RipenTrack : Fruits Ripening Stage Detector

Capstone Project Report

End-Semester Evaluation

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ABSTRACT

The project "Fruit Ripening Detection System Using Arduino nano and Color Detection Sensor" presents a unique and comprehensive method for identifying the ripening phases of fruits and vegetables. The project tackles the critical problem of minimizing food waste and optimizing fruit management across many sectors of the agriculture and food industries by using the possibilities of spectral color data and Internet of Things (IoT) technologies. The core of the project is the strategic integration of physical components, software development, and machine learning approaches. To acquire spectral color data from fruits, a hardware setup consisting of an ESP32 and a color detecting sensor is used. This information is used to forecast fruit ripening phases. The addition of IoT capabilities improves the system's usability and usefulness. The investigation begins with the gathering of the essential hardware components and materials for data capturing. Simultaneously, work on a user-friendly web application that will allow users to engage with the system effortlessly begins. Following the assembly of the hardware, spectral color data is gathered, resulting in a diversified dataset representing numerous fruit and vegetable varieties. This dataset serves as the foundation for the development of a Machine learning model meant to categorize fruits into ripening phases such as Early Ripe, Partially Ripe, Ripe, and Decay. The trained ML model is subjected to extensive testing to confirm its correctness and dependability. Concurrently, the web application is being improved to better incorporate the model and offer forecasts. The system is ready to take spectral color data after successful testing and validation. The project's uniqueness stems from its integrated approach, which combines hardware, software, and machine learning. The system's real-time detection, spectrum color data use, and IoT integration close significant research gaps, providing an unparalleled answer to fruit ripening stage monitoring. The initiative advances agricultural methods by aiding effective fruit management, minimizing waste, and encouraging sustainability. It also highlights the revolutionary power of technology in tackling real-world difficulties.

DECLARATION

We hereby declare that the design principles and working prototype model of the project entitled RipenTrack : Fruits Ripening Stage Detector is an authentic record of our own work carried out in the Computer Science and Engineering Department, TIET, Patiala, under the guidance of Dr. Nitigya Sambyal during 7th semester (2024 batch).

Date: December 12, 2023

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1.1.1 Technical Terminology

Spectral shade Sensor statistics: Measurements of mild intensity throughout extraordinary wavelengths, shooting the spectral traits of the object being sensed.

Sensor Calibration: The procedure of fixing the sensor readings to ensure accuracy and consistency in measuring spectral hues.

Neural network model

Artificial Neural Network (ANN): A computational version inspired by means of the shape and feature of the organic brain, inclusive of interconnected nodes (neurons) organized in layers.

schooling facts: The dataset used to train the neural network, containing enter-output pairs for the version to learn patterns and relationships.

Backpropagation: An optimization algorithm used to update the weights of the neural community at some stage in training, minimizing the difference between anticipated and real outputs.

Activation characteristic: A mathematical operation carried out to the output of a neuron, introducing non-linearity to the version and allowing it to learn complicated patterns.

Loss characteristic: A measure of the distinction among predicted and real outputs, used to manual the optimization manner throughout education.

Epoch: One entire bypass through the entire education dataset for the duration of the training of a neural community.

Hyperparameters: Configurable settings of the neural community, which include studying charge, number of layers, and range of neurons in line with layer.

Model Inference: The procedure of the use of a trained neural community to make predictions on new, unseen records.

Model assessment: A separate portion of the dataset not used for the duration of training, used to evaluate the model's overall performance on unseen data.

Accuracy: A metric indicating the percentage of effectively predicted instances over the full range of instances inside the check set.

Confusion Matrix: A table displaying the real effective, actual bad, false tremendous, and false bad counts, imparting an in depth assessment of model overall performance.

Integration with net application:

Flask Framework : A server-facet scripting language used to have interaction with databases, manner records, and generate dynamic web content material the usage of python as center

Deployment: model Deployment: The manner of making a trained device getting to know model reachable for making predictions, both thru direct integration into an utility or as a separate provider.

1.1.2 Problem Statement

In the realm of mass production and processing of fruits and vegetables, the conventional reliance on human judgment and experience for determining ripeness proves increasingly inefficient and susceptible to inconsistencies as production scales up in factories, marketplaces, and farming operations. The subjective nature of current assessment methods results in substantial wastage due to imprecise timing of harvesting and processing. This lack of precision not only causes economic losses for producers but also contributes to environmental concerns, amplifying the issue of food waste. The challenges associated with manual ripeness determination become critical, especially considering the perishable nature of fruits and vegetables. Addressing this problem is essential for fostering a more sustainable, efficient, and economically viable approach to the production and distribution of fruits and vegetables.

1.1.3 Goal

The goal of the Fruits Ripening Stage Detector - RipenTrack project is to revolutionize the way ripening stages of fruits and vegetables are detected and managed in large-scale production and processing environments. The overarching objective is to address the challenges associated with imprecise ripeness determination, ultimately reducing wastage and promoting a more efficient and sustainable approach to storing and distributing essential food items. The project aims to achieve the following specific objectives:

Automated Ripeness Detection:

Develop an innovative device that integrates spectral color processing with advanced neural network models to automate the detection of ripening stages in fruits and vegetables.

Precision in Ripeness Prediction:

Utilize spectral color data captured by the device to provide precise and accurate predictions of the ripening stages, eliminating inconsistencies associated with human judgment.

Empowering Farmers and Consumers:

Provide a valuable tool for farmers, grocery store managers, and consumers to determine the freshness of produce, enabling informed decision-making and reducing uncertainties in the market.

1.1.4 Solution

The proposed solution involves the integration of spectral color processing with advanced neural network models to create an innovative device capable of accurately identifying the ripening stage of each fruit and vegetable. This system, developed using TensorFlow and utilizing spectral color data captured by the AS7341 visible light sensor, addresses the challenges faced by traditional methods.

Data Collection:

Spectral color data of fruits and vegetables is collected using an Arduino Nano and the AS7341 visible light sensor.

The data is manually labeled into four ripening stages: Early Ripe, Partially Ripe, Ripe, and Decay.

Machine learning Model Model:

Using pycaret highest accuracy giving machine learning models have been figured out and then the top 3 has been ensembled to train the model .The model is designed to interpret the subtle patterns and correlations in the spectral color data, enabling precise ripening stage predictions.

Experimental Validation:

The trained neural network model is tested using a separate set of data to evaluate its accuracy in predicting the ripening stages of various fruits and vegetables.

Experiments are conducted to ensure the reliability and effectiveness of the developed system.

1.2 Need Analysis

Fruit and vegetables ripeness detecting devices have become increasingly popular in recent years due to the growing demand for fresh and high-quality produce. These devices are designed to measure the internal and external characteristics of fruits and determine their ripeness level. This information is valuable to both farmers and consumers, as it can help ensure that the fruits are picked and consumed at their optimal flavor and nutritional quality.

In the real-world scenario, the usefulness of a fruit ripeness detecting device can be seen in several ways. For farmers, these devices can help optimize their harvest schedules and reduce waste. By measuring the ripeness level of their crops, farmers can pick the fruits at the right time, which not only improves the quality of their produce but also reduces the risk of overripe or under ripe fruits being left on the trees. The ability to accurately classify the ripening stages of fruits and vegetables is crucial in the food industry. This is because the ripening stage determines the quality and shelf life of produce, which has a significant impact on food waste, food safety, and consumer satisfaction. A device that can classify the ripening stages of fruits and vegetables can provide numerous benefits in the real world. Here are a few key examples:

Reducing food waste: By accurately identifying the ripeness of produce, the device can help ensure that only the freshest and highest quality fruits and 13 vegetables reach consumers, reducing the amount of food waste caused by overripe or under ripe produce.

Improving food safety: Overripe produce can pose a food safety risk, as it can harbor harmful bacteria and pathogens. The ability to accurately identify the ripening stage of produce can help prevent foodborne illnesses and ensure the safety of the food supply.

Enhancing consumer satisfaction: By providing consumers with consistently fresh and high-quality produce, the device can improve consumer satisfaction and brand loyalty.

Streamlining supply chain management: The device can help suppliers, retailers, and distributors more effectively manage their produce inventory, reducing waste and improving efficiency.

1.3 Research Gaps

To emphasize the gaps in existing research and publications where an integrated system of the sort suggested in this project is lacking. This section explains the gaps that the project intends to fill and highlights the innovative contributions it provides to the field of fruit ripening detection.

1. **Integrated Hardware-Software Solution:** The lack of an integrated hardware-software solution for fruit ripening detection is a key research gap in the existing literature. While some studies concentrate on hardware configurations or machine learning models independently, there is a scarcity of research that integrates these parts into a seamless and linked system.

2. **Spectral Color Data Utilization:** Many present fruit ripening detection systems depend entirely on traditional color-based approaches, or using fruit images data separately ignoring the potential benefits of spectral color data. This study seeks to close the gap by investigating the use of spectral color information to improve the accuracy and precision of ripening stage forecasts.

3. **Multistage Classification rather than traditional binary approach:** Existing research frequently focuses on binary categorization (e.g., ripe or unripe) rather than multistage classification of fruit ripening. This study fills a research vacuum by developing a neural network model that can categorize fruits into several ripening phases, catering to a wide range of agricultural and food industry applications.

4. **Scalability and Accessibility for Small-Scale Users:** Many fruit ripening detection systems established in the literature are intended for large-scale operations or research contexts, requiring sophisticated equipment and computer resources.

1.4 Problem Definition and Scope

Problem Definition The "Fruits Ripening Stage Detector with Spectral Color Data" project addresses the difficulty of reliably detecting the ripening stage of fruits and vegetables on a wider scale, particularly in mass production and processing scenarios. Traditional techniques of judging ripeness based purely on appearance result in enormous waste and inconsistency, threatening the agricultural and food sectors' economic viability and environmental sustainability.

The project's goal is to create a sophisticated gadget that uses spectral color processing in conjunction with an Machine Learning model to correctly determine the ripening stage of fruits and vegetables. The initiative aims to eliminate waste, optimize storage techniques, and improve supply chain management for farmers, businesses, and marketplaces by overcoming the constraints of old approaches.

Scope

The Fruits Ripening Stage Detector gadget and its accompanying ML model arethe focus of the project's design, development, and implementation. The following are the essential components of the project's scope:

Design and build the hardware setup

The device comprises an ESP32/Arduino microcontroller and a spectral color sensor. The hardware should be able to collect spectral reflectance data from a wide variety of fruits and vegetables.

Data Collection

Gather a large and diversified dataset of spectral color data from numerous fruits and vegetables at various stages of ripening. Each data sample must be correctly labeled with its ripeness state.

Data Preprocessing

Prepare the acquired spectrum color data for training the ML model by extracting key features and removing noise.

Machine learning Model Development

Using the preprocessed spectral data, create and train a Machine Learning model. To properly estimate the ripening stage of fruits and vegetables, the model should be tuned.

Develop an end-to-end application

Development of a user-friendly interface that incorporates the trained ML model. The program should be able to estimate the maturity of fruits and vegetables in real time and givevisuals for easy comprehension.

Testing and Evaluation

Use fresh spectrum data frompreviously unknown fruits and vegetables to thoroughly test the device, ML model, and end-to-end application. To evaluate the model's performance, examine its accuracy, precision, recall, and F1-score predictions.

1.5 Assumptions and Constraints

Assumptions

Dataset obtained Independently: The project implies that the dataset used to train the ML model for detecting fruit ripening stage is obtained independently. There are no external datasets used, and no pre-trained models are employed. The team will guarantee that the dataset is curated from the hardware setup, which consists of an ESP32 and a spectral color sensor that captures spectral color data from various fruits and vegetables.

Consistent Lighting settings: The spectral color data gathered from fruits and vegetables is presumed to have been collected under similar and controlled lighting settings. This is necessary to reduce differences in spectral reflectance data causedby changes in illumination and to assure the dataset's correctness and dependability.

Data Labeling: The dataset will be manually tagged with the ripening phases of various fruits and vegetables. It is believed that specialists or qualified employees would appropriately identifyeach data sample according on the ripeness stage observed. The label correctness is critical for training a dependable ML model.

Constraints

Hardware Compatibility: To achieve compatibility with the envisioned system, the hardware configuration, including the ESP32 microcontroller and the spectrum color sensor, must be carefully selected and calibrated. Any limits or constraints ofthe chosen hardware components may have an influence on the quality of the gathered spectral data and the performance of the model.

Limited Diversity in spectral data: While attempts will be made to collect spectral color data from a varied variety of fruits and vegetables, there may be restrictions in terms of accessible food or access to specific types. The dataset's 17 variety may be limited, limiting the model's capacity to generalize to less frequent or unknown fruits and vegetables.

Model Interpretability: Deep learning models, such as the ML model in this research, are notorious for their complexity and lack of interpretability. While the model may reach great accuracy in predicting ripening stage, comprehending the particular causes or attributes impacting its judgments may be difficult.

Environmental Variability: Despite efforts to maintain consistent lighting conditions during data collection, uncontrollable environmental factors such as ambient light fluctuations, humidity, and temperature may introduce noise and variations in the spectral data, affecting the model's robustness.

Hardware Cost and Accessibility: For certain users or stakeholders, the cost of the hardware configuration, particularly the spectrum color sensor, may be prohibitive. It is critical to ensure that the gadget is affordable and accessible to farmers, small food stores, and other prospective users.

1.6 Standards

ISO 9001: Quality Management Systems: The project follows the ISO 9001 standard to maintain a systematic approach to quality management. This standard ensures that all phases of the project, including hardware development, software implementation, and model training, adhere to consistent and rigorous quality control procedures.

ISO 14001: Environmental Management Systems: Given the project's focus on environmental sustainability, the team considers ISO 14001 standards to implement environmental management systems. The project aims to minimize waste generation, optimize energy usage, and reduce the environmental impact of the fruit ripening detection system.

ISO/IEC 27001: Information Security Management Systems: As the project involveshandling sensitive data, including spectral color information, the team ensures compliance with ISO/IEC 27001 standards for information security management. Measures are taken to protect data confidentiality, integrity, and availability throughout the development and deployment process.

W3C Web Accessibility Guidelines (WCAG): For the web application development, the project adheres to WCAG guidelines to ensure that the user interface is accessible to individuals with disabilities. The team aims to provide a user-friendly interface that is navigable and usable by a diverse audience.

