Thesis: Smart Agricultural Robot Based on Computer Vision

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Smart Agricultural robot based on computer vision

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List of Acronyms

CV	Computer Vision
IUT	Islamic University of Technology
YOLO	You Only Look Once
CNN	Convolutional Nural Network
PWM	Pulse Width Modulation
CPU	Central Processing Unit
LiDAR	LIght Detection And Ranging of Laser

Chapter 1

Introduction

1.1 BASIC FUNCTIONALITIES OF AGRICULTURAL HARVESTING ROBOT

The agriculture industry has undergone a dramatic transition in recent years, thanks to advances in robotic technology. Among these advancements, harvesting robots stand out as a game-changing solution to modern farming difficulties. Harvesting robots have the potential to revolutionize agricultural operations by automating the labor-intensive activity of fruit picking, increasing production, and mitigating manpower shortages.

Traditionally, agriculture has relied primarily on manual labor for chores like harvesting, which are frequently monotonous, physically demanding, and vulnerable to seasonal fluctuations in workforce availability. However, as demographics change and urbanization increases, the availability of trained agricultural workers has decreased, creating substantial problems for farm operations around the world. Harvesting robots are a cutting-edge solution that has arisen in response to these difficulties. They use sophisticated technology like robotics, artificial intelligence, and machine learning to do jobs that have historically been performed by human workers. These robots are outfitted with advanced vision systems, motion delivery systems, and end-effectors that are specifically engineered to precisely identify, find, and pick ripe fruits. Harvesting robots have revolutionized agricultural operations and brought about many advantages for farmers, such as higher crop yields, lower labor costs, and enhanced operational efficiency. Furthermore, these robots could solve important problems including the lack of labor, labor reliance, and the requirement for sustainable farming methods. In light of this, the purpose of this study is to present a thorough analysis of harvesting robots, examining their features, potential applications, and effects on the agricultural industry. We aim to shed light on how harvesting robots could revolutionize modern agriculture by analyzing the most recent developments in robotic technologies and how they are being applied to fruit harvesting. We intend to stimulate more research, development, and use of harvesting robots to meet the changing needs of the agricultural business by gaining a greater understanding of these cutting-edge technologies.

1.2 DIFFERENT ASPECTS

Harvesting robots, which integrate a variety of complex systems to solve the urgent problems of labor shortages and resource optimization in agriculture, constitute a significant achievement in agricultural technology. These robots essential features can be combined into several connected parts.

Figure 1.1: Digital farming with agricultural robotics (source: www.AdaptiveAgroTech.com).

Vision Systems:
Harvesting robots rely on modern vision systems that use a variety of sensors such as RGB cameras, multispectral cameras, LiDAR, and depth cameras to perform well. These sensors, when paired with sophisticated image processing techniques and machine learning algorithms, allow robots to properly detect and localize fruits in a variety of demanding settings.

Feature extraction and AI integration:
The visual systems extract critical properties such as color, texture, and shape to distinguish between ripe and unripe fruit. AI and machine learning, particularly neural networks, improve detection accuracy by responding to changing lighting and occlusions, increasing overall harvesting efficiency.

Motion Delivery Systems:
Robots can travel fields and orchards with the use of effective mobility devices, including wheeled or tracked bases. Robust motion planning algorithms guarantee accurate positioning, allowing the robot to access and retrieve fruits situated in different parts of the surroundings.

Manipulation and Control:
The real harvesting process depends on robotic grippers and arms that are managed by accurate motion delivery systems. Sophisticated control algorithms and feedback mechanisms are necessary for these devices to perform the delicate operation of harvesting fruits without causing damage.

End-Effectors:
The end-effector, which consists of harvesting tools and grippers, needs to be thoughtfully made in order to grasp and separate fruits without hurting them. Various end-effector types—such as vacuum-based or soft grippers—are employed based on the fruit variety and plant structure. It's important to make sure that removing the fruit from the plant with as little damage as possible is done. To do this, there must be a harmonious design between the control systems and the end-effectors.

Environmental Adaptability:
Harvesting robots need to be able to function well in a variety of environmental settings, including sun and shade. The robots can continue to operate effectively and adjust to these changes because of their powerful vision and control systems.

Obstacle Avoidance:
To ensure smooth operation and prevent harm to the robot and the plants, effective obstacle recognition and avoidance systems are required in the presence of barriers such as leaves, branches, and support structures.

Artificial Intelligence and Machine Learning:
Artificial intelligence (AI) and machine learning algorithms greatly increase the robot's capacity to precisely identify and categorize fruits. Additionally, these technologies improve decision-making by enabling the robot to modify and optimize its behaviors in response to real-time inputs. During the harvesting process, fast and effective decision-making is made possible by the integration of edge computing technologies and high-performance processors.

Hardware and Software Integration:
The harvesting robot's general architecture comprises the integration of advanced software systems (control algorithms, data processing frameworks) with a variety of hardware components (sensors, actuators, and processors). The smooth operation and coordination of many subsystems are guaranteed by effective integration. Advanced communication technologies, such as wireless connection and the Internet of Things (IoT), provide effective data interchange and control commands, guaranteeing the harmonious operation of the robot's systems.

Economic and Practical Considerations:
Cost-Effectiveness and Deployment: Using creative ideas and materials is one way to try to keep development and deployment costs as low as possible. Maintaining excellent performance under real-world settings, ease of use, and reliability are necessary for practical deployment in commercial orchards.

Effects on Farming:
Harvesting robots have the potential to greatly boost labor productivity, lessen the need for seasonal labor, and enhance overall agricultural efficiency. Maximizing resource utilization and reducing waste, helps sustainable farming methods and solves the labor crisis.

Figure 1.2: Various types of harvesting robots, including those for plums, apples, sweet peppers, strawberries, litchis, tomatoes, and kiwifruits. Photos reprinted with permission from respective sources.

Several cutting-edge technologies come together to form harvesting robots, and each one is essential to enable accurate and productive agricultural operations. Robust motion delivery mechanisms, finely built end-effectors, advanced AI and machine learning, and sophisticated vision systems are all integrated into these robots, which provide a practical answer to the labor shortages and resource optimization issues facing the agriculture sector. To overcome current obstacles and fully achieve the promise of harvesting robots in enhancing agricultural productivity and sustainability, more research and development are necessary.

1.3 BACKGROUND AND MOTIVATION

BACKGROUND

In an effort to alleviate labor shortages and improve fruit picking efficiency, harvesting robots are a noteworthy development in agricultural technology. Usually installed on movable platforms, these robotic systems are outfitted with manipulators and end-effectors and employ advanced machine vision techniques to precisely choose ripe fruits. This technique, called "selective harvesting," combines the effectiveness of machinery with the pickers' customary selectivity (Bac et al., 2014b). Robotic systems have drawn growing attention from academia and industry as the possibility that they could completely replace human labor grows (Sanders, 2005).

Robotic fruit picking has been an area of research and development since the late 1960s. Practical implementation in commercial orchards is still limited despite decades of research and development because of a number of important obstacles. These robots' relatively sluggish harvesting speeds and high production costs are the main challenges. The robots' capacity to recognize and choose ripe fruits is mostly dependent on machine vision systems, which are frequently inadequate. These methods are not very good at identifying fruits that are darkened, hidden by branches and leaves, or green against a green background. They can even mistakenly classify yellow leaves as fruits on occasion (Bac et al., 2014b).

Recent advancements in robotics and artificial intelligence (AI) are making it possible to create more effective harvesting machines. The goal of developing modern AI-powered machine vision systems is to improve fruit identification and selection accuracy. To overcome the limitations of current machine vision technologies, a key focus is on neural network models trained to distinguish various fruit features. However, despite these advancements, the technology isn't yet advanced enough for widespread commercial application. To match the productivity of human labor, these robots need to increase in both speed and accuracy. In agriculture, there are numerous potential benefits of robotic harvesting. It's still one of the most labor-intensive industries in agriculture, with only 15% of the work automated and a significant portion done by hand during harvesting. Because of urbanization, it is now harder to get seasonal labor, which has led to a scarcity of crops and highlighted the urgent need for automated solutions (FAO, 1976). Increased yield, a solution to the agricultural shortage, and a significant reduction in labor costs are all possible with robotic harvesting. Incorporating these robots into existing cultivation systems could further boost their efficiency, making them a viable and practical solution for agricultural harvests in the future.

MOTIVATION

A combination of economic, labor market, and technological factors drives the motivation for developing and deploying harvesting robots.

Labor Shortages:

Horticulture is one of agriculture's most labor-intensive businesses. The availability of labor for fruit picking has been dropping due to urbanization and a decrease in the number of seasonal laborers willing to perform such physically demanding chores (FAO, 1976). This labor scarcity has resulted in crop shortages and higher production costs, necessitating an urgent need for automated solutions that can consistently substitute human work.

Cost Reduction:

Labor expenses make up a considerable component of total production costs in fruit harvesting, accounting for up to 40% of the overall value of the crop (Bac et al., 2014b). Farmers may drastically cut labor expenses by automating the harvesting process, which improves overall profitability and makes the agricultural industry more sustainable in the long run.

Increased Efficiency and Productivity:
Unlike human workers, harvesting robots can operate continuously without the need for breaks or rest, leading to a substantial increase in productivity. These robots can work day and night, maximizing the harvesting window and ensuring that fruits are picked at their optimal ripeness, thereby reducing waste and improving yield (Shewfelt et al., 2014).

Precision and Quality:
Modern harvesting robots are being developed with advanced AI and machine vision systems that can accurately assess fruit ripeness, size, and other quality parameters. This precision ensures that only the best-quality fruits are harvested, maintaining high standards of produce quality and enhancing market acceptance (Bac et al., 2014b). Such selective harvesting also reduces the risk of damaging unripe fruits, which can continue to mature for future harvests.

Technological Advancements:
Rapid advancements in AI and robotics are driving improvements in the capabilities of harvesting robots. Contemporary neural network models and enhanced machine vision systems are being trained to better recognize and differentiate fruits from their surroundings, addressing some of the limitations of earlier prototypes. These advancements are gradually making harvesting robots more reliable and cost-effective, bringing them closer to widespread commercial deployment (Bac et al., 2014b).

Sustainability and Environmental Impact:
Automating the harvesting process can also contribute to more sustainable agricultural practices. Robots can be programmed to follow optimized paths and employ precise picking techniques that minimize damage to plants and the environment. This precision agriculture approach helps in maintaining the health of orchards and reducing the ecological footprint of farming operations.

Chapter 2

Overview

2.1 Introduction

The desire to boost productivity, cut labor costs, and maximize resource utilization is causing a major upheaval in the agriculture sector. The development of harvesting robots is one of the most promising advances in this industry. The purpose of these robots is to automate the process of selecting fruit, which provides a solution to the labor shortage and growing expenses related to manual harvesting. An intricate combination of hardware and software components make up a harvesting robot's architecture, and each one is essential to the machine's successful and efficient operation.

A power supply and power management system are among the hardware parts of the harvesting robot that guarantee a steady and dependable power source for the robot's operations. The ESP32 module, a potent microcontroller that directs the robot's movements, is essential to its operation. The servo motors that control the exact movements of the robot arm assembly, ultrasonic sensors for obstacle detection, and the ESP32-CAM for image capture all work in tandem with this.

On the software side, powerful tools like Fusion 360, MATLAB Simulink, and Simscape are used to design and simulate the robot's physical and dynamic behavior. Fusion 360 helps to create comprehensive CAD models of the robot structure, whereas Simulink and Simscape allow for modeling and optimization of the robot arm's movements. The software suite also contains advanced image processing and object detection capabilities based on the YOLO v3 model, which enables the robot to precisely recognize and locate ripe fruits for harvesting.

