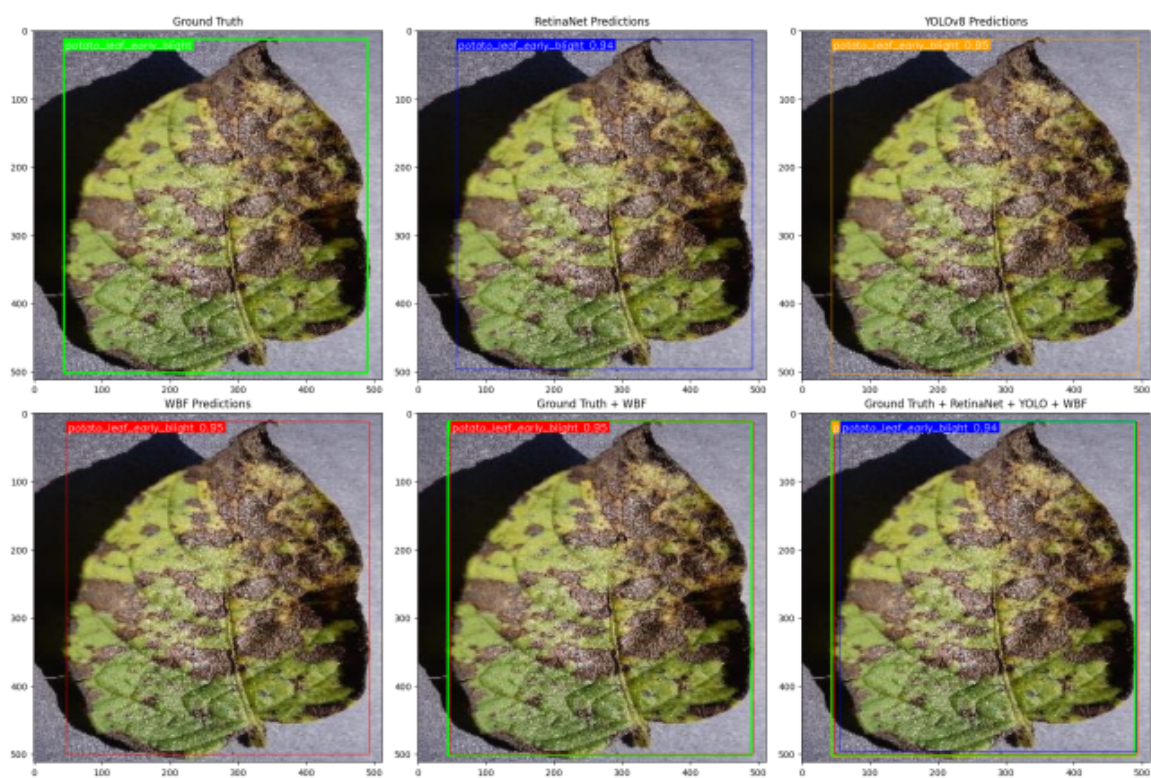


Figure 5.13: Prediction: Late Blight

Chapter 6

Conclusions

This study developed an IoT-based leaf disease detection system to address the challenges of manual plant health monitoring in vertical gardening. By integrating IoT devices with object detection techniques, the system significantly improved the efficiency, scalability, and precision of leaf disease identification and localization. The ensemble method, which combined YOLOv11, RetinaNet ResNet50, and Weighted Box Fusion (WBF), achieved the highest performance among various fusion approaches. The system recorded a mAP of 0.93 at the 50% IoU threshold and 0.93 at the 75% threshold, ensuring precise disease detection and highly accurate bounding box localization. Additionally, the ensemble method outperformed the individual models in terms of both mAP and Average Recall (AR), which reached 0.91, demonstrating its robustness in capturing true positive cases. Beyond its technical performance, this system highlighted the potential of automation in optimizing resource use, reducing labor dependency, and improving crop health, aligning with sustainable urban agriculture practices. The ESP32-CAM edge device successfully transmitted image data to the inference server, which processed and stored predictions in Firebase and Supabase databases. Furthermore, the mobile application provided real-time environmental conditions and daily disease detection summaries, ensuring seamless monitoring of plant health.

6.1 Limitation

In spite of having strong performance, the system had some limitations. The dataset contained only three classes (healthy, early blight, and late blight), leading to cases where other leaf deformities were misclassified as healthy due to their lack of

distinct features. Additionally, the dataset was somewhat biased toward single large leaves, with most images captured against relatively simple backgrounds. These factors hampered methods true ability to generalize to more complex scenarios involving multiple overlapping leaves or diverse environmental conditions.

6.2 Future Prospects

For future improvements, expanding the data set to include more classes of diseases and diverse backgrounds could enhance the robustness of the system. Implementing active learning techniques to refine annotations and minimize false positives could further improve detection accuracy. Furthermore, optimizing the edge processing capabilities of ESP32-CAM could reduce the dependence on cloud-based inference, enabling low-latency real-time disease detection. Integrating multi-sensor data, such as temperature and humidity readings, could also enhance disease prediction, making the system even more effective for smart agriculture applications. Overall, this study demonstrated that combining IoT, edge computing, and machine learning offers a scalable and adaptable solution for automated plant health monitoring. With continued refinements, this approach holds great potential for real-world deployment in sustainable and precision agriculture.

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