Open Source and Open Standards: To promote collaboration and further advancements, the project follows open-source principles and utilizes open standards for data formats and communication protocols. This allows other researchers and developers to build upon the project's outcomes and fosters innovation within the community.

1.7 Objectives

1. To study the various models proposed in the literature for detection of fruit ripening. The objective entails completing a comprehensive literature review in order to comprehend the various techniques and methodologies used in fruit ripening detection. The project seeks to identify best practices, analyze the performance metrics of earlier models, and harness key insights to create an optimized and successful Artificial Neural Network (ANN) model for the Fruits Ripening Stage Detector using Spectral Color Data by reviewing current research.

2. To develop a fruit ripening detection system using Arduino IOT, and visible light sensor.

The objective involves creating a smart and interconnected system that can accurately detect the ripening stage of fruits. The system will utilize an Arduino microcontroller integrated with IoT capabilities and a color detection sensor to capture color information from fruits and classify them into different ripening stages and prepare dataset.

3. To develop a neural network-based model for multistage classification of fruit ripening. The Objective involves building an advanced machine learning model that can accurately classify fruits into multiple ripening stages. The model will be based on neural networks, specifically designed to handle the complexities of spectral color data obtained from the hardware setup.

4.To develop a web application integrated with model to predict ripening stage of fruits and vegetables.

A user friendly web application provides interface for users to input spectral data obtained through the hardware setup, consisting of an MCU and a spectral color sensor and get prediction of ripening stage of various fruits with accuracy.

1.8 Methodology Used

The methodology of the proposed work is shown in Figure 1. The various steps used in the proposed work are as follows:

1. Initially research on color-changing processes of fruits and vegetables in their different stages of ripening.

2. To collate the spectral color data of fruits and vegetables generated by the AS7341 visible light sensor to create a ripening stages data set by spectral color.

3. ESP32 wroom32 will be used to send the data produced by the visible light sensor to generate the csv files of data.

4. A ripening stage (label) will be assigned while obtaining spectral color data for each fruit and vegetable by using four class buttons connected to the Nano 33 IoT: Early Ripe,Partially Ripe, Ripe, Decay.

5. After completing the dataset, Machine learning will be built based on the classification model to interpret the spectral color of varying fruits and vegetables to predict ripening stages.

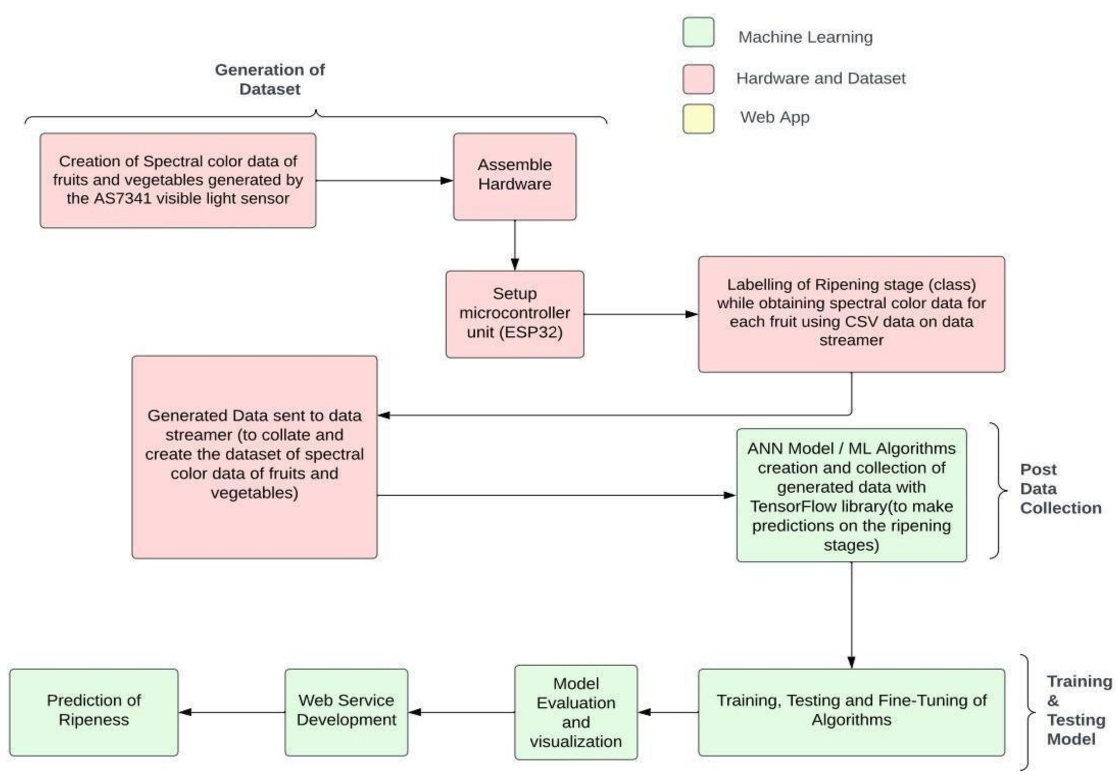


FIGURE 1: Methodology proposed for detection of the ripening stage

1.9 Project Outcomes & Deliverables

Working application of Ripeness Detector will fulfill the following outcomes:

● The primary objective of this project is to design and develop a device that can collect spectral color data of fruits and vegetables and use it to predict their ripeness level through a neural network model. The project aims to provide an accurate and non-invasive method for determining the ripeness level of fruits and vegetables, which could have significant applications in the food industry, agriculture and nutrition.

● The project must successfully showcase a prototype device that collects spectral color data of fruits and vegetables using Tensorflow, an Open Source Machine Learning library developed by Google. The device should contain a 21 sensor (DFRobot AS7341 visible light sensor for this project) to process the data and extract spectral information.

● The project must also fulfill the development of a neural network model to analyze the spectral color data and predict the ripeness levels of fruits and vegetables. The model should be trained on a large dataset of spectral color data of various fruits and vegetables, and should be fine-tuned to improve the accuracy and reduce the false positives.

● The project should demonstrate the potential of Machine Learning and Neural Networks in predicting the ripeness levels of Fruits and Vegetables and must possess significant applications in the food industry, agriculture and nutrition and should have the capability to revolutionize the way we assess fruit and vegetable ripeness.

1.10 Novelty of Work

To highlight the unique and innovative aspects that distinguish this fruit ripening detection system from existing approaches, following points should be considered: Integration of ESP32/Arduino nano and Color Detection Sensor: The proposed project introduces a novel combination of ESP32/Arduino IoT and a color detection sensor to create a smart and interconnected fruit ripening detection system. Spectral Color Data Analysis: The project focuses on utilizing spectral color data captured by the color detection sensor. This approach differs from traditional color-based detection methods, as spectral data provides a more detailed and precise representation of fruit surfaces, enabling a deeper analysis of biochemical changes during ripening. Multistage Classification of Ripening: The system's ability to classify fruits into multiple ripening stages, such as Early Ripe, Partially Ripe,Ripe, and Decay, is a significant novelty. User-Friendly Interface and Visualization: The project places significant emphasis on developing an intuitive user interface with visualization tools. This innovation enables users, including farmers and small businesses, toeasily interact with the system, visualize spectral color data, and interpret ripening stage predictions effectively. Environmental Sustainability: The proposed system has potential implications for environmental sustainability. By enabling more accurate fruit ripening detection and reducing wastage, the project aligns with the global efforts to minimize food loss and promote sustainable agricultural practices.

This section talks about the previous work done in the field of fruit ripen stage prediction. It also tells the software requirement specification along with user, hardware, software interfaces. At the end cost analysis and risk analysis will be discussed.

2.1 Literature Survey

2.1.1Related Work

The table1. shows the various research papers on predicting ripen stage of fruits and vegetables. The table shows the technology used and the major findings in tabular form.

Sno	Paper Title	Technology	Major findings
1	Monitoring Ripeness in Fruits and Vegetables Using the Raspberry Pi [1]	Pic Microcontroller development board, conveyor, motors, and Picamera, raspberry pi	This proposed system is used to detect the ripeness present in different vegetables andfruits. It detects the ripeness by using raspberry pi and python libraries.
2	Ripeness Detector for Vegetables and Fruits [2]	Spectral Analysis, Deep Learning, Artificial Neural Networks (ANN)	It has been shown that different color spaces produce different results with spectral analysis. Also, it is shown by researchers that L*A*B* colorspace is more effective than the others when it comes to working with spectral analysis of components. Using an artificial neural network, this research describes a system that uses the RGB color space.
3	Determination of the level of ripeness and freshness of fruits by electronic sensors. A review. [3]	Digital electronic platform, gas sensors and wireless network	The objective of this work is to design a programmable digital electronic platform, equipped with gas sensors and wireless networks for the development of a low-cost and rapid electronic prototype to monitor and record the levels of volatiles and exchange of oxygen and carbon-dioxide of a fruit and estimate a relationship between the gases in order to find an automated way to the determinate the level of ripeness.

			customers, manage their customer lifecycle, sanction screening against regulatory watch lists.
4	Real-time hyperspectral imaging for the in-field estimation of strawberry ripeness with deep learning. [4]	Spectral Analysis, AlexNet CNN, Deep learning and Hyperspectral Imaging (HSI) system.	This proposed system is used to detect ripeness of fruits, particularly strawberries. The ripeness of the strawberry is estimated using the hyperspectral imaging system in field and laboratory conditions in this study. Spectral feature wave-lengths are selected using the sequential feature selection algorithm. Two wavelengths selected for field (530 and 604 nm) and laboratory (528 and 715 nm) samples, respectively. Then, reliability of such spectral features are being validated based on the support vector machine classifier. At last, pre-trained AlexNet is used to classify the early ripe and ripe strawberry samples.
5	Determination of Ripeness and Grading of Tomato using Image Analysis on Raspberry Pi [5]	Raspberry pi, conveyor	The objective of this work is to inspect the quality of tomato based on shape, size and degree of ripeness. An edge detection algorithm is used to estimate the shape and size of tomato and color detecting algorithm is used for the ripeness determination. All these algorithms are implemented on Raspberry Pi development board to measure ripeness of tomato and can also be used for other fruits and vegetables.

TABLE 1 : LITERATURE SURVEY

2.1.2 Research gap of Existing Literature

To emphasize the gaps in existing research and publications where an integrated system of the sort suggested in this project is lacking. This section explains the gaps that the project intends to fill and highlights the innovative contributions it provides to the field of fruit ripening detection.

1. Integrated Hardware-Software Solution: The lack of an integrated hardware-software solution for fruit ripening detection is a key research gap in the existing literature. While some studies concentrate on hardware configurations or machine learning models independently, there is a scarcity of research that integrates these parts into a seamless and linked system.

2. Spectral Color Data Utilization: Many present fruit ripening detection systems depend entirely on traditional color-based approaches, or using fruit images data separately ignoring the potential benefits of spectral color data. This study seeks to close the gap by investigating the use of spectral color information to improve the accuracy and precision of ripening stage forecasts.

3. Multistage Classification rather than traditional binary approach: Existing research frequently focuses on binary categorization (e.g., ripe or unripe) rather than multistage classification of fruit ripening. This study fills a research vacuum by developing a neural network model that can categorize fruits into several ripening phases, catering to a wide range of agricultural and food industry applications.

4. Scalability and Accessibility for Small-Scale Users: Many fruit ripening detection systems established in the literature are intended for large-scale operations or research contexts, requiring sophisticated equipment and computer resources.

2.1.3 Detailed Problem Analysis

Existing solutions for fruit ripening stage detection may encounter various challenges:

1. **Accuracy and Reliability:** The accuracy of fruit ripening stage detection iscrucial for making informed decisions in the supply chain. Existing systems may face challenges in accurately determining the ripening stage, especially when dealing with complex or heterogeneous fruits.

2. **Calibration and Maintenance:** Sensor-based solutions require regularcalibration and maintenance to ensure accurate readings. Calibration drift and sensor failures can impact the reliability of the data collected.

3. **Cost:** Implementing certain sensor technologies and sophisticated imaging systems can be expensive. Cost considerations may limit the adoption of some solutions, especially for small-scale farmers or businesses.

4. **Data Privacy and Security:** IoT-based solutions that involve data transmission and storage could raise concerns about data privacy and security, especially when sensitive information is involved.

2.1.4 Survey of tools and Technologies Used

Programming Language:

Python : Python is a popular choice for developing machine learning and computer vision algorithms due to its extensive libraries like NumPy, Pandas, OpenCV, and scikit-learn.

Machine Learning Libraries:

TensorFlow : An open-source machine learning framework developed by Google that offers comprehensive support for building and training neural networks.

Computer Vision Libraries:

OpenCV : An open-source computer vision library that provides various image processing and analysis functions, essential for fruit image preprocessing and feature extraction.

IoT Development Platforms:

ESP32-WROOM32 : A small, affordable single-board computer that can be used for IoT applications and data processing.

Arduino : A popular microcontroller platform often used for sensor integration and data collection.

Integrated Development Environments (IDEs):

Jupyter Notebook: A web-based interactive computing environment for data exploration, prototyping, and documentation.

Google Colaboratory: A web based application for running python scripts provided by google.

Visual Studio Code: An open source working Development environment to work upon several programming languages.

2.1.5 Summary

The literature survey provides a comprehensive overview of the current research and technology in fruit ripening stage detection. It reviews various studies which utilize different methods and tools, such as Raspberry Pi, spectral analysis, electronic sensors, and hyperspectral imaging, to monitor and determine the ripeness of fruits and vegetables. The studies explore the effectiveness of various technologies, including using LAB color space for spectral analysis, developing digital electronic platforms with gas sensors for monitoring volatile levels, and employing image processing techniques on Raspberry Pi for tomato grading.

The survey also identifies several challenges in this field: accuracy and reliability of ripening stage detection, especially with diverse fruit types; the need for regular calibration and maintenance of sensor-based systems; the high cost of advanced sensor technologies and imaging systems; and concerns about data privacy and security in IoT-based solutions.