2.2 Topic Relevance

Modern agriculture has made great strides thanks to smart agricultural robots, especially harvesting robots that meet global sustainability targets and solve important difficulties. Using recent findings and scholarly works on robotics and precision agriculture, this part investigates the applicability of these machines.

Precision Agriculture and Technology Integration

Through the use of technology and data-driven methods, precision agriculture seeks to maximize farming techniques. Through targeted applications of fertilizers, herbicides, and water, precision agriculture decreases environmental impact, increases crop yields, and improves resource efficiency (Gómez-García et al., 2020). Farmers can get more precision in field operations, which improves resource management and promotes sustainable farming methods, by incorporating intelligent agricultural robots into their operations.

Addressing the SDGs, or Sustainable Development Goals

Several UN Sustainable Development Goals (SDGs) are directly impacted by intelligent agricultural robots which are : Goal 2, Zero Hunger: Harvesting robots can help satisfy the world's growing food demand without adding more agricultural land, which will increase food security by raising agricultural productivity and efficiency; Goal 8 (Decent Work and Economic Growth): By lowering physical strain and dangerous surroundings, automation of labor-intensive jobs like harvesting can enhance working conditions for farmers (UN, 2022); Goal 12 (Responsible Consumption and Production): Smart agricultural robots reduce waste and maximize resource utilization to support sustainable production methods, which lessens the environmental impact of agriculture (FAO, 2021).

Technological Progress and Research Areas of Interest

Research on intelligent agricultural robots is moving quickly forward, with the goal of improving the robots' capacities for a range of agricultural duties. For example, Saeys et al. (2020) discuss developments in robotics for fruit harvesting, focusing on the creation of multiple-degree-of-freedom robotic arms and advanced sensor technologies for precise fruit handling and detection.

Issues Handled in the Agriculture Sector

Several issues that the agriculture industry faces are addressed by intelligent agricultural robots such as ,Labor Scarcity: Automation lessens the need for seasonal labor, which is frequently expensive and in short supply, especially during the busiest harvesting seasons (Valente et al., 2020); Climate Variability: Robots with sensors and AI algorithms built in can function in a range of weather scenarios, guaranteeing steady output and lowering crop hazards associated with weather (FAO, 2021).

Case Study: Application in Fruit Harvesting

Because fruit harvesting requires careful handling and exact timing, there are unique obstacles involved. In order to carefully choose and harvest ripe fruits without harming them, robotic arms, machine learning algorithms, and vision systems are all used in fruit harvesting robots, such those created by Swarztrauber et al. (2019). This increases crop quality and marketability overall.

2.3 Research Needs and Gaps

Recently, there have been notable developments in the field of smart agricultural robotics, particularly harvesting robots. But in order to reach their full potential, a great deal of research demands and holes still need to be filled. By highlighting the interdisciplinary nature of the opportunities and problems in this field, this topic addresses a variety of these requirements and gaps.

2.3.1 Perception and Sensation

Object Detection and Recognition: Particularly in dense foliage, current systems frequently have trouble correctly recognizing and differentiating between fruits, leaves, and stems. To improve the precision and dependability of sensors and algorithms used in object identification and recognition, research is required. Environmental Adaptability: Harvesting robots must function well in a variety of weather situations, light conditions, and crop varieties. One of the biggest challenges yet ahead is creating resilient perception systems that can adjust to these changes. 3D Mapping and Localization: Precise localization in the field and accurate 3D mapping of the surroundings are essential for efficient navigation and harvesting. It is imperative to enhance SLAM (Simultaneous Localization and Mapping) algorithms specifically designed for agricultural environments.

2.4 Disguise and Acquisition Methodologies

End-Effector Design: A major field of study is the creation of adaptable and soft end-effectors that can handle many crop varieties without inflicting harm. In order to create harvesting instruments that are suitable, this involves researching the biomechanics of various fruits and veggies. Manipulative dexterity: It is crucial to improve robotic arm dexterity so that it can resemble human movement in subtle tasks. We need to do research on more advanced actuation techniques and control algorithms. Force Sensing and Feedback: By including sophisticated force sensing and feedback technologies, robots can reduce crop damage and increase harvesting efficiency by adjusting their grasp and movements in real-time.

2.5 Autonomy and Decision

The development of effective algorithms for path planning is crucial in order to maximize the robot's mobility and efficiently cover the field while consuming the least amount of time and energy. Real-Time Decision Making: By putting cutting-edge AI and machine learning techniques into practice, harvesting performance can be greatly enhanced by enabling real-time decision-making based on the sensory information received by the robot. Choosing when and how to harvest each fruit falls under this category. Adaptive Learning: Over time, robots should be able to learn and adjust to changing surroundings and crops. It is imperative to do research into adaptive learning algorithms that enable robots to gain experience and enhance their performance.

2.6 Integration of Farm Management Systems

Data Integration: Harvesting robots provide massive amounts of data, which might be useful for farm management. Creating methods to combine this data with existing farm management software for real-time monitoring and decision assistance is a critical area of research. IoT and Connectivity: To ensure coordinated operations, robots, sensors, and central management systems must communicate and connect reliably. Research into reliable IoT solutions and network designs for agricultural environments is required.

2.7 Energy Efficiency and Sustainability

Power management is required since harvesting robots must operate for extended periods of time in the field. Research into energy-efficient power systems, including renewable energy sources such as solar power, is critical to ensuring their long-term viability. Environmental Impact: Evaluating and limiting the environmental impact of deploying large numbers of robots in agricultural fields is a growing topic. More research into the environmental impact of robotic agricultural practices is required.

2.8 Economic and Social Implications

Cost-Effectiveness: Creating low-cost solutions that make robotic harvesting economically viable for farmers of all sizes is a key problem. More research into low-cost materials, production procedures, and scalable solutions is required. Labor Dynamics: It is critical to understand how robotic harvesting affects farm labor dynamics, such as job displacement and the possibility of new types of employment. Research on how to best incorporate robots into the present workforce can aid in mitigating harmful social consequences. Barriers to adoption: Identifying and addressing adoption challenges, such as technological complexity, farmer training, and aversion to change, is critical to the widespread use of harvesting robots.

Chapter 3

Methodology

This chapter describes the full process used in the development of a smart agricultural robot. The process includes requirement collection via research and analysis, rigorous design, implementation, testing and validation, and meticulous documenting and reporting. Each phase is critical to the harvesting robot's successful design and deployment.

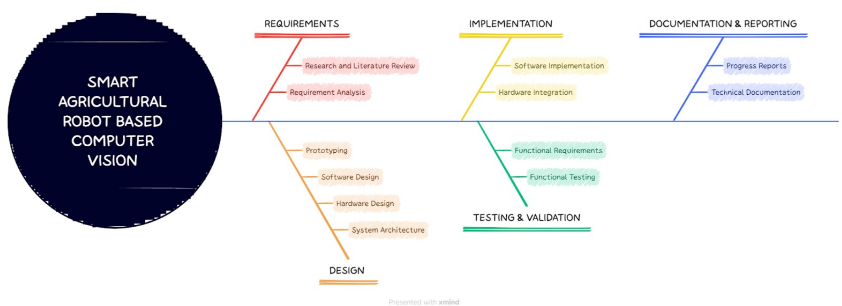


Figure 3.1: Methodology

3.1 The Requirements

3.1.1 Research and Literature Review

The first phase entails a thorough study and literature review to better understand the current state of harvesting robots and identify technological gaps and obstacles. Key actions include:
-Reviewing academic papers, journals, and articles about agricultural robots.
-Analyzing existing harvesting robots to determine their capabilities, limitations, and technology.
-Identifying the sorts of fruits that can be gathered effectively with robots, as well as the precise requirements for each.

3.1.2 Requirement Analysis

According on the findings, particular needs for the harvesting robot are identified. This includes: Specifying the types of fruits to be picked and their unique features (e.g., size, shape, and delicacy). Identifying the environmental conditions in which the robot will operate (for example, temperature, humidity, terrain). Establishing the robot's technical characteristics, such as precision, speed, and battery life. Identifying the components required for both hardware (motors, sensors, CPUs) and software (control algorithms, user interfaces).

3.2 Design and Hardware Implementation

3.2.1 System Architecture.

The system architecture provides an overview of the hardware and software components, as well as how they interact. The hardware design outlines the robot's physical components, such as the power supply, motor driver, sensors, robotic arm, and control units. Software Design: Describes the software components, including control algorithms, image processing software, and user interface. This includes the implementation of machine learning models for fruit detection and picking. Prototyping entails constructing initial prototypes to validate design concepts. This process entails creating mock-ups or small-scale versions of the robot and testing its fundamental functions.

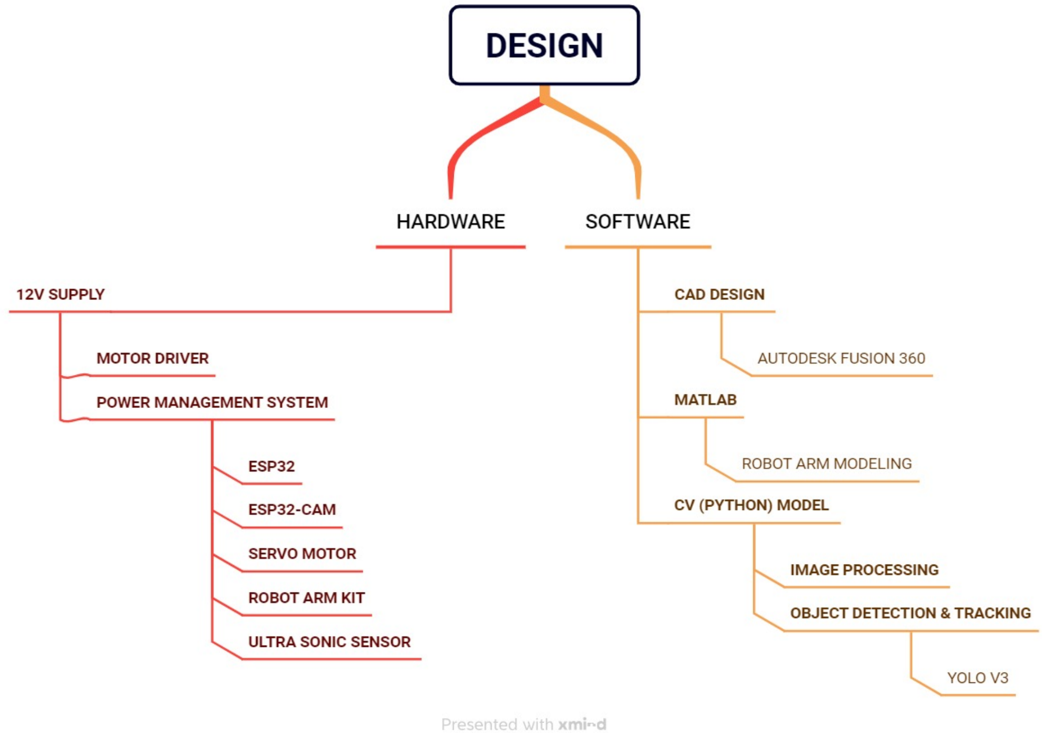


Figure 3.2: Architecture.

Hardware Components

Power Supply and Power Management System: The power supply is the source of energy for the entire robot. It typically consists of rechargeable batteries that can provide sufficient power to operate all the electronic and mechanical components of the robot for an extended period. Power Management System: This system is responsible for distributing power from the supply to various parts of the robot. It ensures that each component receives the correct voltage and current, prevents power surges, and manages battery life to optimize performance and longevity.

ESP32 Module: The ESP32 is a versatile microcontroller with built-in Wi-Fi and Bluetooth capabilities. It acts as the brain of the robot, coordinating the actions of various sensors and actuators. It processes input from the camera, ultrasonic sensor, and other inputs, and executes the necessary control commands.

ESP32-CAM: The ESP32-CAM is a camera module integrated with the ESP32 micro-controller. It captures high-resolution images and streams video, which are crucial for real-time image processing and object detection. This module is compact, low-cost, and capable of capturing detailed visual information.

Ultrasonic Sensor: This sensor is used for measuring distances to obstacles in the robot's path. It emits ultrasonic waves and measures the time it takes for the echoes to return, thus calculating the distance to objects. This helps the robot navigate through the orchard without colliding with trees, fruits, or other obstacles.

Servo Motors: Servo motors are precise actuators that control the movement of the robot's arm and end-effectors. Each joint of the robot arm is driven by a servo motor, allowing for controlled and precise movements. The servo motors ensure that the robot can reach the desired position and angle to harvest the fruits without causing damage.

Robot Arm Assembly: The robot arm consists of multiple segments connected by joints. These segments are typically made from lightweight and durable materials such as aluminum or carbon fiber. The design of the robot arm allows for a wide range of motion, enabling the robot to reach fruits at various heights and angles. The end-effector, attached to the arm, is designed to gently grasp and pick the fruits.

Software Components

CAD Modeling:

Fusion 360: This software is used for designing and simulating the physical structure of the robot. It allows engineers to create detailed 3D models of the robot arm, sensor placements, and overall assembly. Simulation features help in testing the design virtually to identify any issues before physical manufacturing.

Robot Arm Modeling, MATLAB Simulink and Simscape:

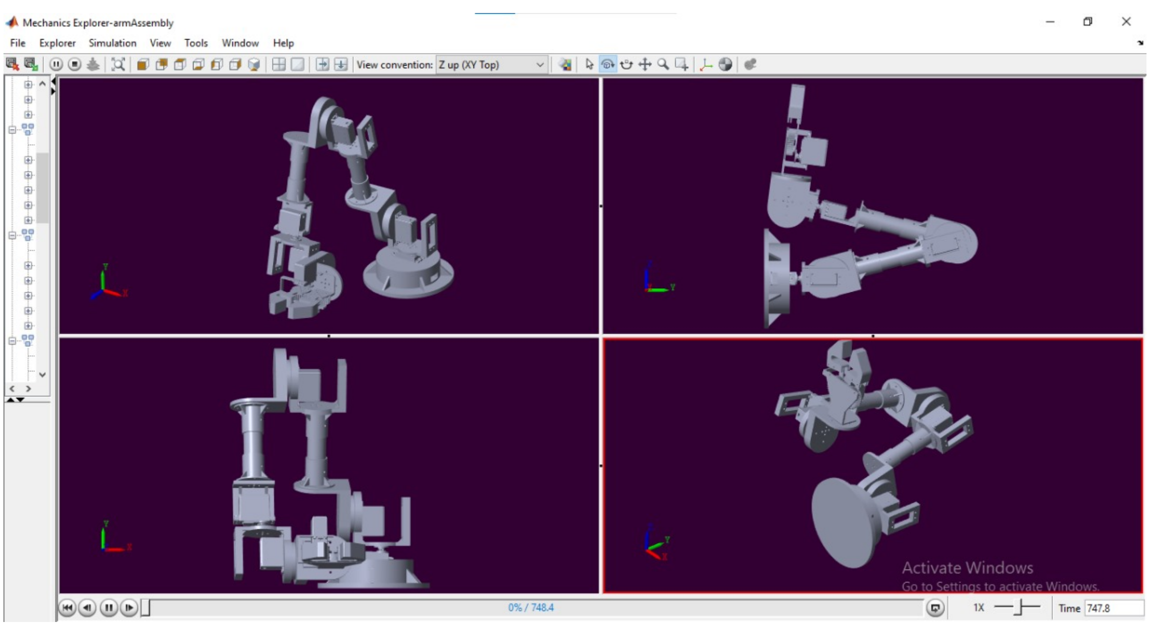


Figure 3.3: Robot Arm Modeling.

These tools are used to model the dynamic behavior of the robot arm. Simulink provides a graph-

ical environment for simulating the control algorithms, while Simscape allows for the modeling of physical systems such as motors and mechanical linkages. This combination helps in optimizing the arm's performance and ensuring precise control over its movements.
Image Processing and Object Detection,YOLO v3 : YOLO v3 is an advanced object detection algorithm that processes images in real-time. It can detect and localize multiple objects within a single frame with high accuracy. YOLO v3 is used to identify ripe fruits in the images captured by the ESP32-CAM. The algorithm provides the coordinates of the detected fruits, which are used by the robot's control system to position the arm for harvesting.

3.2.2 Integration of Hardware and Software

The architecture of the harvesting robot integrates both hardware and software components to achieve seamless operation.

Power Management: The power supply provides energy to all hardware components, managed by the power management system. This ensures stable and efficient operation, preventing power surges or depletion that could damage the robot

ESP32 Control: The ESP32 module acts as the central controller. It receives data from the ESP32-CAM and ultrasonic sensor, processes this data, and sends control signals to the servo motors. The ESP32 handles the real-time processing and decision-making necessary for the robot's operation.

Image Capture and Processing: The ESP32-CAM captures real-time images of the fruit canopy. These images are sent to the ESP32 module, where they are processed using the YOLO v3 algorithm. The algorithm detects and localizes ripe fruits within the images, providing their coordinates for further action.

Sensor Feedback: The ultrasonic sensor continuously measures distances to nearby obstacles. This data is used by the ESP32 module to navigate the robot safely through the orchard, avoiding collisions and ensuring it can reach the desired locations.

Robot Arm Operation: The ESP32 module sends commands to the servo motors based on the coordinates provided by the image processing algorithm. The servo motors move the robot arm to the precise location of the ripe fruit. The end-effector then gently grasps and picks the fruit, minimizing damage.

System Design and Simulation: The overall design and structure of the robot, including the arm assembly and sensor placements, are created using Fusion 360. This ensures that all components fit together and function as intended. MATLAB Simulink and Simscape are used to simulate and optimize the dynamic behavior of the robot arm, ensuring precise and efficient movements.

3.3 Hardware Implementation

A harvesting robot's design and hardware implementation require some specialized components, each of which plays an important part in assuring the robot's functionality, efficiency, and dependability. This chapter delves into the detailed design and hardware aspects of a harvesting robot powered by a 3300mAh 12V battery, which includes key components such as a motor driver, power management system, ESP32 module, pan-tilt mechanism with SG90 servo motors for the ESP32-CAM, an ultrasonic sensor, and a robot arm.

3.3.1 Power Supply: 12V Battery of 3300mAh

The harvesting robot's major power source is a 12V, 3300mAh rechargeable battery. This battery supplies enough voltage and current to power the robot's motors, sensors, and other electronic components.

-**Voltage and Capacity**: The 12V rating provides enough power to run a variety of motors and electronic components, while the 3300mAh capacity strikes a balance between operating duration and battery size.

-**Rechargeability:** Using a rechargeable battery lowers operating expenses and reduces environmental impact. The battery may be recharged with a compatible charging circuit, allowing the robot to be deployed several times with minimal downtime.

-**Battery Management System (BMS):** A BMS is provided to prevent the battery from overcharging and deep discharge. It monitors the battery's state and assures safe operation.

3.3.2 Motor Driver

The motor driver is an essential component that regulates the movement of the robot's wheels and arm. It serves as an interface between the microprocessor and the motors, allowing for fine control over speed and direction.

-**Functionality:** The motor driver receives control signals from the microcontroller (ESP32) and changes the power sent to the motors accordingly. This guarantees smooth and accurate movement.

-**Specifications:** An H-bridge motor driver, such as the L298N, is commonly utilized. It can handle currents of up to 2A per channel and voltages up to 46V.

-**Connections:** The motor driver communicates with the ESP32 via digital pins, which send PWM signals to regulate motor speed and direction

3.3.3 Power Management System

The power management system is in charge of transferring power from the battery to various components while assuring effective use and protecting against over-voltage and under-voltage situations.

-**Voltage Regulation:** Voltage regulation ensures that each component receives the right working voltage, which is commonly accomplished with voltage regulators such as the LM7805 for 5V components and the LM317 for adjustable voltages.

-**Protection Mechanisms:** Overcurrent protection, thermal shutdown, and short circuit protection are among the characteristics used to prevent component damage.

-**Power Distribution Board:** The Power Distribution Board A bespoke power distribution board can be utilized to improve connections and provide consistent power delivery to all components.

3.3.4 ESP32 Module

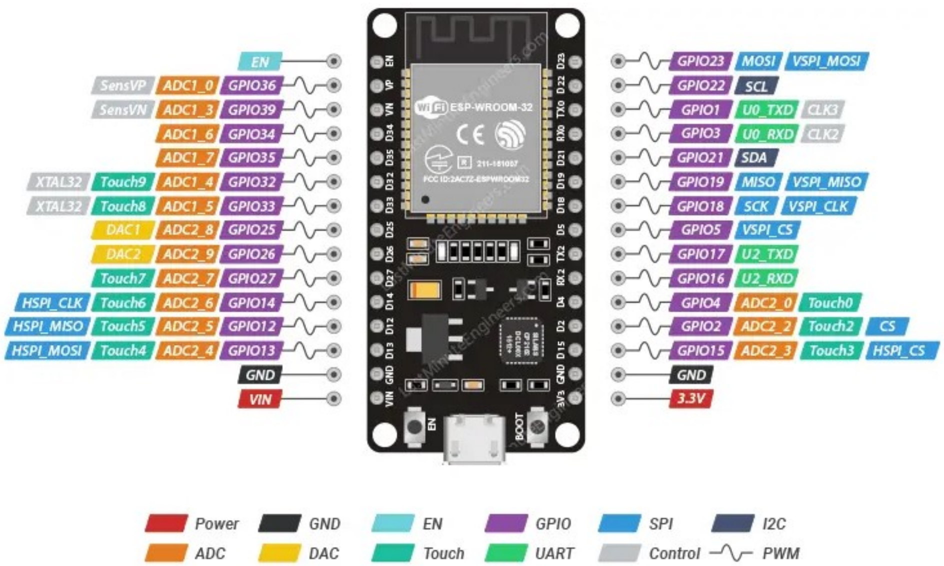


Figure 3.4: ESP 32 PINOUT(source: last minute engineer.com)

The ESP32 module is the core processor unit, handling all control and communication operations. It is a powerful microcontroller with Wi-Fi and Bluetooth support, making it suitable for a wide range of applications.

-Processing Power: The ESP32, which has a dual-core CPU and a variety of peripherals, can perform complicated tasks including image processing, sensor data analysis, and motor control.

-Connectivity: The built-in Wi-Fi and Bluetooth provide remote monitoring, control, and data transmission, allowing for real-time updates and modifications. -Programming: The ESP32 may be programmed using either the Arduino IDE or the ESP-IDF framework, which allows for the development and deployment of bespoke algorithms and control logic.

-Pin Configuration: The ESP32 includes several GPIO pins for connecting to sensors, motors, and other peripherals. Careful planning of pin assignments is required to eliminate conflicts and assure dependable functioning.

3.3.5 Pan-Tilt Mechanism with SG90 Servo Motors for ESP32-CAM

The pan-tilt mechanism enables the ESP32-CAM (camera module) to move in numerous directions, offering a wide field of view for monitoring and target identification.