Furthermore, the survey outlines the tools and technologies commonly used in this research area. Python is highlighted as a preferred programming language, supported by libraries like NumPy, Pandas, OpenCV, and scikit-learn. TensorFlow and OpenCV are noted for their roles in machine learning and computer vision, respectively. Raspberry Pi and Arduino are mentioned as key platforms for IoT applications and data processing. Additionally, IDEs like Jupyter Notebook, Google Colaboratory, and Visual Studio Code are emphasized for their usefulness in development and programming. Overall, the literature survey synthesizes the diverse approaches, challenges, and tools in the evolving field of fruit ripeness detection, emphasizing the technological variety and the complexities involved in accurately determining the ripeness stages of fruits.

2.2 Software Requirements Specification

2.2.1 Introduction

2.2.1.1 Purpose

To develop a device that can detect and classify the ripening stages of fruits and vegetables using spectral color interpretation and a neural network model. The ultimate goal is to assist companies involved in the processing of fruits and vegetables, as well as farmers, grocery store managers, and consumers, in handling produce more efficiently and sustainably.

Intended Audience and Reading Suggestions:

Farmers: Farmers are one of the primary target audiences as they can benefit from accurate ripening stage detection to make informed decisions about when to harvest and sell their fruits. This information can help optimize their farming practices, reduce losses, and improve their overall yield.

Food Processing Companies: Companies involved in the processing and packaging of fruits can use the device to ensure they receive produce at the optimal ripening stage. This will help them streamline their production processes, reduce wastage, and maintain product quality.

Retailers and Supermarkets: Retailers and supermarkets can benefit from the device's ripening stage classification to display and sell fruits at their peak freshness. This enhances customer satisfaction and promotes sustainability by minimizing food waste. Overall, the Fruit Ripen Stage Detector targets a wide range of stakeholders involved in the fruit industry, with the common goal of optimizing ripening stage assessment, minimizing food wastage, and promoting sustainability throughout the supply chain.

2.2.1.3 Project Scope

This project aims to develop a device that accurately detects and classifies the ripening stages of fruits addressing various challenges in the agricultural and retail sectors:

Mass Production and Processing: Large-scale production and processing of fruits often lead to wastage due to difficulties in determining ripeness. The device's accurate detection helps minimize wastage by enabling timely harvesting, processing, and selling of produce.

Prediction for Farmers: Farmers struggle to predict the optimal ripening time, leading to uncertainties in marketing their crops. The device provides valuable information to farmers, allowing them to make informed decisions on when to forward their produce to the markets.

Efficient Storage and Consumption: Companies, grocery store managers, and consumers need to know the ripening stage of fruits for proper storage and consumption. The device provides this crucial information, ensuring fresher and better-quality produce reaches consumers.

Sustainable Approach: The project promotes sustainability by reducing food wastage through accurate ripening stage classification. This benefits the agricultural and retail sectors by improving supply chain management and minimizing unnecessary waste. With its classification system categorizing fruits into four ripening stages, the device empowers users to take appropriate actions, leading to improved handling and management of produce while reducing food waste. Overall, the project contributes to a more efficient and sustainable approach in the fruit and vegetable industry.

2.2.2 Overall Description

2.2.2.1 Product Perspective

● The fruit ripening stage detector addresses the challenges faced by farmers, producers, distributors, and retailers in accurately determining the ripeness levels of fruits. By providing real-time and non-destructive ripeness assessments, the detector helps reduce food waste, optimize the supply chain, and enhance overall product quality.

● The fruit ripening stage detector enables better quality control throughout the supply chain. Farmers can harvest fruits at their optimum ripeness, leading to improved taste, texture, and nutritional value. Distributors and retailers can ensure that only high-quality, properly ripened fruits reach consumers, enhancing customer satisfaction.

● By automating the ripening stage detection process, the detector saves time and labor for farmers and operators. It reduces the need for manual inspection and subjective judgments, streamlining the overall fruit handling process and lowering operational costs.

● The detector's ability to identify overripe and under ripe fruits helps reduce food waste at different stages of the supply chain. Minimizing waste contributes to more sustainable agricultural practices and reduces the environmental impact of food production.

2.2.2.2 Product Features

● The system shall collect Spectral colour data of fruits generated by AS7341 Visible Sensor to prepare a dataset.

● The system should be able to assign the ripening stage corresponding to the spectral colour data of fruit using buttons of Arduino Nano correctly for completing the dataset.

● Before the model creation, pre-processing of the collected dataset to be done before training ML Model to predict the fruit's ripeness stage

● ML model clubbed with web service shall provide an interface to input a fruit in the setup and the ripeness stage shall get predicted.

2.2.3 External Interface Requirements

2.2.3.1 User Interfaces

Website Interface: This is the primary user interface where users can input values related to the fruit and receive output about the ripeness class. This interface is user-friendly and intuitive.

2.2.3.2 Hardware Interfaces

ESP32 and Light Sensor Connection: The way the light sensor is connected to the ESP32 is a hardware interface. This involves the physical connection (wiring) and any necessary configuration to ensure they communicate effectively.

2.2.3.3 Software Interfaces

Arduino Firmware: The software running on the Arduino that processes the sensor data and communicates with the machine learning model.

Machine Learning Model Interface: The interface between the data processed by the ESP32 and the machine learning model that classifies the fruit.

Website Backend: The server-side software that receives input from the user via the website, interacts with the machine learning model, and sends the output back to the website.

2.2.4 Other Non-functional Requirements

2.2.4.1Performance Requirements

As with web application, our product should be responsive in real time, so that as soon as the fruit is inputted in the setup the prediction is displayed on the website. The system shall have a responsive user interface that can handle multiple requests simultaneously.

2.2.4.2 Safety Requirements

- All materials used in the construction of the device, including its casing and components, should be non-toxic, food-safe, and free from harmful chemicals that could contaminate the fruits.

● The user interface should be intuitive and straightforward to prevent user errors that could lead to incorrect readings.

2.2.4.3 Security Requirements

Implement measures to safeguard the data collected from fruits and users. Use encryption techniques to protect data both during transmission and storage. Ensure compliance with data privacy regulations, especially if personal or sensitive information is involved.

2.3 Cost Analysis

- ESP 32 wroom 32 - Rs. 500 (approx.)
- AS7341 Light Sensor - Rs. 1800 (approx.)
- Breadboard and other hardware - Rs. 500 (approx.)

2.4 Risk Analysis

Technical Risks:

● **Complexity of Machine Learning:** Developing accurate machine learning algorithms for fruit ripening stage detection may be challenging due to the diverse characteristics and ripening patterns of different fruits.

● **Sensor Integration Issues:** Integrating sensor technology and ensuring its seamless interaction with the rest of the system may face technical hurdles and require careful calibration.

● **Overfitting and Underfitting:** The machine learning model might overfit or underfit the data, leading to inaccurate predictions on unseen fruit samples.

● **Image Quality Variability:** Variations in image quality and lighting conditions can affect the accuracy of image analysis algorithms.

Data Risks:

● **Data Anomalies:** Inaccurate or inconsistent data annotations could lead to biased training of the machine learning model.

● **Privacy and Security:** Handling sensitive data and ensuring data privacy is essential, especially if the detector involves cloud storage or user data collection.

Implementation Risks:

- **Resource Constraints:** Limited budget, time, and technical expertise may impact the successful implementation of the project.
- **Hardware Compatibility:** Ensuring the detector works with various sensor types, cameras, and microcontrollers may require additional effort and compatibility testing.

METHODOLOGY ADOPTED

3.1 Investigative Techniques

1. Experimental Setup:

1.1 Gather a variety of fruits and vegetables that exhibit distinct color changes during ripening stages.

1.2 Acquire an AS7341 visible light sensor and an Arduino Nano 33 IoT board for spectral color data collection.

2. Data Collection:

2.1 Connect the AS7341 sensor to the Arduino Nano 33 IoT board.

2.2 Develop Arduino code to interface with the sensor and collect spectral color data from each fruit/vegetable sample.

2.3 During the ripening stages of each sample, place it under the sensor and collect spectral color data at regular intervals.

2.4 Record the collected data in a structured format, including spectral color information.

3. Web Application Development:

3.1 Design a user interface where researchers can input sample information and attach the collected spectral color data files.

3.2 Implement functionality to associate each data entry with corresponding ripening stage labels (e.g., unripe, semi-ripe, ripe, overripe).

4. Data Management:

4.1 Ensure that the web application securely stores the collected data and maintains a clear link between data entries and ripening stage labels.

5. Data Preprocessing:

5.1 Preprocess the collected spectral color data to remove noise, outliers, or artifacts that might affect model training.

5.2 Normalize the data to bring all features to a common scale.

6. Machine learning Training:

6.1 Split the dataset into training, validation, and testing subsets.

6.2 Design an ML architecture suitable for spectral color data classification.Consider using libraries like TensorFlow or PyTorch for model implementation.

6.3 Train the model on the preprocessed data, using the spectral color data as input features and ripening stage labels as target outputs.

7. Model Evaluation:

7.1 Evaluate the trained model’s performance using the testing dataset.

7.2 Use metrics like accuracy, precision, recall, and F1-score to assess the model's ability to predict ripening stages accurately.

8. Model Deployment and Testing:

8.1 Deploy the trained model as a prediction model within the web application.

8.2 Allow users to input new spectral color data and receive predictions for the corresponding ripening stages.

9. Performance Refinement:

9.1 Continuously monitor and gather new data to improve the model's accuracy over time.

9.2 Periodically retrain the model using the updated dataset to account for changes in fruit and vegetable characteristics.

3.2 Proposed Solution

The proposed solution aims to develop a cutting-edge device called the "Fruits Ripening Stage Detector - RipenTrack." This innovative device utilizes advanced spectral color processing technology combined with a powerful neural network model. Its primary goal is to revolutionize the way we detect and manage the maturation stages of fruits and vegetables, leading to a substantial reduction in food waste and the establishment of a more efficient and sustainable approach to storing these crucial food items. The implementation of the RipenTrack device could also lead to cost savings for both producers and consumers. Farmers can avoid losses due to premature harvesting orspoilage, while consumers can enjoy fresher, longer-lasting fruits and vegetables. The device's user-friendly design allows for widespread adoption across different levels of thefood supply chain, from small-scale farmers to large-scale distributors and retailers.

Through the implementation of advanced spectral color processing, the RipenTrack device possesses the capability to conduct meticulous analysis of the evolving color patterns in ripening fruits and vegetables. The data derived from this process is subsequently fed into a powerful neural network model, which harnesses cutting-edge machine learning algorithms. The primary objective of this integration is to achieve unparalleled accuracy in determining the precise stage of maturation for each individual fruit or vegetable. By harnessing the potential of spectral color processing, the RipenTrack device is able to capture and interpret subtle changes in color that occur as fruits and vegetables progress through their ripening stages. This data-driven approach enables the device to discern the exact moment when each item reaches its optimal state of maturity for harvesting or consumption.

The neural network model, which lies at the heart of the RipenTrack device, is designed to continuously learn and adapt based on the vast amount of data it processes. Through ongoing exposure to a wide array of fruits and vegetables at varying stages of maturation, the model becomes increasingly adept at distinguishing between different levels of 39 ripeness with unprecedented accuracy. The synergy between spectral color processing and the neural network model empowers the RipenTrack device to function as a sophisticated and reliable tool for producers, distributors, and consumers alike. By providing real-time and accurate information about the ripening status of fruits and vegetables, the device facilitates informed decision-making at every stage of the supply chain.

The device integrates spectral color processing with advanced neural network models to precisely identify the ripening stage of each fruit and vegetable. The spectral color data captured by the device carries crucial information about the biochemical changes that occur during ripening. The neural network model, trained on an extensive and diverse dataset of spectral color information, can discern subtle patterns and correlations, allowing for highly accurate and reliable ripeness predictions.

The potential applications of this technology are vast and diverse. It can benefit large-scale fruit and vegetable processing factories by reducing waste and optimizing production processes. Marketplaces can enhance their supply chain management, ensuring only ripe produce reaches consumers, reducing spoilage, andincreasing customer satisfaction. For farmers, the device can serve as a valuable tool to determine the optimal harvest time, leading to better yields and improved profitability. Additionally, it can assist not only farmers but also grocery store managers and consumers in determining the freshness and optimal time to consume the produce.

To develop this advanced system, the project involves creating a custom dataset by employing a hardware setup consisting of an ESP32 and a spectral color sensor. The primary goal is to collect spectral color data from various fruits and accurately label them into four ripening stages: 1. Early Ripe, 2. Partially Ripe, 3. Ripe, and 4. Decay. The collected dataset is utilized to train an ML model to make accurate predictions based on the spectral color data.

Before building and testingthe neural network model, we collect spectral color data of 40 fruits and vegetables generated by the AS7341 visible light sensor to create a ripening stages dataset by spectral color. Then we use an ESP32 to send the data produced by the visible lightsensor and directly extract data into an Excel file from the port. We manually assign a ripening stage (label) for each category of fruits and vegetables (Early Ripe, Partially Ripe, Ripe, Decay) while obtaining spectral color data.

The subsequent phase of this project involves constructing an ML model utilizing TensorFlow, a powerful deep learning framework, to forecast maturation stages (labels) predicated on spectral color data. This step represents a critical advancement in the development of the RipenTrack device. Once the ML is set up, the system is put through rigorous testing to assess its accuracy and reliability in predicting the maturation stages of various fruits and vegetables. The testing phase involves subjecting the neural network model to diverse datasets containing spectral color information from different types of produce at various stages of ripening. Through these meticulously designed experiments, the neural network's ability to generalize and discern patterns in the spectral color data is evaluated. The overarching goal is to ascertain the model's proficiency in accurately identifying the specific maturation stages of fruits and vegetables across a wide range of cases. To achieve robustness and generalization, the neural network is fine-tuned and optimized based on the feedback and insights gathered from the experimental results. This iterative process iterates until the model achieves a satisfactory level of accuracy in its predictions.Ultimately, the culmination of these efforts is the realization of a powerful and reliable neural network model that can predict the maturation stages of fruits and vegetables with a high degree of precision. This achievement marks a significant milestone in the development of the RipenTrack device and showcases the potential to revolutionize the detection and management of ripening stages.

3.3 Work Breakdown Structure

Figure 3. shows the work Breakdown structure where Planning was done initially then tools and tech stacks chosen, further integration of hardware and software and at the end the evaluation parameters and testing.