-SG90 Servo Motors: These lightweight and inexpensive servos allow for fine control over the camera's alignment. Each servo has a range of motion of about 180 degrees.

-ESP32-CAM Integration: The ESP32-CAM module is installed to the pan-tilt mechanism, and the ESP32 micro controller manages the servos, allowing enabling real-time modifications based on the robot's needs.

-Control Signals: The servos are controlled using PWM signals from the ESP32. The duty cycle of these signals controls the angle of the servos, allowing for accurate camera orientation.

3.3.6 Ultrasonic Sensor

An ultrasonic sensor is used to identify obstacles and measure distances, ensuring that the harvesting robot navigates safely and efficiently.

Figure 3.5: Fusion 360 CAD model

-Functionality: The sensor generates ultrasonic waves and measures the time it takes for the echo to return. This information is utilized to determine the distance between items in the robot's route.

-Integration: The sensor connects to the ESP32, which evaluates the distance data and modifies the robot's direction or actions to prevent collisions.

-Mounting: The ultrasonic sensor is usually installed on the front of the robot to give a clear detection path. It may also be installed on a servo motor to scan the surroundings.

-Data Processing: Include algorithms in the ESP32 firmware for processing sensor data and making navigation decisions.

Figure 3.6: Fusion 360 model 2

3.3.7 Implementation

Assembly and Integration

-**Power Supply Setup:** The 12V battery is connected to the power management system, which distributes the appropriate voltage to the ESP32, motors, and sensors. correct gauge wiring is utilized to meet the current demands of the motors and other components. Connectors facilitate assembly and maintenance,also fuses and protective circuits to prevent short circuits and overloads.

-**Motor Driver Connection:** The motor driver is connected to both the ESP32 and the motors. The robot's wheels and arm move as a result of ESP32 control impulses. PWM Control: the ESP32 is Set up to generate PWM signals for regulating motor speed and direction using the motor driver. Feedback: encoders are Install as feedback mechanisms on the motors to give accurate control and monitoring of the motor's position and speed. -**ESP32 Programming**: The ESP32 is programmed to handle ultrasonic sensor inputs, drive the pan-tilt mechanism, and coordinate the movements of the robot arm. Code Development: firmware is written with the Arduino IDE or ESP-IDF, including libraries for motor control, sensor data collecting, and camera handling.

- **Pan-Tilt Mechanism Assembly**: The SG90 servo motors are installed on a frame, and the ESP32-CAM is connected to enable a complete range of motion. Calibration: Check the servos for proper movement and alignment of the camera. Integration: the ESP32-CAM is attached to the pan-tilt mechanism and connected the servo control wires to the ESP32. - **Sensor Integration:** The ultrasonic sensor is installed on the robot and connected to the ESP32, allowing for real-time obstacle detection. Mounting Position: the sensor is aligned to maximize its field of vision and detect range. Data Processing: algorithms are included in the ESP32 firmware for processing sensor data and making navigation decisions. -**Robot Arm Installation:** The robot arm is constructed and attached to the robot, with each joint motor connected to the ESP32 for precise control. End-Effector: the end-effector are attached and testing its gripping mechanism to ensure it can handle the desired fruits without harm. Movement Algorithms: Create and fine-tune algorithms that regulate the arm's movements for efficient and precise fruit picking.

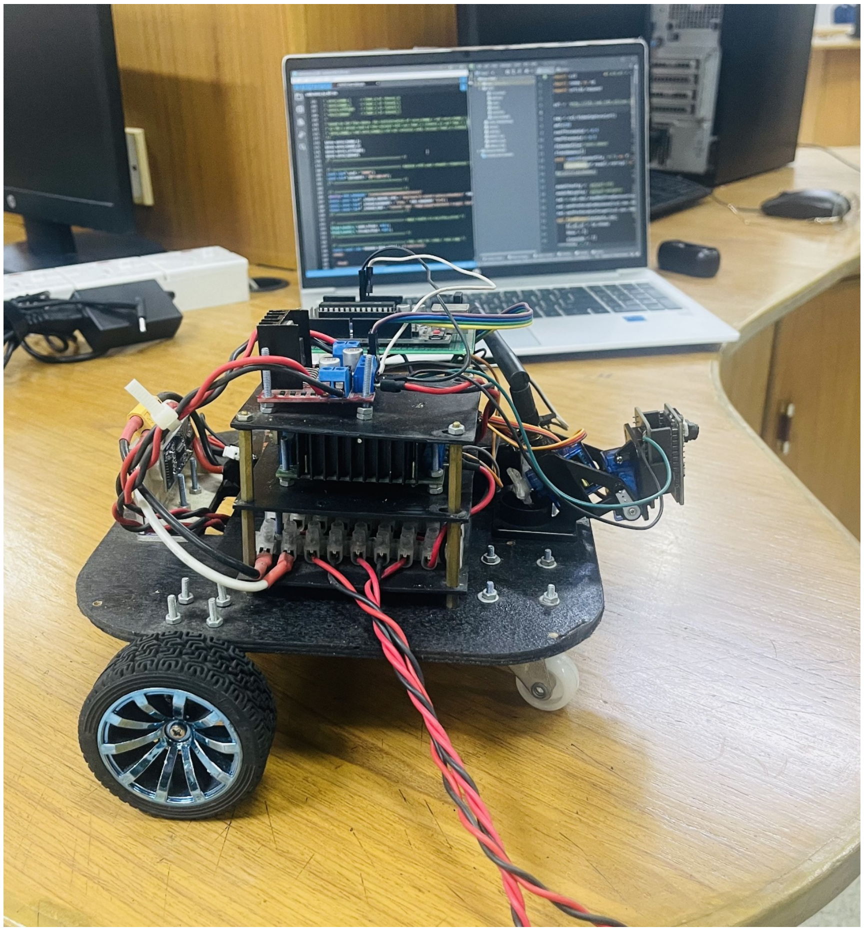


Figure 3.7: Assembled robot

Testing and Calibration

Initial testing should be performed to ensure that each component, such as the power supply, motor driver, ESP32, pan-tilt mechanism, ultrasonic sensor, and robot arm, functions properly. Testing all components to verify they function together effortlessly. Evaluate the robot's ability to maneuver, identify obstacles, and harvest fruit; Calibrate sensors and actuators to improve performance. Adjust the ultrasonic sensor's sensitivity, pan-tilt mechanism angles, and robot arm movements.The field testing involves deploying the robot in a real-world agricultural context to assess its performance under actual working conditions. Examine its capacity to handle various sorts of fruits and navigate the environment successfully.

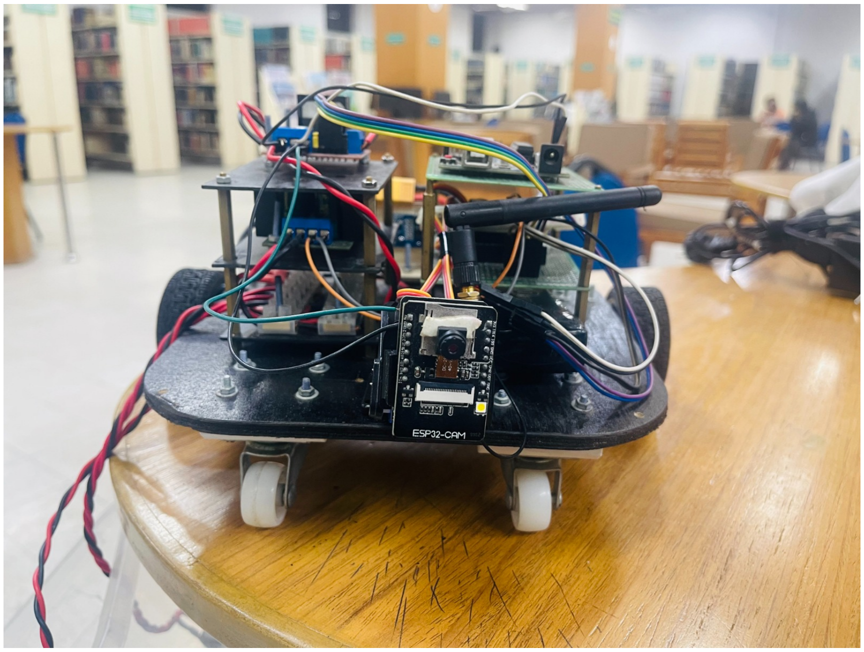


Figure 3.8: Assembled robot with With navigation capabilities and image processing

3.4 Software and Algorithm

3.4.1 YOLO

It has been demonstrated that one of the most reliable methods for tackling object detection is through deep learning algorithms [1]. In terms of speed and accuracy, YOLOv4 [2] has emerged as the best model for object recognition in recent times. The 2016 release of YOLOv4's precursor, You Only Look Once, or YOLO was created by Joseph Redmon and was regarded as one of the first CNNs with real-time speed. The term "You Only Look Once" originated from the one-shot detection method that was responsible for its quickness. This mechanism concurrently predicted the bounding box coordinates and class probabilities from a picture. YOLO predicts bounding boxes with appropriate confidence of having spotted an object of class C after dividing an input image into S x S grids (Figure 1).

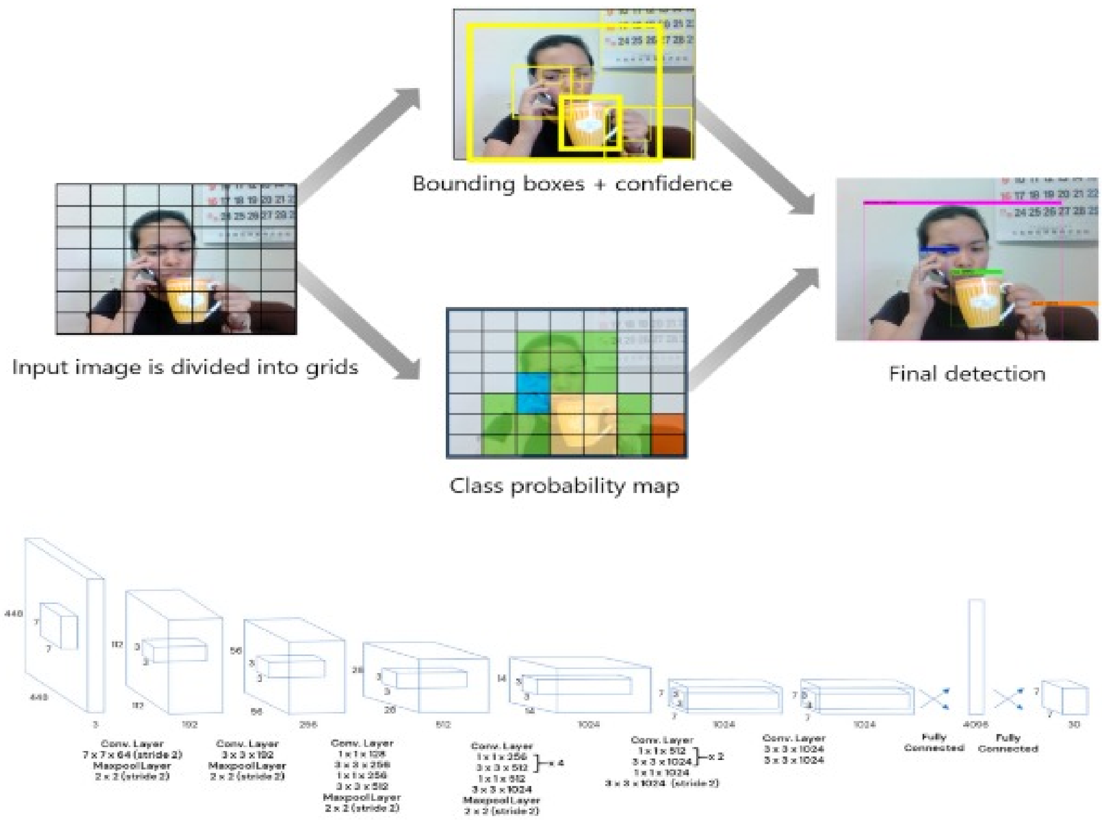


Figure 3.9: (Top) General workflow of YOLO ; (Bottom) YOLO Architecture.s.

The YOLO (Object Detection Loading) model, initially used for detecting small objects and unusual aspect ratios, faced challenges in detecting objects with unusual aspect ratios and localization errors. In 2017, YOLOv2 was introduced, which improved accuracy through anchor boxes, batch normalization, and high-resolution classifiers. YOLOv3 followed, with improvements in binary cross-entropy, logistic regression, and feature extraction. YOLOv4 was introduced in 2020, more accurate and faster than YOLOv3, running two times faster than EfficientDet and enabling training on a single conventional GPU. YOLOv4's structure was modified to enable scaling for different applications, with YOLOv4-tiny and YOLOv4-CSP being developed to maximize speed and computational cost. This study compared the performances of YOLOv4, YOLOv4-tiny, and YOLOv4-CSP in detecting pear fruits. A backup system, such as object tracking, was developed to ensure accuracy in counting, providing a more reliable measure of object count in case of detection system failure.

3.4.2 Example of Online and Real-Time Tracking with Convolutional Neural Networks

Deep SORT has shown to be one of the most reliable and quick methods for tracking many objects [3]. Originally designed as a basic method of detection-based online tracking, the Simple Online and Real-time Tracking (SORT) algorithm aimed to efficiently associate object detections on each frame. It made use of convolutional neural networks' stellar reputation for precise object detection. Moreover, the tracking components included the Hungarian algorithm and the Kalman filter, two traditional techniques for motion prediction and data correlation. Because of its low complexity, SORT outperformed other cutting-edge trackers by a factor of 20. In the MOT (Multiple Object Tracking) Challenge 2015, it also performed better than the conventional online tracking techniques using Faster R-CNN [30] as the detector.

The primary limitations of SORT were occlusions and shifting angles of view. Wojke et al. [3] created Deep SORT, an expanded form of SORT, to address this problem (shown in Figure 2). Deep SORT incorporates a deep appearance-based metric from the convolutional neural network in addition to motion-based metrics for data association. Higher robustness from occlusion, viewpoint changes, and the use of a nonstationary camera for lower identity switches were the outcomes of this modification. Deep SORT was determined to run at a runtime speed of 25–50 frames per second on contemporary GPUs [3]. Because of its robustness and adaptability for real-time tracking, In this work, the tracking method chosen to count the pear fruits in real time was Deep SORT.

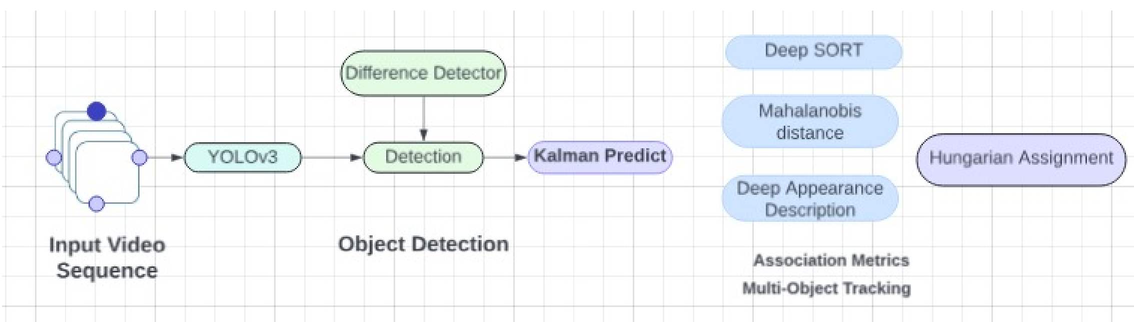


Figure 3.10: The architecture of Deep SORT.

3.4.3 Example : Fruit Detection Using YOLO

Yolo based models have been applied to fruit detection in several research. Using their Mango-YOLO model, which demonstrated an F1 score of 0.968, an AP of 98.3%, and an inference speed of 14 FPS on an NVIDIA GeForce GTX 1070 Ti GPU, Koirala et al. carried out real-time mango fruit detection. Though this was still insufficient for real-time detection (greater or equal to 24 FPS), Liu et al. and Lawal [4] also proposed their YOLOv3-based tomato detection systems that demonstrated similarly remarkable AP values of 96.4% and 99.5%, respectively, and a faster speed of around 19 FPS for both studies using an NVIDIA GeForce GTX 1070 Ti GPU and an NVIDIA Quadro M4000 GPU, respectively. Li et al..To detect lemon fruits, [5] also created Lemon-YOLO, in which they used a SEResGNet34 network instead of Darknet-53. With the powerful Tesla V100

GPU, their system achieved an AP of 96.28% and a detection speed of 106 FPS. Several other research assessed how well YOLO-based models performed in identifying different fruits, including apples, lemons, bananas, and cherries. It is significant to highlight that the majority of the research did not provide loss curves for their models, making it challenging to confirm whether the dataset was over- or underfitted. Additionally, without overfitting, it is challenging to verify if they have attained the best achievable performance criteria

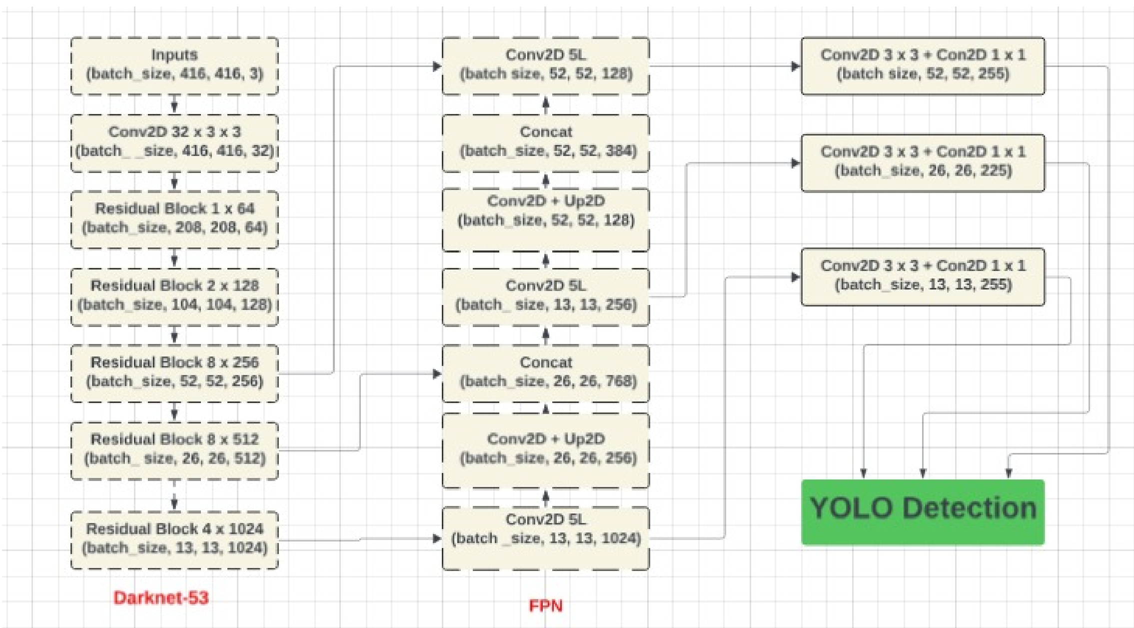


Figure 3.11: YOLOv2 architecture.

3.4.4 Fruit Counting in Real-Time using an Object Tracking Algorithm and YOLO

For fruit counting, only one study integrated YOLO with a multiple object tracking system. Itakura et al. [6] counted pear fruits from a movie using YOLOv2 and the Kalman filter, achieving an AP of 97% in detection and an F1 score of 0.972 in counting. Their counting system's pace was not specified, though. Furthermore, it was unclear if the tracking algorithm approach was offline (processes all data in one batch) or online (present forecasts rely only on historical data). Real-time counting is better suited for online tracking. Offline tracking, also known as batch tracking, is not a desirable alternative for real-time counting because processing doesn't happen until after all observations are collected, even if it can be more precise. It is challenging to determine whether their technology is relevant in real-time due to the absence of information regarding their tracking methodology.

Experimental plateforme and Performance Evaluation

In this study, the experiments were conducted on a computer that has AMD Ryzen 5 3500U with Radeon Vega Mobile Gfx 2.10 GHz quad-core CPUs, and a NVIDIA GeForce GTX 1070Ti GPU.

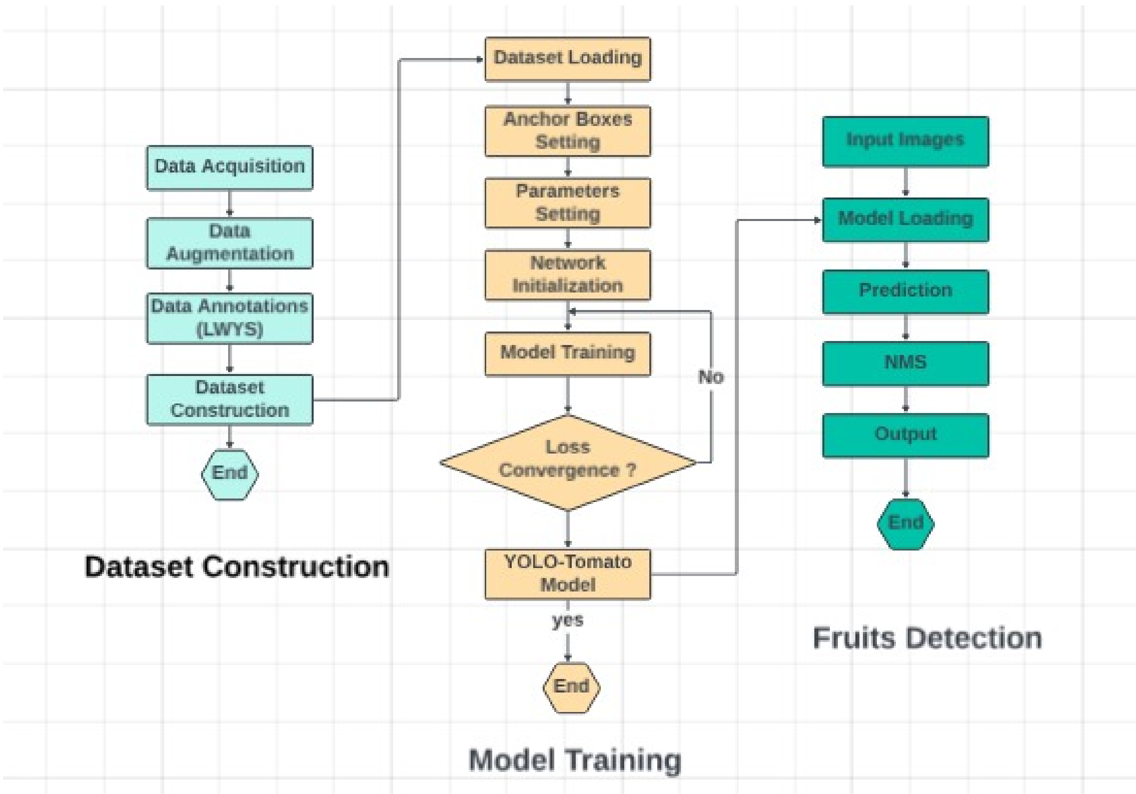


Figure 3.12: YOLO-fruits model flowchart for dataset, training and detection process.