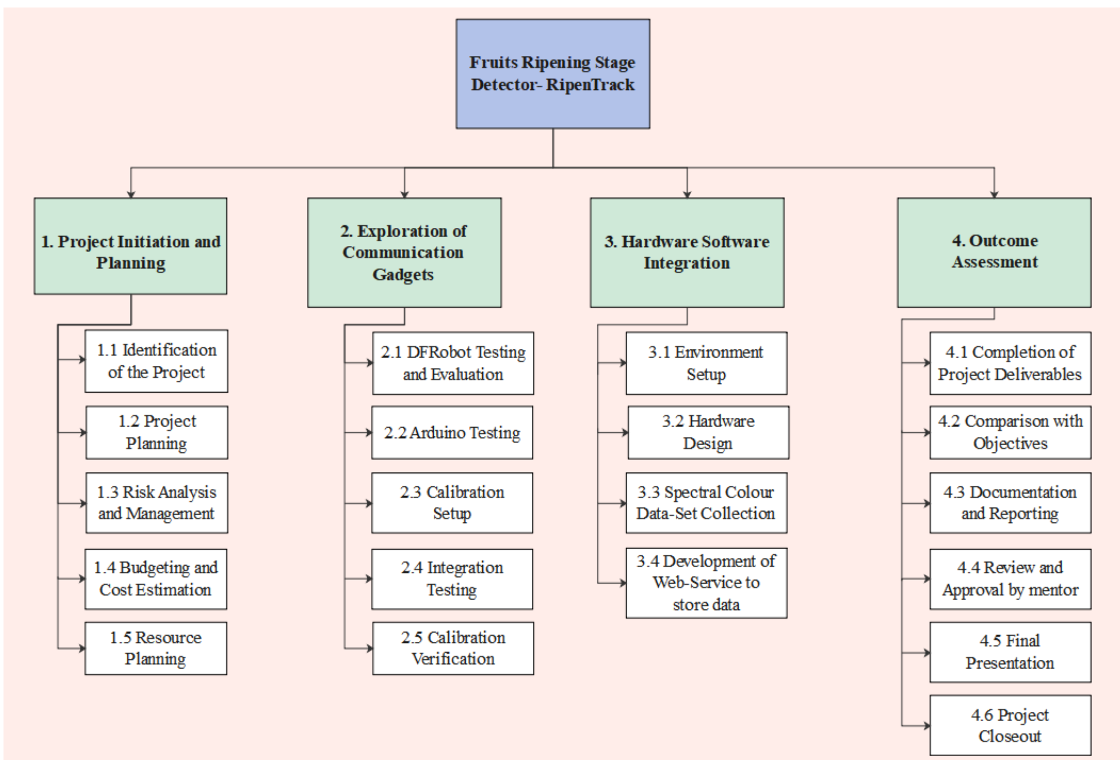


Figure 3: Work Breakdown Structure

3.4 Tools & Technology

- Arduino Nano IOT
- Web Development Frameworks (Flask)
- IDEs (Jupyter Notebook , Visual Studio Code)
- Google Colaboratory
- Tensorflow
- Artificial Neural Network
- ESP32 Wroom32

4.1 System Architecture

4.1.1 Block Diagram

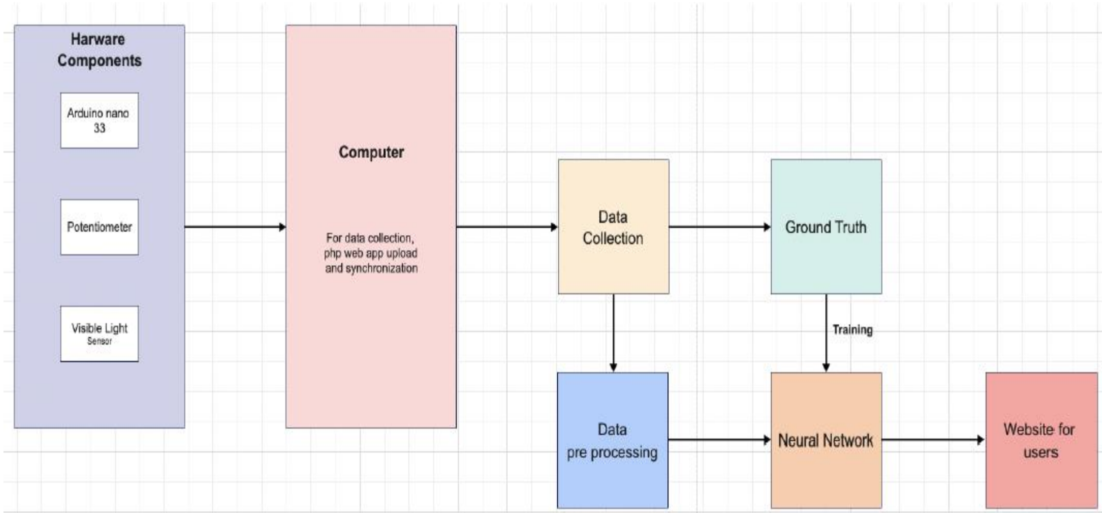


Figure 4: Block Diagram

Figure 4 illustrates the Block diagram of fruit ripen stage detector which provides a functional view of a system and explains how the different elements of that system interlink.

- The hardware components used in the project include ESP32 wroom32, potentiometer and a visible light sensor.
- A computer is used for data collection, uploading of photos on web application and synchronization.
- Then we work on collection of data and making of dataset, followed by preprocessing of that dataset, then making of neural network and training of the ML model.
- In the end all of this is integrated into a website and made available to users.

4.1.2 Product Perspective

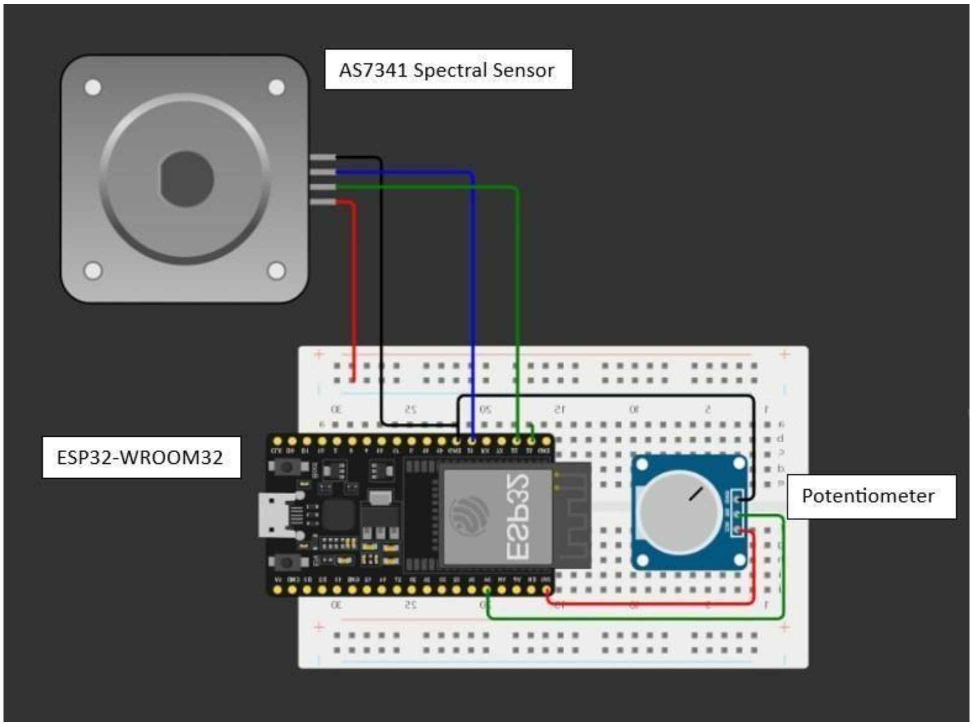


Figure 5: Tinkercad Visualization Of Hardware

4.1.3 Activity Diagram

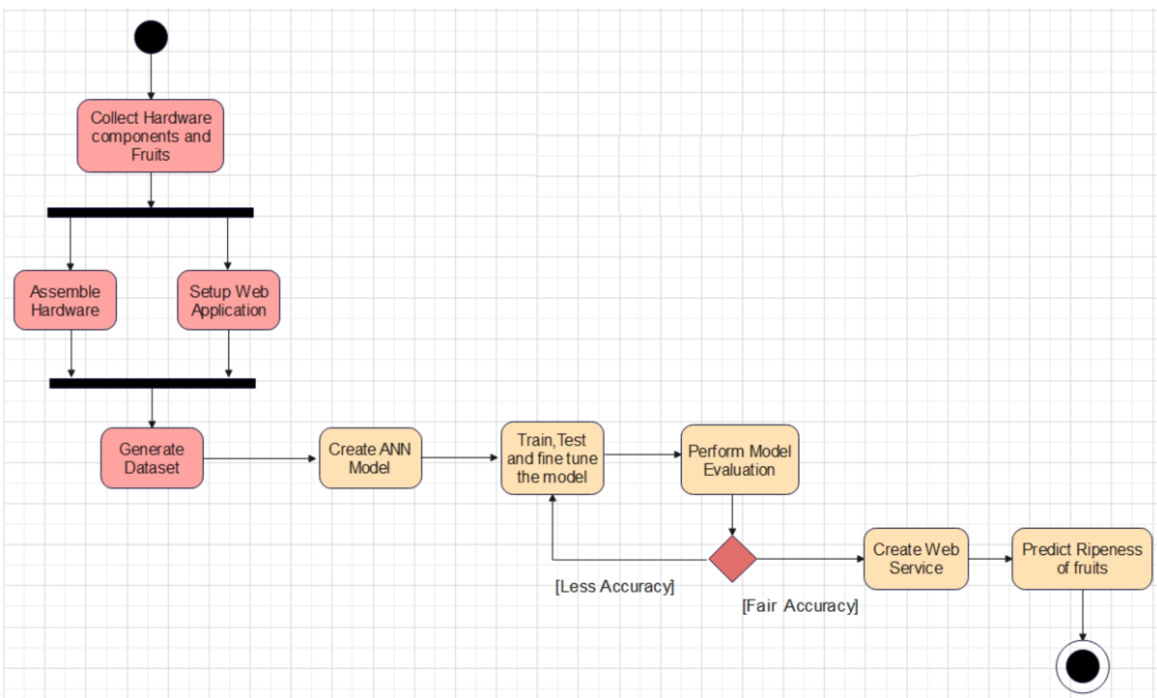


Figure 6: Activity Diagram

Figure 6. Activity Diagram illustrates the sequential and parallel activities involved in the development process. It provides a visual representation of the project's workflow, starting from the initial hardware setup to the final implementation of the web application and prediction of ripening results.

1. **Collect Hardware Components and Fruits:** The process begins with the collection of hardware components, including the ESP32 microcontroller and the color detection sensor.

   In parallel, fruits and vegetables are gathered to be used for data collection and training purposes.

   Setup Web Application and Assemble Hardware: Once the hardware components are collected, the process of setting up the web application begins. Simultaneously, the hardware components are assembled, connecting the ESP32 setup with the color detection sensor.
2. **Generate Dataset:** After the hardware setup and web application initialization, the system enters the phase of data collection. Spectral color data is captured from the fruits and vegetables using the color detection sensor.
3. **Create ML Model:** With the dataset in hand, the project moves to building the model. The dataset is used to train the model to classify fruits into different ripening stages based on spectral color data.
4. **Test Model:** Parallel to model creation, the trained ML model is tested using validation datasets to assess its accuracy and performance.

Iterative refinement of the model may occur to enhance its predictive capabilities.

5. **Develop Web Application to Display Results:** After successful testing of the model, attention shifts to the web application. The web application is further developed to incorporate the trained ML model and display predictions in a user-friendly format.
6. **Predict and Display Ripeness Results:** The final stage involves using the developed web application to predict and display ripening results.

4.2 Design Level Diagrams

4.2.1 Use Case Diagram

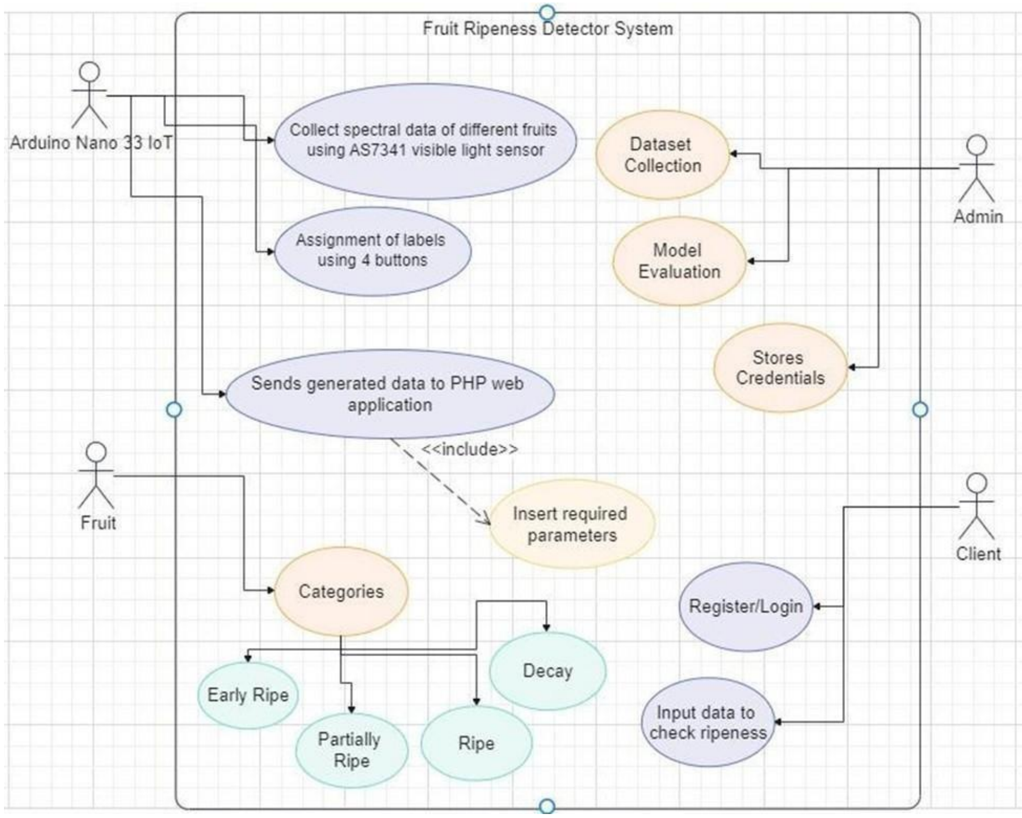


Figure 7 : Use Case Diagram

The Figure 7. represents the dynamic behavior of the system. The ovals inside the box represents use cases that are the functionalities of our system. The actors in the diagram that are outside the box represent all the things and persons that interact with the system.