Rather than creating excessively specialized predictors using the default anchor box configuration provided by YOLOv3, it is vital to determine the size of the anchor box that is most likely to be counted from the created dataset before training and testing. Based on the three detection layer scales displayed in Figure3.8, nine clusters measuring 416 $\times$ 416 pixels were produced using the K-mean clustering technique. The YOLO-tomato models were enhanced by assigning the anchors to each scale in descending order. Three distinct nine clusters were produced as a result of the tomato datasets being divided into Raw, 0.5 ratio, and 0.25 ratio categories. According to the average IoU values, the raw ratio is 77.45%, the 0.5 ratio is 78.33%, and the 0.25 ratio is 78.55%.

Images with 416 $\times$ 416 pixels are fed into the model. Training loss20 is decreased by adjusting the learning rate. Given that the input photos consist of two classes—ripe and unripe tomatoes—a learning rate of 0.001 between 0 and 4000 iterations with a maximum batch size of 4000 was used. Batch and Subdivision were set to 64 and 16, respectively, to minimize memory use. The weight decay was set to 0.0005 and the momentum to 0.9. Additionally, the YOLO-Tomato was trained using random initialization, whereas YOLOv3 and YOLOv4 were trained using official pre-trained weights.

Using Precision, Recall, F1-score, and AP as assessment metrics, the trials performed on the trained YOLO-tomato, YOLOv3, and YOLOv4 models were found to be effective. The equations (3.1)–(3.4) illustrate the computation process.

$$Precision = \frac{TP}{TP + FP} \tag{3.1}$$

$$Recall = \frac{TP}{TP + FN} \tag{3.2}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{3.3}$$

In these equations, TP, FN, and FP are abbreviations for True Positive (correct detections), False Negative (missed detections), and False Positive (incorrect detections). F1 score was conducted as a trade-off between Recall and Precision to show the comprehensive performance of the trained models8, defined in Eq. (3.3). Average Precision–AP was adopted to show the overall performance of the models under different confidence thresholds, expressed as follows:

$$AP = \sum_{n} (r_{n+1} - r_n) \cdot \max p(f) \tag{3.4}$$

Where P(f) is the measured precision at recall f

Results and discussion

Model performance

To ensure consistency with the training picture resolution, the trained models were tested using an image resolution of 416 × 416 pixels set at batch size 1. The test dataset's tomato count is detected by the YOLO-tomato models, which produce accurate detection results. The YOLOv3 and YOLOv4 models were compared with the computed Precision, Recall, F1-score, and AP of the identified tomatoes. Tables 1 (raw), Table 2 (0.5 ratio), and Table 3 (0.25% ratio) display the experimental outcomes.

Methods	**Precision (%)**	**Recall (%)**	**F1 (%)**	**AP (%)**
YOLOv3	97.4	96.2	96.8	97.8
YOLOv4	97.4	100.0	98.7	99.5

Table 3.1: Model performance evaluation with Raw dataset under 416×416 pixels' resolution.

Methods	**Precision (%)**	**Recall (%)**	**F1 (%)**	**AP (%)**
YOLOv3	94.4	98.0	96.2	97.3
YOLOv4	98.0	99.9	99.0	99.5

Table 3.2: Model performance evaluation with 0.5 dataset under 416×416 pixels' resolution.

Methods	**Precision (%)**	**Recall (%)**	**F1 (%)**	**AP (%)**
YOLOv3	96.3	95.9	96.1	97.1
YOLOv4	98.0	100.0	99.0	99.0

Table 3.3: Model performance evaluation with 0.25 dataset under 416×416 pixels' resolution.

Based on the assumptions outlined in Tables 1, 2, and 3, we discovered that all approaches perform exceptionally well because tiny datasets are used.

The assessed performance varies depending on the approach used. According to the AP comparison results in the tables, the YOLO-Fruits-A model rose by 0.4% in Table 1, 1.2% in Table 2, and 1.2% in Table 3. This is a result of DenseNet's feature enhancements, which improve the model's ability to identify tiny tomatoes. Precision, Recall, F1-score, and AP all increased when Mish was activated in the models.

Because Raw, 0.5 ratio, and 0.25 ratio all had the identical configuration file, we saw little to no variation in their detection times. As a result, Table 4 shows the average detection time of the YOLO-Tomato model for each image.

YOLO-Tomato Visualization

The results of the YOLO-Fruits visualization were obtained, and the detected tomatoes, along with their respective percentages, are illustrated in Figures 3.13. The improved performance of the model is evident from the appropriate detections in YOLOv3 (Figure:3.13). The enhanced accuracy in identifying tomatoes demonstrates the advancements made in the model's performance. The improved detection capabilities can be attributed to the refined algorithms and enhanced training data used in YOLOv3, which allow for more precise and reliable identification of tomatoes in the images.

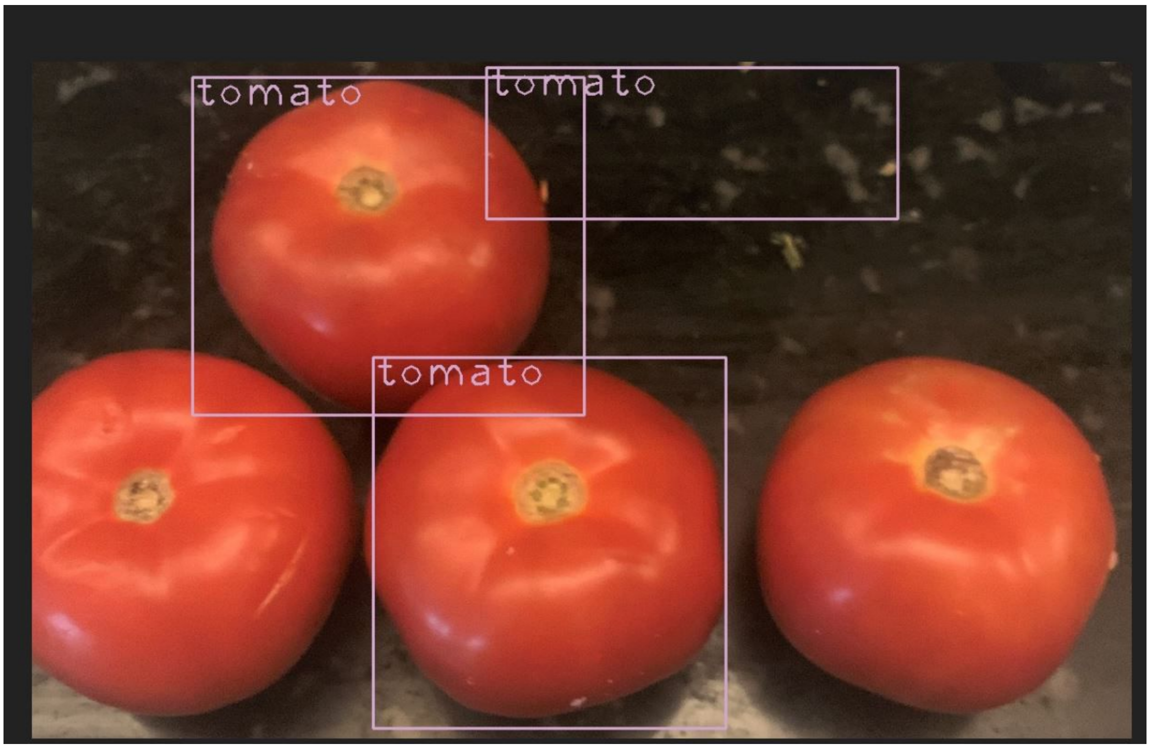


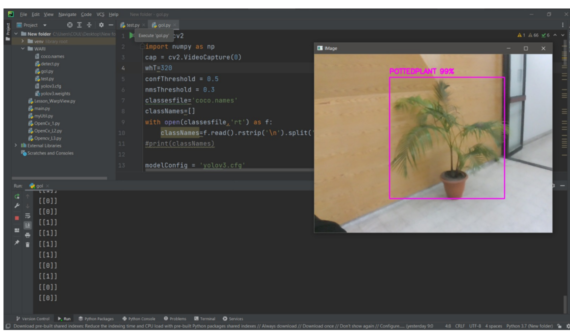
Figure 3.13: Detection results of the generic YOLOv3

Chapter 4

Results and Discussion

4.1 Results

4.1.1 Object Detection, Segmentation and Identification



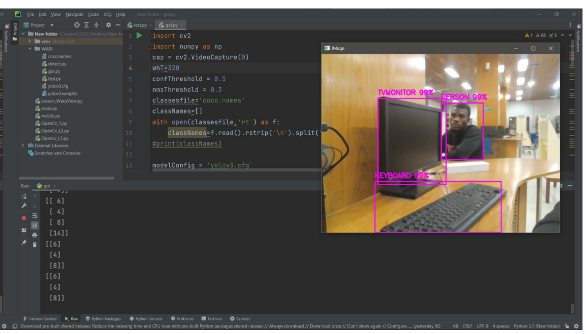


Figure 4.1: flower identification

Figure 4.2: Caption for the second image

Figure 4.3: Esp streaming and Object Detection

Figure 4.4: Robot front view

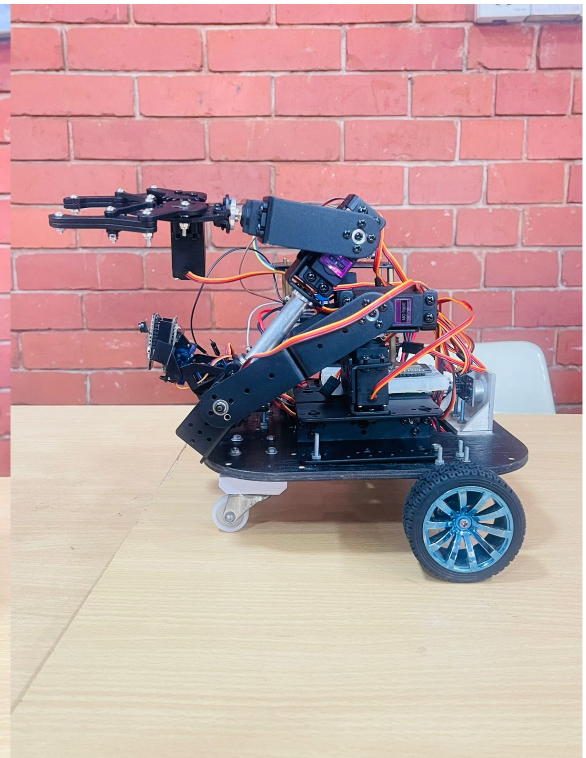


Figure 4.5: Robot side view

Figure 4.6: Robot view

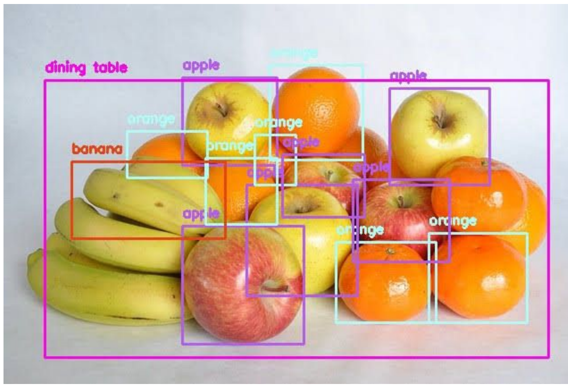


Figure 4.8: Apple detection

Figure 4.7: Fruits classification

Figure 4.9: Fruits detection

4.2 Discussion

Implementing and integrating a harvesting robot involves several critical components and technologies. One of the standout features of this robot is its use of YOLO V3 (You Only Look Once version 3) for object detection. The following discussion will explore the results as illustrated in various figures, highlighting their significance and implications for the robot's performance in harvesting tasks.

Object Detection with YOLO V3

Figures 4.4, 4.6 show the robot's object detecting skills using the YOLO V3 algorithm. YOLO V3 is a cutting-edge, real-time object identification technology that processes photos swiftly and reliably, detecting several items inside a single frame. Accuracy: YOLO V3's ability to identify and classify things means that the robot can distinguish between various varieties of fruits, greenery, and potential impediments. Speed: The real-time processing capabilities enables the robot to make rapid decisions based on detected objects, which is critical for efficient and productive harvesting. The results in these figures show that the robot can dependably recognize things in its environment, which is critical for targeted harvesting operations.

Complete Assembly

Figures 4.7, 4.8 show the harvesting robot's complete assembly, including all of the hardware components detailed earlier. Power Management: The robot is fueled by a 3300mAh 12V battery, which allows it to function for long periods of time in the field. Control System: The ESP32 module serves as the robot's brain, processing data from various sensors and carrying out commands. Motion and Actuation: The motor driver, DC motors, and pan-tilt mechanism collaborate to produce precise movement and positioning. Sensing and Feedback: The pan-tilt mechanism's ultrasonic sensors and camera enable the robot to effectively traverse and interact with its environment. The complete assembly ensures that all components work together seamlessly, resulting in a functional and reliable harvesting robot.

Fruit Detection for Harvesting

Figures 4.7 and 4.8 show the robot's capacity to detect fruits for harvesting purposes. Precision: The robot can discover and identify ripe fruits among foliage, allowing for selective picking while avoiding damage to other sections of the plants. Efficiency: By using the discovered data, the robot can precisely position its arm to pick the fruit, reducing waste and increasing yield. The fruit detection capability is crucial for the robot's primary task – harvesting. Accurate fruit detection ensures that the robot can perform its duties efficiently, improving overall productivity.

4.2.1 Challenges Faced During the Harvesting Robot Project

Developing a smart agricultural robot involves overcoming numerous challenges to ensure the system's functionality, efficiency, and reliability. This section discusses some of the significant challenges encountered during the project, particularly focusing on power management and the computational limitations of using a micro-controller like the ESP32-CAM to effectively run a computer vision algorithm.

Power Management

One of the critical challenges in the development of the harvesting robot was managing the power requirements of various components while ensuring the overall system's efficiency and longevity. - **Battery Capacity and Power Consumption**: The robot is powered by a 3300mAh 12V battery, which provides enough power to all components, including the ESP32 module, motor driver, DC motors, servos, and sensors. It was difficult to balance power usage while also ensuring that the battery could operate for an extended amount of time.
-**Voltage Regulation:** Different components required varying voltage levels. It was critical to use dependable and efficient voltage regulators to reduce the battery voltage to these levels while minimizing losses.
-**Power Distribution:** To avoid failures, dependable and consistent power distribution across all components was critical. Power spikes or decreases could possibly harm sensitive components or cause abnormal behavior.
-**Battery Management System (BMS):** Adding a BMS to monitor battery health, prevent overcharging or deep draining, and regulate power distribution increased system complexity.

Computational Limitations of ESP32-CAM

The ESP32-CAM, while a powerful micro-controller for its size and cost, presented several computational challenges, especially in running sophisticated computer vision algorithms like YOLO V3.
-**Processing Power: YOLO** V3 is a deep learning-based object identification method that requires significant computational resources to operate in real time. The ESP32-CAM's insufficient processing capability in comparison to more robust systems such as GPUs or high-end CPUs made it difficult to run YOLO V3 efficiently.
-**Memory Constraints:** The ESP32-CAM's RAM and flash memory are restricted, making it difficult to store and process big datasets for deep learning models. Efficient memory management

and optimization were required to avoid system crashes and maintain smooth performance.
-Latency and Real-Time Processing: Because of the ESP32-CAM's limited computational capabilities, it was difficult to detect objects in real time. This had an influence on the robot's capacity to make quick decisions based on visual information, potentially affecting harvesting efficiency.
-Algorithm Simplification: In order to conduct computer vision tasks on the ESP32-CAM, the YOLO V3 algorithm needed to be significantly simplified and optimized. This entailed decreasing the model size, compromising detection accuracy and speed, and striking a balance that worked within the hardware limits. **-Heat Dissipation:** Running demanding computational activities on the ESP32-CAM generates heat, which must be handled to avoid overheating and ensure long-term reliability.

4.3 Future Prospects

The harvesting robot project has established a solid platform for future advances and applications in agricultural robotics. Building on its triumphs and lessons learnt, there are several interesting potential for future development and innovation:

4.3.1 Advanced Object Detection and AI Integration

Deep Learning Enhancements: We are continuing to tune and optimize object detection techniques such as YOLO V3 to improve accuracy and speed. Exploration of innovative algorithms or hybrid approaches that use AI techniques like reinforcement learning to make adaptive decisions. Edge Computing: The integration of edge computing solutions to offload computational chores from the micro-controller, allowing for more complicated algorithms and real-time data processing without sacrificing speed. Sensor fusion is the process of combining data from various sensors (such as cameras, LiDAR, and infrared) to improve perception capabilities, resulting in comprehensive environmental awareness and strong object detection in a variety of settings.

4.3.2 Enhanced Power and Energy Efficiency

Alternative Power Sources: The use of renewable energy sources such as solar panels to supplement or replace battery power, hence increasing operational autonomy and lowering environmental effect. Energy Harvesting: Investigation of energy harvesting systems (e.g., kinetic, thermal) for harnessing ambient energy and supplementing power requirements, hence boosting the robot's sustainability and decreasing reliance on traditional energy sources. Smart Power Management: The implementation of intelligent power management systems that use predictive analytics and machine learning algorithms to optimize energy use, extend battery life, and improve overall efficiency.

4.3.3 Autonomous Navigation and Intelligent Control

SLAM (Simultaneous Localization and Mapping): Use of advanced SLAM algorithms to enable autonomous navigation and mapping in complicated settings. Integration with object detection allows for real-time adaptive path planning and obstacle avoidance. Multi-Robot Coordination: Swarm robotics capabilities are being developed to allow for coordinated operations among several harvesting robots, enabling collaborative activities and scalability in large-scale agricultural settings. Human-Robot Collaboration: Creating user-friendly human-machine interfaces (HMIs) and collaborative frameworks to enable seamless interaction between robots and human operators, increasing productivity and operational safety.

4.3.4 Modular and Scalable Design

Modular design: Designing the robot with a modular design that allows for easy component updates, maintenance, and customization. This allows for rapid response to emerging technical improvements and specific agricultural requirements. Scalability: Creating scalable systems that can be tailored to diverse crop varieties, farm sizes, and geographical regions. This entails creating adaptive grippers and tools for various harvesting operations and settings.

4.3.5 Data Analytics and Decision Support Systems

Big Data Analytics: Using data collected by the robot to perform predictive analytics, yield forecasting, and crop health monitoring. Integration with cloud-based platforms enables centralized data storage, analysis, and real-time decision assistance. IoT Integration: Connecting the harvesting robot to IoT (Internet of Things) devices and agricultural sensors to improve data collection and environmental monitoring. This enables precision agriculture and educated decision-making based on real-time data.

4.3.6 Impact and Benefits

The future prospects outlined for the harvesting robot project hold immense potential to transform agriculture by:
-**Improving Efficiency:** Boosting productivity with automation and precision agricultural techniques, lowering labor expenses, and optimizing resource utilization.
-**Enhancing Sustainability:** Encouraging sustainable farming methods by limiting environmental effect, lowering chemical use, and preserving resources.
-**Supporting Global Food Security**: Addressing global food demand concerns through increased agricultural production and resilience to climate change and environmental stressors.

Chapter 5

Conclusion

The harvesting robot project demonstrates the power of technical innovation in tackling pressing issues in modern agriculture. This project not only demonstrates the promise of robots in improving agricultural output, but it also lays the framework for future breakthroughs in the industry by combining advanced hardware and software components.

To summarize, the harvesting robot project successfully incorporates innovative technology to meet critical difficulties in modern agriculture. By overcoming challenges in power management and computing efficiency, the study demonstrates the viability and benefits of deploying robotics for agricultural chores. The accomplishments of this research demonstrate robotics' potential to revolutionize agriculture, making it more efficient, sustainable, and productive. As the agricultural business evolves, the use of such robotic systems will become increasingly important in satisfying the growing worldwide need for food in a sustainable and efficient manner. The project's insights and innovations pave the path for future breakthroughs, ushering in a new era of technological integration in agriculture.

Chapter 6

Demonstration of Outcome Based Education (OBE)

6.1 INTRODUCTION

The rapid advancement of technology in agriculture, particularly the creation of smart agricultural robots, has the potential to transform traditional farming practices. In this context, Outcome-Based Education (OBE) offers a structured framework for aligning educational programs with the skills needed to design, develop, and implement new solutions such as harvesting robots. This demonstration will explain how the OBE approach handles course outcomes (COs), program outcomes (POs), knowledge profiles, and the characteristics required to solve complex technical challenges in smart agriculture.

Smart agricultural robots, particularly those developed for harvesting, pose numerous issues that necessitate a thorough understanding of robotics, automation, sensor technology, artificial intelligence, and sustainable practices. The educational program, which is based on OBE principles, ensures that students obtain not just theoretical knowledge but also practical skills necessary for tackling real-world agricultural challenges. This demonstration illustrates the use of OBE in the development of abilities that are directly applicable to the agriculture sector's changing needs.

6.2 COURSE OUTCOME (COs) ADDRESSED

The following table shows the COs for EEE 4700/4800

COs	CO Statement	POs
CO1	Identify a contemporary real life problem related to electrical and	PO2
CO2	Determine functional requirements of the problem considering	PO4
CO3	Select a suitable solution and determine its method consideringprofessional ethics, codes and standards.	PO8
CO4	Adopt modern engineering resources and tools for the solution of the problem	PO5
CO5	Prepare management plan and budgetary implications for the solution of the problem.	PO11
CO6	Analyze the impact of the proposed solution on health, safety, culture and society.	PO6
CO7	Analyze the impact of the proposed solution on environment and sustainability.	PO7
CO8	Develop a viable solution considering health, safety, cultural, societal andenvironmental aspects.	PO3
CO9	Work effectively as an individual and as a team member for the accomplishment of the solution.	PO9
CO10	Prepare various technical reports, design documentation, and deliver effective presentations for demonstration of the solution.	PO10
CO11	Recognize the need for continuing education and participation in professional societies and meetings	PO12

Table 6.1: Summary of different types of harvesting robots and their key features.

6.3 ASPECTS OF PROGRAM OUTCOMES (POs) ADDRESSED

The following table shows the aspects addressed for certain Program Outcomes (POs) addressed in EEE 4700/4800 for Project and Thesis.