- ESP32 wroom32 is used for collection of data from different fruits using a visible light sensor and has 4 buttons to assign classes to them accordingto their ripeness.
- A fruit has 4 categories according to its ripeness stage - early ripe, partially ripe, ripe and decay.
- A client can register/login and then input his data to check the ripeness of fruit.
- Whereas the admin has to do dataset collection, model evaluation and stores the credentials of the users.

4.2.2 Use Case Template

1.	**Use Case Title**	Login
2.	**Abbreviated Title**	Login
3.	**Use Case Id**	1
4.	**Actors**	Client/Admin
5.	**Description**	Registered user can login to the site.
5.1	**Pre Conditions**	Client should have registered to the site.
5.2	**Task Sequence**	1. Enter Username. 2. Enter Password. 3. Click on login.
5.3	**Post Conditions**	Client should be able to successfully login to his account.
6.	**Modification History**	May 5, 2023
7.	**Author**	Saloni

1.	**Use Case Title**	Check Ripeness
2.	**Abbreviated Title**	Check Ripeness
3.	**Use Case Id**	2
4.	**Actors**	Client
5.	**Description**	The user inputs the spectral data values to check the ripeness of fruit.
5.1	**Pre Conditions**	1. User should have the required data for collection. 2. Data for the required fruit must be in the system.
5.2	**Task Sequence**	1. Search screen will be shown by the system. 2. Input the 8 required parameters. 3. On clicking check button, system will show results.
5.3	**Post Conditions**	1. User can view his desired results. 2. User can go for another search
6.	**Modification History**	May 5, 2023
7.	**Author**	Saloni

1.	**Use Case Title**	Dataset Generation
2.	**Abbreviated Title**	Dataset Generation
3.	**Use Case Id**	3
4.	**Actors**	Admin
5.	**Description**	Using our device to collect spectral data for different fruits over a course of few days and send data to web application with labelling.
5.1	**Pre Conditions**	Web Application should be set up.
5.2	**Task Sequence**	1. Data along with labelling received from ESP32 wroom 32. 2. Web Application inserts the incoming data as a new row to thecsv file by adding the current date and prints.
5.3	**Post Conditions**	Data should be stored in csv file along with current date and prints.
6.	**Modification History**	April 2, 2023
7.	**Author**	Saloni

1.	**Use Case Title**	Model Evaluation
2.	**Abbreviated Title**	Model Evaluation
3.	**Use Case Id**	4
4.	**Actors**	Admin
5.	**Description**	Evaluating the ML model.
5.1	**Pre Conditions**	The ML model should be trained on training dataset.
5.2	**Task Sequence**	1. Build Neural Network Model with Tensor Flow in Python. 2. Train the model with the dataset to obtain the best possible resultsand predictions. 3. Testing the model by using the testing set.
5.3	**Post Conditions**	The evaluated accuracy of the model should be high.
6.	**Modification History**	April 10, 2023
7.	**Author**	Saloni

1.	**Use Case Title**	Collect Spectral Data
2.	**Abbreviated Title**	Collect Spectral Data
3.	**Use Case Id**	5
4.	**Actors**	ESP 32
5.	**Description**	Programming the ESP32 to obtain the required parameters.
5.1	**Pre Conditions**	ESP32 should be set up along with AS7341 visible light sensor.
5.2	**Task Sequence**	1. Set up device. 2. Collect data for 10 days, 5 times a day for different fruits. 3. Set up web application on Raspberry Pie. 4. Data along with labelling sent to web application.
5.3	**Post Conditions**	Data collected to be sent to web application.
6.	**Modification History**	March 30, 2023
7.	**Author**	Saloni

1.	**Use Case Title**	Assign Labels
2.	**Abbreviated Title**	Assign Labels
3.	**Use Case Id**	6
4.	**Actors**	ESP32
5.	**Description**	The data collected by ESP32 is manually labelled into 4 categories i.e early ripe, partially ripe, ripe and decay.
5.1	**Pre Conditions**	1. Device set up. 2. Spectral data of fruits collected.
5.2	**Task Sequence**	1. Data collected by sensors. 2. Use the 4 buttons on Arduino and manually assign the labels.
5.3	**Post Conditions**	Labelled data send to web application
6.	**Modification History**	March 30, 2023
7.	**Author**	Saloni

Table2. Use Case Template

4.2.3 ER Diagram

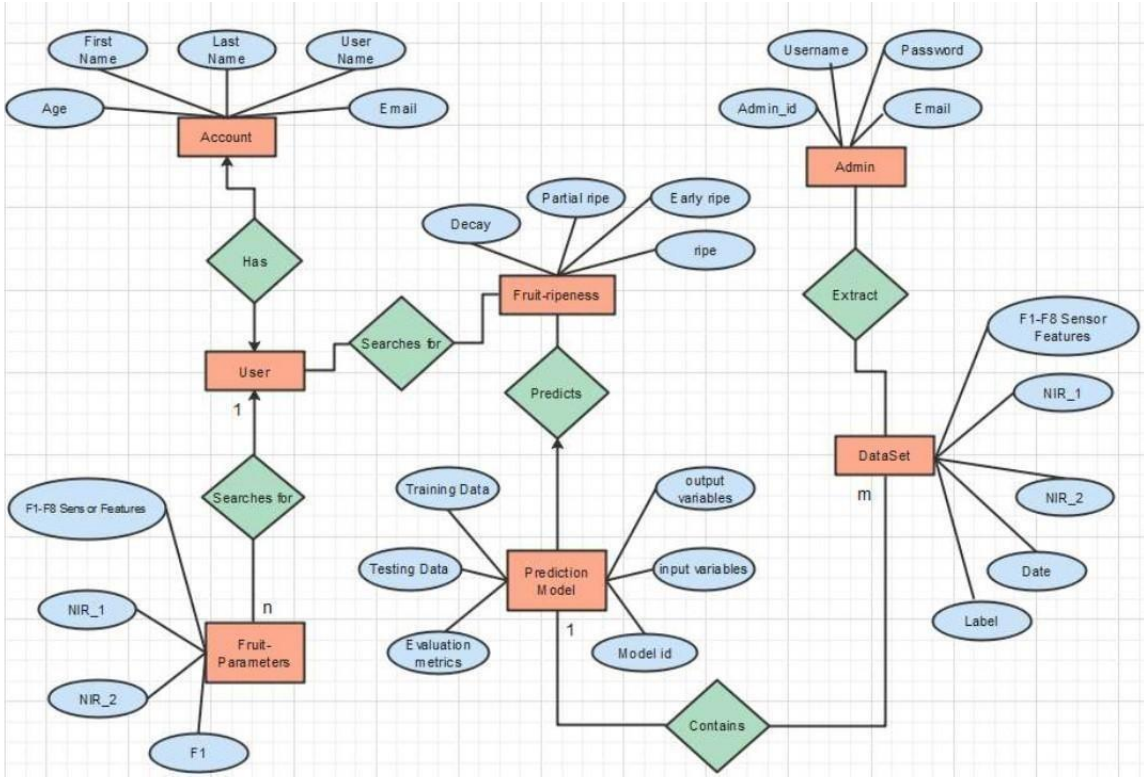


FIGURE 8: ER Diagram

The Entity-Relationship (ER) diagram illustrates a comprehensive fruit-searching and prediction system. In Figure 8. Users can create accounts with their personal details, including Name, Age, and Username. These user accounts allow for personalized fruit searches.

- The "User-Searches-Fruit" relationship enables users to explore various fruits based on specific parameters. The "Fruit" entity represents the collection of fruits in the system, with attributes like "Fruit Name" and "Parameters" for detailed information storage.

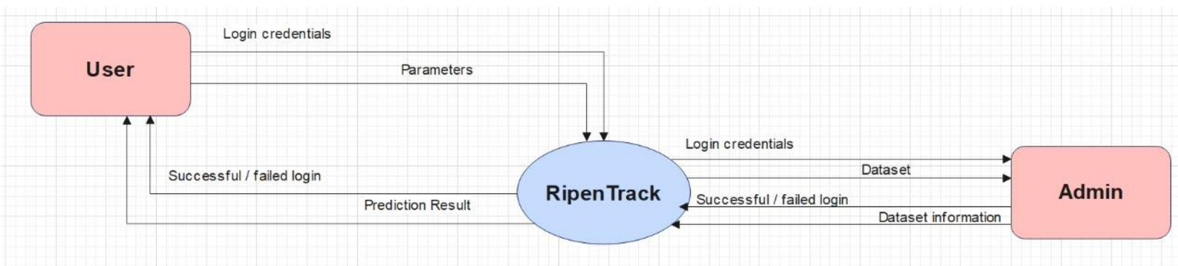
- The "User-Searches-FruitRipeness" relationship allows users to explore fruits based on ripeness stages. The "FruitRipeness" entity includes ripeness types such as "decay," "partial ripe," "early ripe," and "ripe," providing precise ripeness-based searches. The system integrates a robust "Prediction Model" entity for accurate fruit ripeness assessment. It uses "Training Data" to learn patterns and relationships, and "Testing Data" to evaluate performance. "Input Variables" are used to make predictions, and "Output Variables" represent predicted fruit ripeness stages. Each prediction model is uniquely identified by a "Model ID" for effectivemanagement .

- An "Admin" entity has special privileges to extract data from the system, ensuring efficient data management and system maintenance.

4.3 User Interface Diagram

4.3.1 Data Flow Diagram

LEVEL 0



LEVEL 1

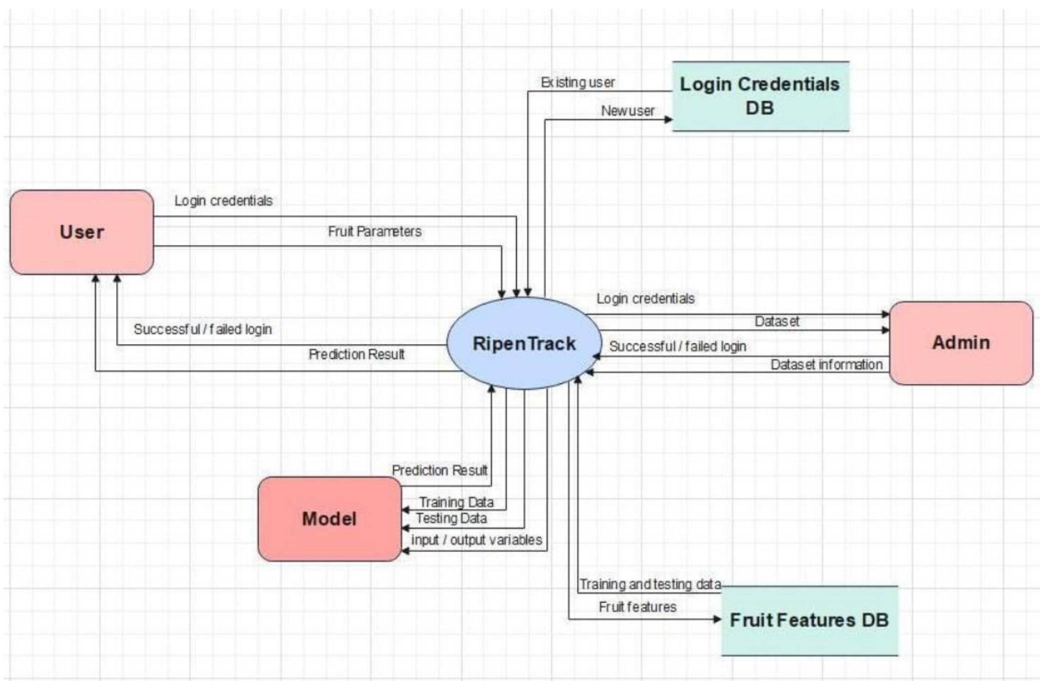


FIGURE 9: DFD

- Figure 9. The Data Flow Diagram (DFD) shows the information flow and interactions within the system "RipenTrack." At its core is the process "RipenTrack," which functions as the central component. Users, represented as the entity, can input their login credentials and fruit parameters to the RipenTrack process. This can result in two outcomes: successful or failed login attempts. The process also provides testing data, training data, and input/output variables to a newly introduced entity called "Model," which likely represents a predictive model.
- The administrative role comes into play as the administrator shares login details and data specifics with the RipenTrack process. The system relies on two databases: one containing login credentials and the other storing fruit features. The latter database includes testing and training data along with fruit parameters. These databases supply essential information to the RipenTrack process for its functionality. Ultimately, the RipenTrack process leverages these inputs to generate prediction results, which are then conveyed to users.