	Statement	**Different Aspects**	**Put Tick (✓)**
PO3	Design/development of solutions: Design solutions for complex electrical and electronic engineering problems and design systems, components or processes that meet specified needs with appropriate consideration for public health and safety, cultural, societal, and environmental considerations.	Public health	
		Safety	✓
		Cultural	
		Societal	✓
		Environmental	
PO4	Investigation: Conduct investigations of complex electrical and electronic engineering problems using research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of information to provide valid conclusions.	Design of experiments	✓
		Analysis and interpretation of data	✓
		Synthesis of information	✓
PO6	The engineer and society: Apply reasoning informed by contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to professional engineering practice and solutions to complex electrical and electronic engineering problems.	Societal	✓
		Health	
		Safety	✓
		Legal	✓
		Cultural	
PO7	Environment and sustainability: Understand and evaluate the sustainability and impact of professional engineering work in the solution of complex electrical and electronic engineering problems in societal and environmental contexts.	Societal	
		Environmental	

PO8	Ethics: Apply ethical principles embedded with religious values, professional ethics and responsibilities, and norms of electrical and electronic engineering practice.	Religious values	
		Professional ethics and responsibilities	
		Norms	
PO11	Project management and finance: Demonstrate knowledge and understanding of engineering management principles and economic decision-making and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.	Engineering management principles	
		Economic decision-making	
		Manage projects	
		Multidisciplinary environmental	

Table 6.2: Summary of different types of harvesting robots and their key features.

The following table explains or justifies how the COs and corresponding POs have been addressed in EEE 4700/4800 (Project and Thesis)

COs	**Explanation/Justification**	**POs**	**Put Tick (✓)**
CO1	A contemporary real-life problem related to agricultural harvesting robots involves the development of robust and adaptable robotic systems that can effectively handle the complexities of diverse agricultural environments and crop varieties	PO2	✓
CO2	The agricultural harvesting robot can be adapted to provide feasible and efficient solutions that align with the complexities and demands of modern agricultural practices. Synthesizing information from various disciplines including robotics, AI, agriculture, and engineering is crucial in shaping the design and development of such advanced robotic systems.	PO4	✓
CO3		PO8	✓
CO4	One modern engineering resource for addressing the challenge of developing robust and adaptable agricultural harvesting robots is advanced sensor technology. This includes high-resolution cameras, LiDAR (Light Detection and Ranging), GPS (Global Positioning System), and other sensors that can provide real-time data about crop maturity, environmental conditions, and terrain variability.	PO5	✓
CO5		PO11	✓
CO6		PO6	✓
CO7		PO7	✓

CO8	The development of agricultural harvesting robots can impact society, safety, and the environment in the following ways: **Society,** Changes in employment dynamics and labor market. Access to consistent and efficient harvesting in regions with labor shortages; **Safety:** Reduced risk of injuries and occupational hazards for agricultural workers. Potential reduction in chemical exposure through targeted harvesting. **Environment**: Optimization of resource utilization and reduction of waste. Minimization of soil compaction and potential for improved soil health. Contribution to reduced emissions and improved energy efficiency. These impacts highlight the potential benefits and considerations associated with the integration of agricultural harvesting robots.	PO3	✓
CO9	We are developing a smart agricultural robot based on computer vision that integrates individual work with teamwork and collaboration in multidisciplinary situations advancing sustainable agriculture. Work with teamwork and collaboration in multidisciplinary situations.	PO9	✓
CO10	It is crucial to effectively convey the solution to the engineering community and the general public through the use of technical reports, design documentation, and compelling presentations in order to provide clear instructions for building and operating the intelligent agricultural robot.	PO10	✓
CO11		PO12	✓

Table 6.3: Table summarizing COs, POs, and Explanation/Justification for agricultural harvesting robots.

6.4 KNOWLEDGE PROFILES (K3 – K8) ADDRESSED

The following table shows the Knowledge Profiles (K3 – K8) addressed in EEE 4700/4800 (Project and Thesis).

K	**Knowledge Profile (Attribute)**	**Put Tick (✓)**
K3	A systematic, theory-based formulation of engineering fundamentals required in the engineering discipline	✓
K4	Engineering specialist knowledge that provides theoretical frameworks and bodies of knowledge for the accepted practice areas in the engineering discipline; much is at the forefront of the discipline	
K5	Knowledge that supports engineering design in a practice area	✓
K6	Knowledge of engineering practice (technology) in the practice areas in the engineering discipline	✓
K7	Comprehension of the role of engineering in society and identified issues in engineering practice in the discipline: ethics and the engineer's professional responsibility to public safety; the impacts of engineering activity; economic, social, cultural, environmental and sustainability	✓
K8	Engagement with selected knowledge in the research literature of the discipline	

Table 6.4: Table summarizing the Knowledge Profile (Attribute) for the engineering discipline.

The following table explains or justifies how the Knowledge Profiles (K3 – K8) have been addressed in EEE 4700/4800 (Project and Thesis).

K	**Explanation/Justification**
K3	Addressing a systematic, theory-based formulation of engineering fundamentals required for a Smart Agricultural Harvesting Robot involves a structured approach that integrates various disciplines and theoretical foundations. The following steps can guide the development of such a formulation: Problem Definition and Scope, Multidisciplinary Analysis, Conceptual Design and Modeling, Integration of AI and Automation, Feasibility and Performance Analysis, Safety and Ethical Considerations, Prototyping and Validation, Regulatory and Standards Compliance, Documentation and Knowledge Transfer
K4	
K5	In the practice area of designing agricultural harvesting robots, essential knowledge includes robotics and automation, sensing and perception systems, mechanical engineering and design, agricultural science, energy systems and power management, data analysis and decision making, and human-robot interaction and safety. This multidisciplinary knowledge is crucial for developing robots capable of efficiently and safely harvesting crops while minimizing environmental impact and enhancing agricultural productivity.
K6	Use of gain expertise in relevant technologies such as sensors, actuators, image processing algorithms, and machine learning models.
K7	Engineering in Society explores the ethical, societal, and environmental implications of engineering solutions in agriculture, emphasizing public safety, sustainability. In order to address these problems, a comprehensive strategy that takes into account technological innovation's wider social, economic, cultural, and environmental ramifications is needed. To make sure that intelligent agricultural robots benefit both agriculture and society at large, engineers in this discipline must place a high priority on sustainability, public safety, and ethical decision-making.
K8	

Table 6.5: Table summarizing the Explanation/Justification for each Knowledge Profile (K) in the context of Smart Agricultural Harvesting Robots.

6.5 ATTRIBUTES OF RANGES OF COMPLEX ENGINEERING PROBLEM SOLVING (P1 – P7) ADDRESSED

The following table shows the attributes of ranges of Complex Engineering Problem Solving (P1 – P7) addressed in EEE 4700/4800 (Project and Thesis).

P	**Range of Complex Engineering Problem Solving**	**Put Tick (✓)**
Attribute	**Complex Engineering Problems have characteristic P1 and some or all of P2 to P7:**	**Put Tick (✓)**
Depth of knowledge required	P1: Cannot be resolved without in-depth engineering knowledge at the level of one or more of K3, K4, K5, K6 or K8 which allows a fundamentals-based, first principles analytical approach	✓
Range of conflicting requirements	P2: Involve wide-ranging or conflicting technical, engineering and other issues	✓
Depth of analysis required	P3: Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models	
Familiarity of issues	P4: Involve infrequently encountered issues	✓
Extent of applicable codes	P5: Are outside problems encompassed by standards and codes of practice for professional engineering	✓
Extent of stakeholder involvement and conflicting requirements	P6: Involve diverse groups of stakeholders with widely varying needs	✓
Interdependence	P7: Are high level problems including many component parts or sub-problems	✓

Table 6.6: Table summarizing the Range of Complex Engineering Problem Solving and corresponding attributes.

The following table explains or justifies how the attributes of ranges of Complex Engineering Problem Solving (P1 – P7) have been addressed in EEE 4700/4800 (Project and Thesis).

P	**Explanation/Justification**
P1	Developing an agricultural harvesting robot requires a deep understanding of engineering principles, agricultural science, robotics and automation, data analytics, AI, ethical considerations, regulatory compliance, and interdisciplinary collaboration. This comprehensive knowledge base is essential for creating effective and efficient robotic solutions tailored to agricultural needs.
P2	Developing an agricultural harvesting robot involves managing conflicting requirements such as precision vs. speed, adaptability vs. standardization, power efficiency vs. performance, autonomy vs. human intervention, cost vs. capability, environmental impact vs. productivity, and regulatory compliance vs. technological advancement. Balancing these factors is crucial for creating an effective and efficient robotic solution for agricultural harvesting.
P3	Developing agricultural harvesting robots requires a comprehensive analysis of crop characteristics, environmental factors, efficiency, precision, crop health, and integration with existing agricultural systems.
P4	Understanding the issues related to agricultural harvesting robots involves considering crop variability, terrain challenges, labor efficiency, crop health, and integration with existing agricultural systems.
P5	The applicable codes for agricultural harvesting robots encompass safety standards, environmental regulations, product quality standards, data privacy and security regulations, robotic industry standards, and ethical guidelines. These codes ensure the robot's safe operation, environmental compliance, product quality, data security, industry compatibility, and ethical harvesting practices.
P6	The development of agricultural harvesting robot involves diverse stakeholders with varying needs, including farmers, researchers, policymakers, and technology providers.
P7	Engineering tasks are complex and involve many interconnected components, such as hardware design, software development, and environmental considerations.

Table 6.7: Table summarizing the Explanation/Justification for each P attribute in the context of developing agricultural harvesting robots.

6.6 ATTRIBUTES OF RANGES OF COMPLEX ENGINEERING ACTIVITIES (A1 – A5) ADDRESSED

The following table shows the attributes of ranges of Complex Engineering Activities (A1 – A5) addressed in EEE 4700/4800 (Project and Thesis).

A	**Range of Complex Engineering Activities**	**Put Tick (✓)**
Attribute	**Complex activities means (engineering) activities or projects that have some or all of the following characteristics:**	(✓)
Range of resources	A1: Involve the use of diverse resources (and for this purpose resources include people, money, equipment, materials, information and technologies)	✓
Level of interaction	A2: Require resolution of significant problems arising from interactions between wide-ranging or conflicting technical, engineering or other issues	✓
Innovation	A3: Involve creative use of engineering principles and research-based knowledge in novel ways	✓
Consequences for society and the environment	A4: Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation	
Familiarity	A5: Can extend beyond previous experiences by applying principles-based approaches	✓

Table 6.8: Table summarizing the Range of Complex Engineering Activities and corresponding attributes.

The following table explains or justifies how the attributes of ranges of Complex Engineering Activities (A1 – A5) have been addressed in EEE 4700/4800 (Project and Thesis).

A	**Explanation/Justification**
A1	To develop an agricultural harvesting robot, several resources are required, including hardware, software, data, funding and support and human resources. Considering the complexity of developing an agricultural harvesting robot, a multidisciplinary approach involving mechanical, electrical, and software engineering, as well as agricultural expertise, is essential
A2	It is imperative to address significant obstacles that may arise from the interplay of many technical, engineering, and agricultural concerns. This means resolving conflicts between needs, integrating various technologies, and optimizing the effectiveness of intelligent agricultural robots in complex agricultural environments.
A3	Innovative agricultural harvesting robot development involves interdisciplinary collaboration, adaptive design, data-driven decision making, sustainable solutions, human-robot interaction, field testing, and regulatory compliance.
A4	Agricultural harvesting robots can impact society by changing employment dynamics and requiring workforce training, while also affecting the environment through resource conservation and potential soil health implications.
A5	To extend beyond previous experiences in developing an agricultural harvesting robot, apply principles-based approaches such as holistic systems thinking, iterative development, data-driven decision making, risk management, ethical considerations, and regulatory compliance. These approaches will help create a robust, adaptable, and socially responsible solution that aligns with established engineering and agricultural principles.

Table 6.9: Table summarizing the Explanation/Justification for each A attribute in the context of developing agricultural harvesting robots.

Chapter 7

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