4.3.2Class Diagram

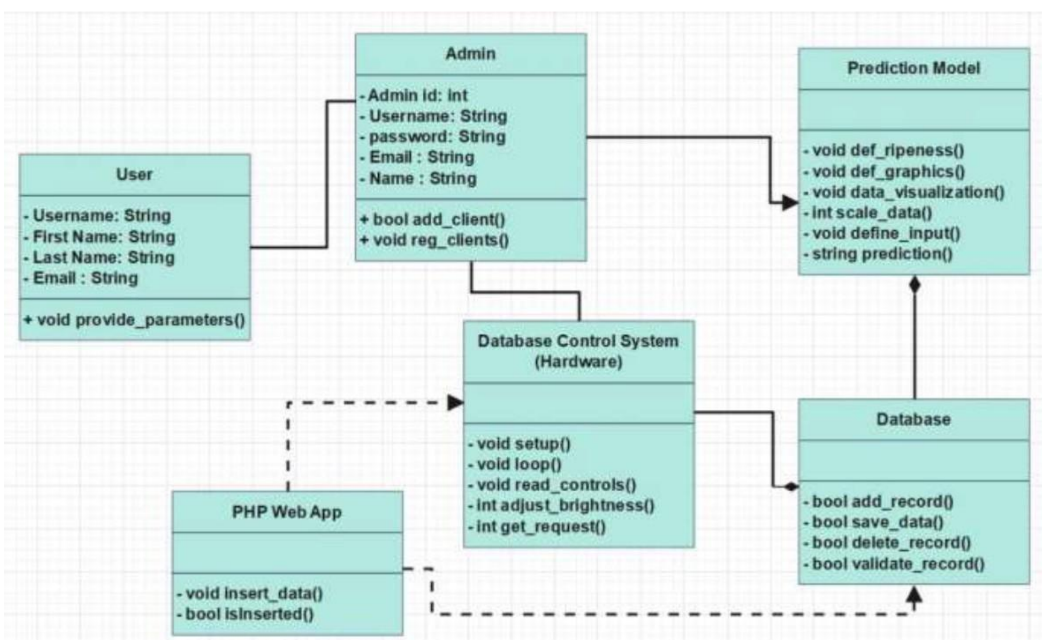


FIGURE 10: Class Diagram

- The class diagram depicts a system composed of interconnected classes that represent different functionalities. The "User" class contains attributessuch as username and name, as well as the function "provide_parameters." This class is associated with the "Admin" class, which contains attributes such as admin ID, username, password, email address, and name. "Admin"class functions include "add_clients" and "reg_clients." These classes provide information to the "PredictionModel" class, which is responsible for predicting the ripeness of produce.
- In addition, the "Admin" class is linked to the "Database Control System" class, which contains methods such as "setup," "loop," "read_controls," "get_req," and "adjust_brightness." This hardware class depends on the "Database" class, which provides methods for validating the presence of data, determining its validity, saving it. This arrangement describes a system in which users and administrators interact with a prediction model, with the administrator also managing hardware control and data storage via a comprehensive database system.

5.1 Experimental Setup

The experimental setup for the project involves integrating a ESP32 WROOM 32, a light sensor, and a potentiometer on a breadboard for the purpose of collecting data of fruits.

Connections:

ESP32 Wroom 32: Connect the power (VCC) and ground (GND) of the Node MCU to the respective rails on the breadboard. Connect the data pins (SDA, SCL) to the analog pins of Light sensor.

Light Sensor: Connect the power (VCC) and ground (GND) of the light sensor to the breadboard's power and ground rails. Connect the analog pins of the light sensor to available default / data pins on the Node MCU.

Potentiometer: Connect the power (VCC) and ground (GND) of the potentiometer to the breadboard's power and ground rails. Connect the middle pin of the potentiometer to an analog pin on the Node MCU.

In the Arduino IDE, code has been developed and successfully uploaded to the ESP32, enabling it to read data from the light sensor and potentiometer. The code is designed to collect information on ambient light levels, potentially representing different frequencies of fruit characteristics. The setup allows for adjustments in potentiometer settings to simulate various levels of fruit ripeness, while the Node MCU captures and processes the corresponding data along with Wi-Fi facility. This experimental configuration enables the monitoring and analysis of fruit-related data in real-time.

5.2Experimental Analysis

5.2.1Data

The spectral color data from fruits and vegetables is collected using an ESP32 Wroom32 and the AS7341 visible light sensor setup. This sensor provides accurate spectral information, enabling a detailed analysis of the color characteristics of the objects. The gathered data is manually categorized into four ripening stages: Early Ripe, Partially Ripe, Ripe, and Decay. The spectral information, including 8 frequency values and 2 near-infrared values obtained through the hardware setup, is stored in a CSV file usingthe data streamer. The dataset comprised approximately 5200 rows, covering a diverse range of fruits such as apples, bananas, guavas, plums, lemons, and more. This extensive dataset serves as a valuable resource for training the model studying the spectral signatures associated with different ripening stages across various fruits and vegetables, offering insights into potential applications for quality assessment and producemonitoring.

5.2.2 Performance Parameters

In evaluating the performance of various models for a multiclass classification task with four distinct classes, we observed noteworthy accuracy metrics. The k-Nearest Neighbors (KNN) model demonstrated a commendable accuracy of 93.79%, showcasing its abilityto classify instances based on their nearest neighbors within the four-class framework. The Support Vector Machine (SVM) model exhibited an accuracy of 85.4%, illustrating its effectiveness in creating a hyperplane that distinguishes among the four classes. The Naive Bayes model achieved an accuracy of 89.94%, leveraging probabilistic assumptions for classification across the multiple classes. Combining the strengths of individual models, an ensemble model using a Voting Classifier yielded an impressive training accuracy of 96.04% within the multiclass setting. Furthermore, the ensemble model maintained a robust generalization performance on a separate testing dataset,attaining an accuracy of 94.38% across the four classes.

The Figure 11. Class report including precision, recall, f1 score and support is mentioned below: The classification report visualizer displays the precision, recall, F1, and support scores for the model. In order to support easier interpretation and problem detection, the report integrates numerical scores with a color-coded heatmap.

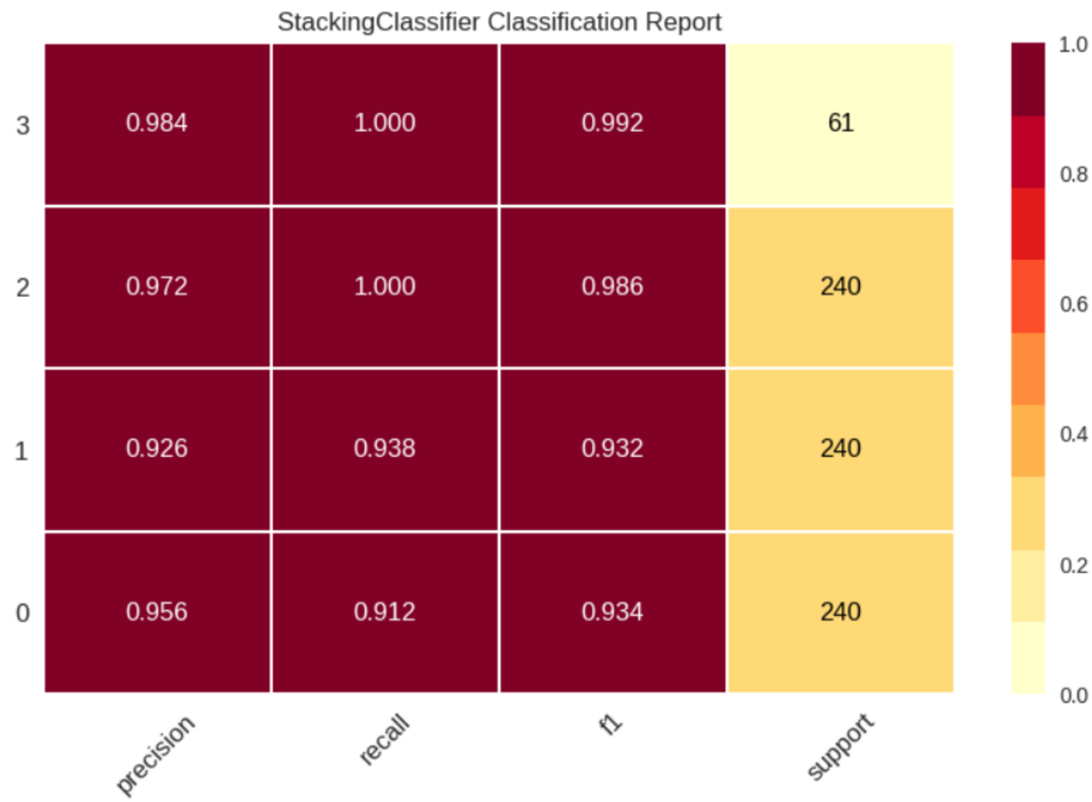


Figure 11 : Classification Report

5.3 Working of the project

5.3.1 Procedural Workflow

The hardware setup comprises an ESP32 WROOM 32 microcontroller, an AS7341 visible light sensor, a potentiometer, a breadboard, and various connecting wires. The ESP32 serves as the brain of the operation, providing the necessary processing power and communication capabilities. The AS7341 sensor, a key component, captures spectral color data by measuring light intensity across different wavelengths.

Assembling the components involves carefully connecting the sensor, potentiometer, and ESP32 on the breadboard, ensuring proper wiring for data and power. Once the physical setup is complete, the focus shifts to collecting spectral colour data from a range of fruits in different ripening stages, including early ripe, partially ripe, ripe, and decay.

In the Arduino IDE, a customized code is developed and successfully uploaded to the ESP32, allowing it to interact with both the light sensor and the potentiometer. The code is designed to collect ambient light levels, which can potentially represent different frequencies indicative of various fruit characteristics. The potentiometer settings can be adjusted to simulate different levels of fruit ripeness, and the ESP32 captures and processes corresponding data, facilitated by its Wi-Fi capability.

The generated data is then sent to a data streamer to collate and create a comprehensive dataset in CSV files. This dataset encompasses 8 frequency values and 2 near-infrared values for each fruit. The next step involves manual labelling of the ripening stage during the acquisition of spectral colour data for each fruit using the CSV data. To enhance the analysis of the dataset, Principal Component Analysis (PCA) is applied. PCA is crucial as it reduces the dimensionality of the dataset while preserving its important features. This not only simplifies the data but also aids in identifying patterns and trends.

Normalization is then applied to standardize the dataset, ensuring that each variable contributes equally to the analysis. Normalization is essential as it prevents certain features from dominating the model due to differences in scale, thereby enhancing the model's accuracy. Using the Pycaret library, the dataset is subjected to various machine learning models to identify the one with the highest accuracy. Ensemble learning techniquesare subsequently employed to train the dataset, combining the strengths of multiplemodels to improve overall performance.
Model evaluation and visualization are conducted, with plots drawn to illustrate the accuracy and efficiency of the trained models. The final step involves deploying a website service integrated with the trained model for predicting the ripeness of fruits. Users can input spectral colour data, and the model, based on its training, provides accurate predictions regarding the ripening stage of the fruit.

In summary, this comprehensive hardware and software integration not only facilitates the collection and analysis of spectral colour data from fruits but also demonstrates the potential of machine learning models in predicting fruit ripeness based on this data. The deployment of a user-friendly web service further enhances the practical application of the developed system.

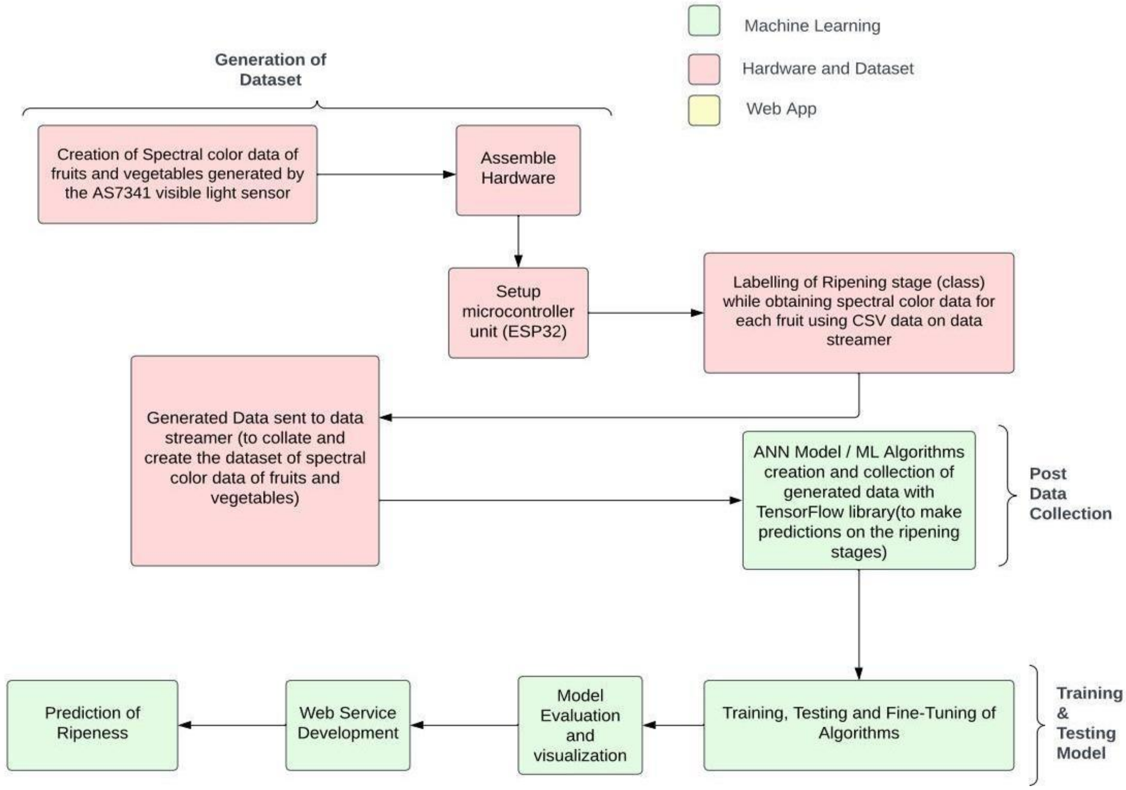


FIGURE 12 : Methodology Diagram

5.3.2 Algorithmic Approaches Used

In the exploration of spectral colour data from fruits and vegetables, the implementation of Principal Component Analysis (PCA) plays a pivotal role in the initial stages of the analysis. PCA serves to reduce the dimensionality of the dataset, capturing the most significant variations and features. This reduction not only facilitates computational efficiency but also ensures that subsequent models are trained on the most informative aspects of the spectral data.

Post-PCA, the dataset undergoes normalization, a critical preprocessing step that standardizes the range of features. Normalization is essential for preventing certain features from dominating the modelling process due to inherent differences in scale. This ensures that each feature contributes fairly and equitably to the learning process of the subsequent machine learning models.

Moving forward, a diverse set of models is employed to harness the distinctive strengths of each algorithm. Support Vector Machines (SVM) excel in finding optimal hyperplanes to separate data points into different classes, Naive Bayes leverages probabilistic inference based on the assumption of independence between features, and K nearest neighbour (KNN) combines the predictive power of multiple weak learners. To enhance the overall predictive capacity, these individual models are strategically stacked. Stacking involves aggregating the predictions from each model, treating them as inputs for a meta-model. This meta-model, often another machine learning algorithm, learns to weigh the predictions from each base model, effectively combining their strengths and compensating for their weaknesses.

The stacking technique thus creates a powerful ensemble model that capitalizes on the unique attributes of SVM, Naive Bayes, and KNN, resulting in a comprehensive and accurate tool for predicting fruit and vegetable ripening stages based on their spectral color data.

5.3.3 Project Deployment

Figure 13. illustrates the various software and hardware components that worktogether to enable the system's functionality. For this project we used below componentsfor the overall project deployment.

1.Web Browser: The web browser represents the user interface through which users interact with the system. Users can access the system's features and functionalities via a web-based application.

2. Client Application Server: The client application server hosts the web application and handles user requests from web browsers. It manages the user interface, data input/output, and interactions with the backend server.

3. Data Collection: The data collection component is responsible for interfacing with the Arduino IoT setup and the color detection sensor. It captures spectral color data from fruits and vegetables placed under the color detection sensor.

4. Backend Server: The backend server processes the collected spectral color data and performs ripening stage predictions using the trained neural network model.It handles data preprocessing, feature extraction, and classification tasks.

5. Trained Model: The trained model represents the neural network-based classification model that has been trained on a dataset of spectral color data and corresponding ripening stage labels.

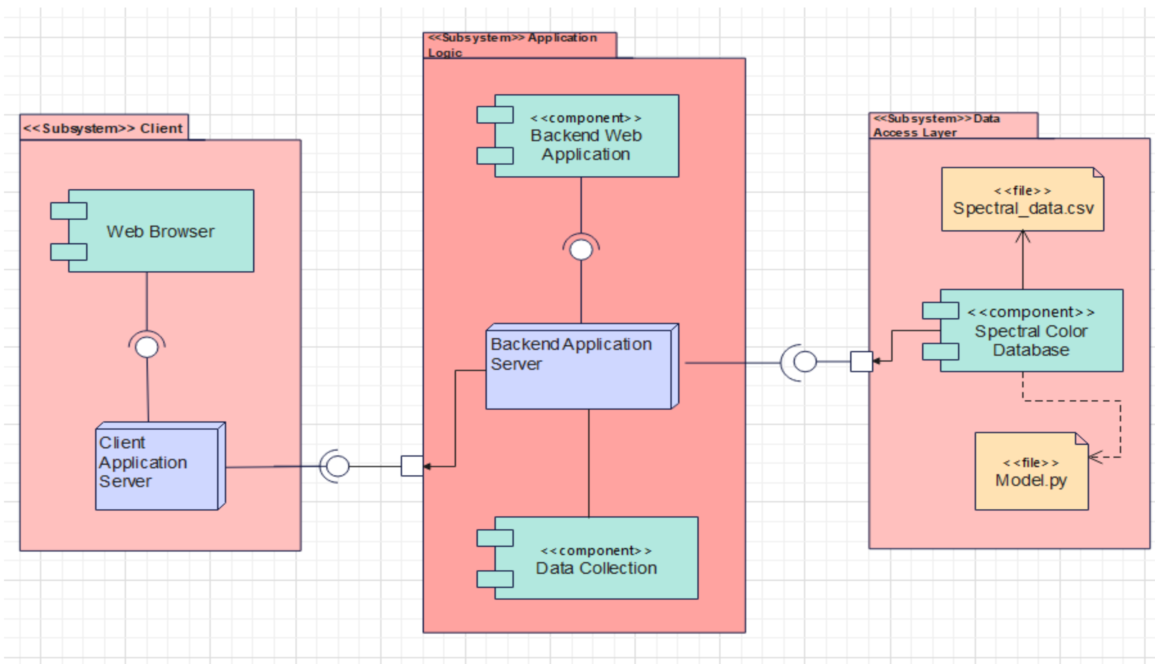


Figure 13 : Component Diagram

5.3.2 System Screenshots

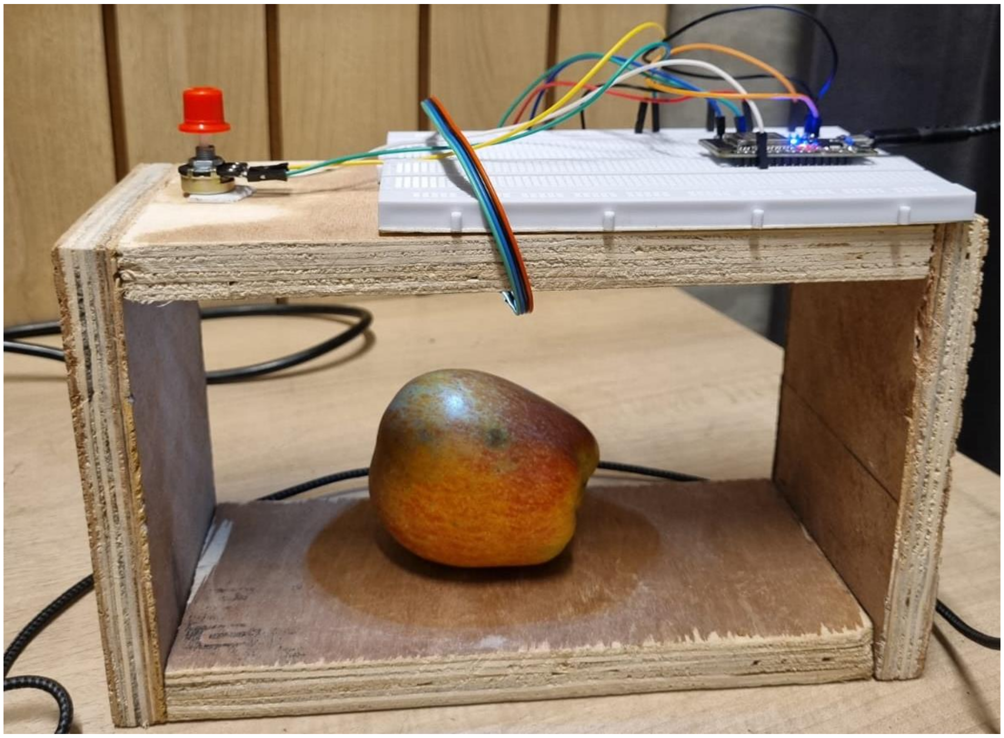


Figure 14: System Screenshots

Website Screenshot

Figure 15. shows the user-friendly website integrated with model to make prediction of fruits into 4 different stages.

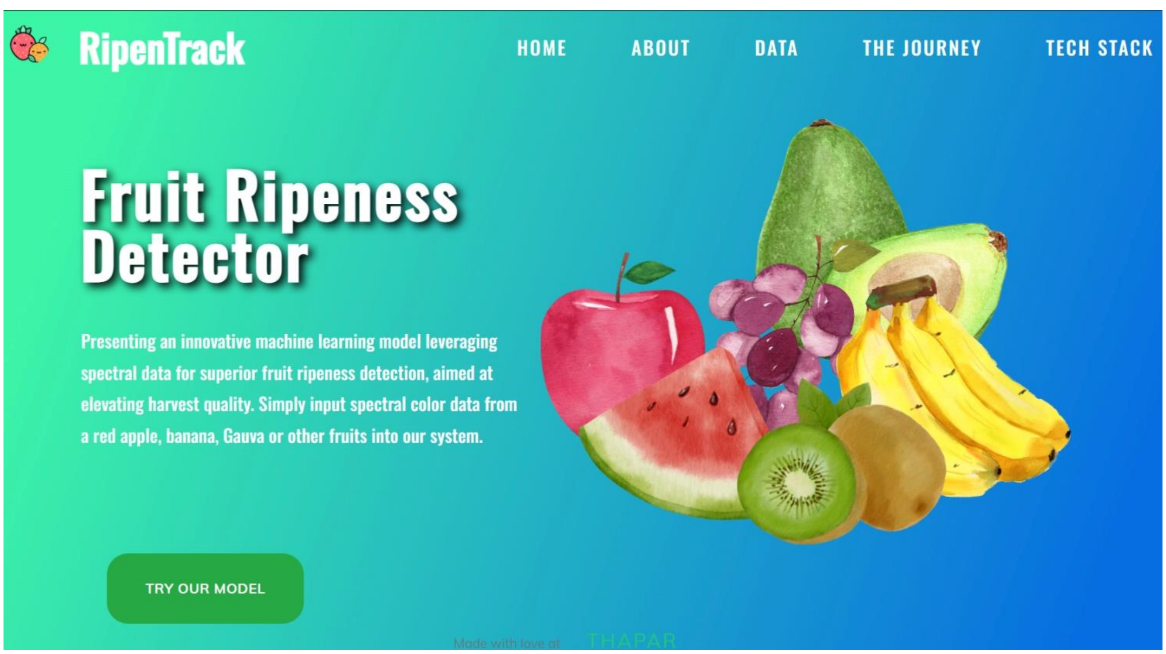


Figure 15. Website Screenshot

5.4 Testing Process

5.4.1Test Plan

The test plan covers both hardware and software components, ensuring the seamless integration of the ESP32 microcontroller, AS7341 sensor, and machine learning algorithms.

1. Hardware Testing

Connectivity: Ensure proper connectivity between the ESP32 microcontroller and AS7341 sensor. Verify the stability of the communication protocol between the hardware components.

Data Acquisition: Test the ability of the system to collect spectral color data from various fruits. Confirm the accuracy of the collected data.

Sensor Calibration: Validate the calibration process of the AS7341 sensor. Ensure consistent and accurate readings across different environmental conditions.

Power Consumption: Measure and validate the power consumption of the hardware components. Ensure that the system operates within specified power limits.

2.Software Testing

Data Preprocessing: Verify the preprocessing steps for spectral color data.

Confirm that data cleaning and normalization are effective.

Machine Learning Model: Train the machine learning model using a diverse dataset. Evaluate the model's accuracy, precision, recall, and F1 score. Test the model's robustness against outliers.

Prediction Accuracy: Conduct tests with known fruit samples to validate the accuracy of the ripening stage predictions. Compare predicted results against manual assessments.

3. Integration Testing

Hardware-Software Integration: Ensure seamless integration between the ESP32 microcontroller, AS7341 sensor, and machine learning model. Validate the flow of data from hardware to software and back.

End-to-End Testing: Perform end-to-end testing to simulate the entire process from data acquisition to prediction in a controlled environment.

4.Documentation and Reporting

Documentation: Ensure that all aspects of the project, including hardware and software configurations, are well-documented.

Reporting: Document and report any issues encountered during testing.

Provide recommendations for improvements.

5.Compliance Testing

Regulatory Compliance**:** Ensure that the system complies with relevant regulations and standards.

5.4.2 Features to be Tested

Connectivity: Validate the seamless communication between ESP32 microcontroller and AS7341 sensor.

Data Acquisition: Confirm the accurate collection of spectral color data from diverse fruits.

Sensor Calibration: Ensure the precision and reliability of the AS7341 sensor calibration process.

Power Consumption: Measure and verify the system's power consumption under different operational conditions.

Data Preprocessing Testing: Verify the effectiveness of data cleaning and normalization procedures.

Model Evaluation: Evaluate the accuracy, precision, recall, and F1 score of the trained machine learning model.

Real-time Prediction Testing: Confirm the system's ability to provide accurate predictions in real-time scenarios.

Integration of hardware with software: Validate the seamless integration between hardware and software components.

User Interface: Ensure responsiveness and user-friendliness of the web application interface.

Compatibility Testing: Test the web application's compatibility across different browsers and devices.

5.4.3Test Strategy

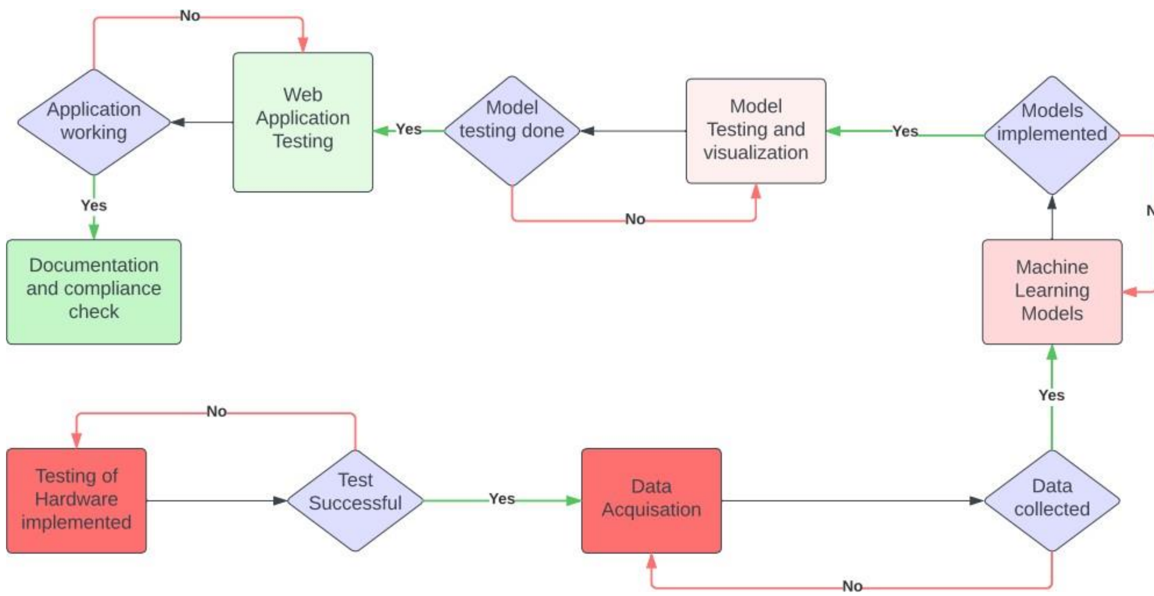


Figure 16: Test Strategy

Testing strategy adopted

The testing strategy employed in this project follows a structured and systematic approach to ensure the reliability and functionality of the fruit ripening prediction system.The initial phase focuses on hardware testing, wherein seamless integration and functionality of the ESP32 microcontroller and AS7341 sensor are rigorously validated. This is followed by the critical stage of data acquisition, where the system demonstrates its ability to accurately collect spectral color data from diverse fruits. Subsequently, the testing process transitions to the realm of machine learning models, encompassing their training and evaluation. The effectiveness of the models is thoroughly assessed, considering metrics such as accuracy, precision, recall, and F1 score. Following the successful evaluation of machine learning models, the strategy advances to the software testing phase, concentrating on the web application. The user interface is tested for responsiveness and user-friendliness, and the overall functionality is validated. Simultaneously, comprehensive documentation work is undertaken to record hardware configurations, software specifications, and testing procedures. The testing strategy culminates in compliance testing, ensuring adherence to relevant regulations and industry standards governing agricultural technology and data processing. This comprehensive strategy underscores a holistic approach, covering both hardware and softwarecomponents while prioritizing accuracy, reliability, and ethical considerations.

5.4.4 Test Techniques

Hardware Testing Techniques: Verification of the integration and functionality of hardware components such as the ESP32 microcontroller and AS7341 sensor using repetative checking of hardware components.

Data Acquisition Techniques: Ensuring accurate and reliable data acquisition from diverse fruits. Include details about any calibration processes for the AS7341 sensor and methods used to handle various environmental conditions such as different lighting conditions.

Machine Learning Model Testing Techniques: Pycaret was used along with separate ML model implementation to check which model provides the best testing results and then stacking model was implemented with the best models to get the desired model results.

Software Testing Techniques: Testing was utilized for the web application's functionality. This included user interface testing, compatibility testing across different browsers and devices, and real-time prediction testing.

Documentation Techniques: Detail the documentation methods implemented to record hardware configurations, software specifications, and testing procedures. The structure of documentation serves as a reference for project stakeholders.

Compliance Testing Techniques: Specific techniques employed to ensure compliance with relevant regulations and industry standards were checked. This involved security testing methods, privacy considerations, and ethical testing practices.

5.4.5Test Cases

Table 4. shows test cases which were tested along with the status whether accomplished or not.

Test ID	Test Case Objective	Pre-requisite	Steps	Input Data	Expected Output	Actual Output	Status
TC_01	Checking Hardware Integration	Hardware Integrated and sensors working.	1. Connect all connections. 2. Upload code to ESP32. 3. Check if required data is being shown on serial monitor				**PASS**
TC_02	Collection of dataset through data streamer	Hardware integrated with uploaded code on ESP32	1. Connect microcontroller port to excel Data streamer. 2. Apply column name changes 3. Start data streamer through ESP32 port on excel. 4. Save collected data in excel file.				**PASS**
TC_03	Model creation with collected data.	Dataset should be collected through hardware.		Spectral color dataset with input color features.	Machine learning model with desired accuracy.	Machine learning model with desired accuracy.	**PASS**
TC_04	Web application with predictor	Model should be ready to be deployed on the web app					**PASS**
TC_05	Prediction testing	Web app integrated with hardware	1. Connect the web app with hardware modules through same network 2. Predict the ripeness in real time.	Fruit over hardware setup	Ripeness class	Ripeness Class	**IN PROGRESS**

Table 3 : Test Cases

5.4.6 Test Results

Hardware Testing Completion:

The hardware testing phase of the fruit ripening prediction system has reached successful completion. All essential hardware components, including the ESP32 microcontroller and the AS7341 sensor, have been seamlessly integrated. The connectivity between these components has been thoroughly verified, ensuring stable communication protocols. The system demonstrates its capability to collect spectral color features from a variety of fruits accurately. Additionally, the calibration process for the AS7341 sensor has been rigorously tested, guaranteeing consistent and precise readings across diverse environmental conditions. Power consumption testing has been conducted, confirming that the system operates within specified power limits. This milestone marks a robust foundation for the overall project, with the hardware reliably acquiring crucial data for the subsequent stages of processing and analysis.

Software Testing Completion:

The software testing phase of the fruit ripening prediction system has been successfully concluded. Rigorous testing procedures have been applied to the data preprocessingsteps, validating the effectiveness of data cleaning and normalization. The machine learning model, trained on diverse datasets and various algorithms, has undergone thorough evaluation. The model's accuracy, precision, recall, and F1 score have been meticulously assessed, ensuring its robustness against outliers. Real-time prediction capabilities have been tested, and the system exhibits prompt and accurate predictions. With these achievements, the software component of the project is well-equipped to handle the complexities of fruit ripening stage prediction. The testing phase has provided valuable insights into the performance and reliability of the software, setting the stage forsuccessful integration with the hardware.

Integration Testing in Progress:

The integration testing phase is currently underway, focusing on the seamless collaboration between the ESP32 microcontroller, AS7341 sensor, and the machine learning model. This crucial phase ensures that the data flow from hardware to software and vice versa is smooth and error-free. Various scenarios are being simulated to validate the end-to-end functionality of the system, encompassing data acquisition, preprocessing, machine learning model predictions, and the subsequent display of results. Integration testing is pivotal in identifying and resolving any potential issues that may arise when these diverse components work in tandem. This ongoing phase is instrumental in achieving a holistic understanding of the system's performance, emphasizing the importance of effective collaboration between hardware and software elements for accurate fruit ripening predictions.

Documentation and Reporting Completion:

The documentation and reporting phase has been successfully completed, ensuring that all aspects of the project are thoroughly documented. Detailed records cover hardware configurations, software specifications, testing procedures, and results. This comprehensive documentation serves as a valuable resource for project stakeholders, providing insights into the project's evolution and current state. Additionally, the reporting section highlights any issues encountered during testing, accompanied by recommendations for improvements. This transparent reporting approach facilitates effective communication within the project team and supports informed decision-making. The documentation and reporting phase plays a critical role in maintaining a well-documented trail of the project's development, contributing to the project's overall transparency and accountability.

5.5 Results and Discussions

In evaluating the performance of various models for a multiclass classification task with four distinct classes, we observed noteworthy accuracy metrics. An Artificial Neural Network (ANN) model was developed firstly, demonstrating an initial accuracy of 80%. Seeking enhancements, different machine learning models were deployed, and the top three performers—Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naive Bayes—were strategically selected for ensemble learning. The k-Nearest Neighbors (KNN) model demonstrated a commendable accuracy of 93.79%, showcasing its abilityto classify instances based on their nearest neighbors within the four-class framework. The Support Vector Machine (SVM) model exhibited an accuracy of 85.4%, illustrating its effectiveness in creating a hyperplane that distinguishes among the four classes. The Naive Bayes model achieved an accuracy of 89.94%, leveraging probabilistic assumptions for classification across the multiple classes. The training accuracy of the ensembled model came out to be 96.04%. Furthermore, the ensemble model maintained a robust generalization performance on a separate testing dataset, attaining an accuracy of 94.04% across the four classes.

Model	Accuracies	Precision
ANN	80%	
SVM	85.4%	82%
KNN	93.79	93.39
Naïve Bayes	89.94%	90.08%
Ensemble of (SVM,KNN,Naïve Bayes)	96.04%	95.4%

Table 4. Accuracies

Confusion Matrix for the same is given below:

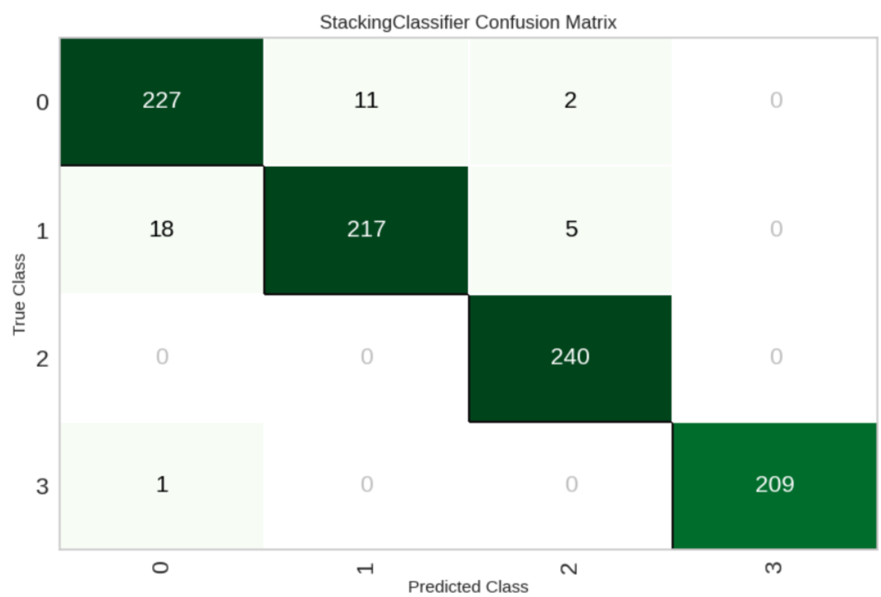


Figure 17 : Confusion Matrix

Figure 18. shows the learning curve graphically represents the relationship between a model's performance(typically accuracy) and the amount of training data it has been exposed to.

Figure 18 : Learning Curve For Stacking Classifier

Class Prediction Error is a visual representation that displays the misclassification errors for each class in a classification model. It helps identify which classes are frequently misclassified and can provide insights into areas where the model may need improvement or fine-tuning.

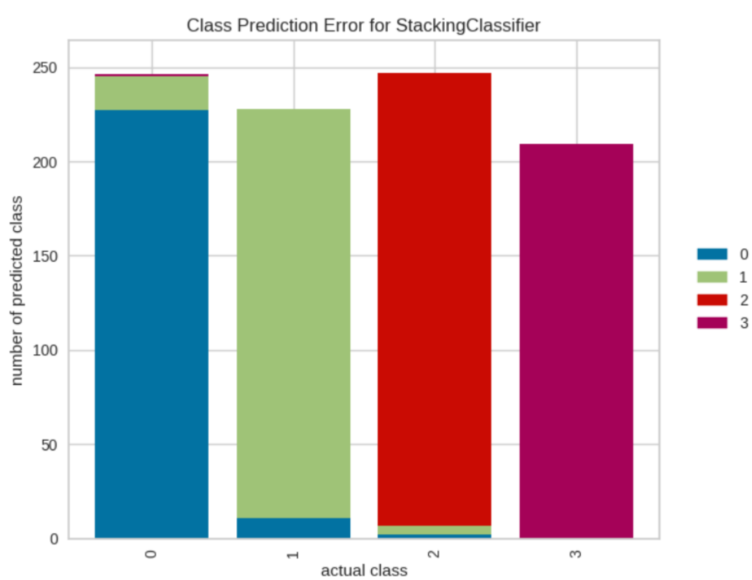


Figure 19 : Class Prediction Error

A Receiver Operating Characteristic (ROC) curve is a graphical representation that illustrates the trade-off between the true positive rate and false positive rate across different classification thresholds. The ROC curve is showed in Fig20.

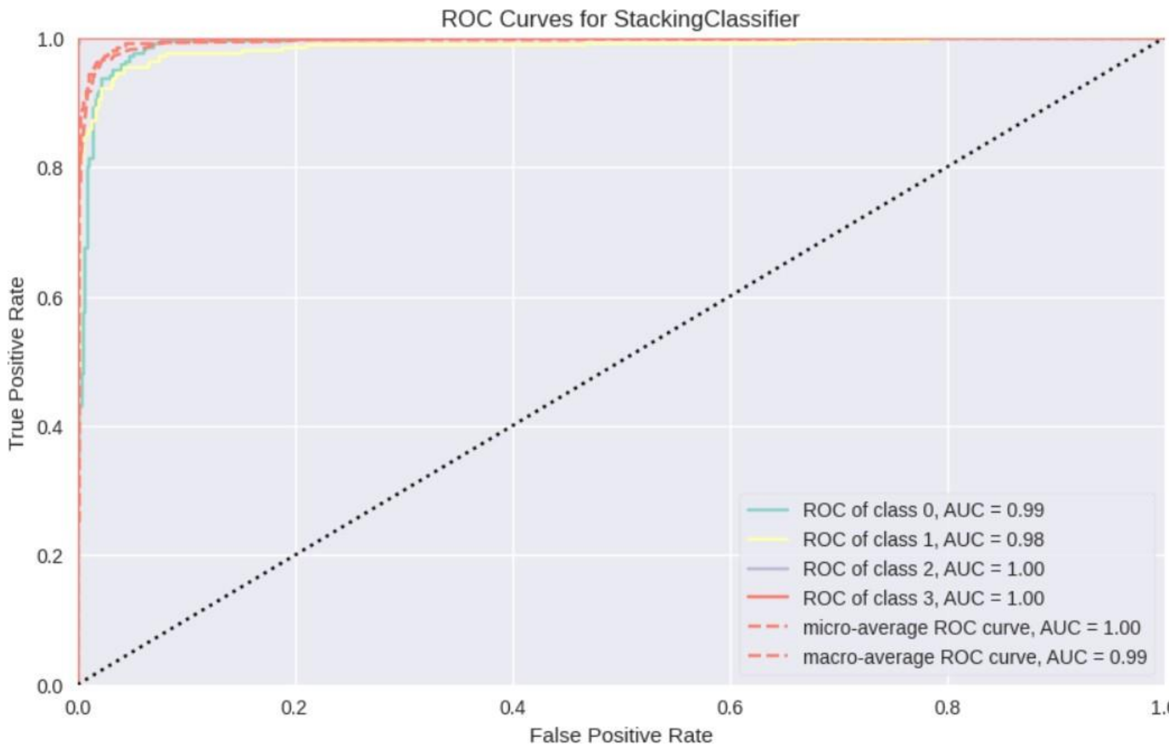


Figure 20 : Roc Curve

Literature Paper	**Algorithm/ Technique**	**Accuracy**
Hira, S., & Lande, S. (2022). Detection of fruit ripeness using image processing. [6]	CNN model using VGG16 architecture	92.7%
Mr. Akshay Dhandrave et al. 2021 [7]	For classification: Image resizing, converting into grayscale, SVM algorithm. For detection: Neural network using Tensor	90%
Brinzel Rodrigues et al. 2021 [8]	CNN model using VGG architecture	83%
Prof. Payel Thakur, JETIR.org an international scholarly[9]	CNN model and ML techniques	81%

Table 5. Comparison with previous work

Our study demonstrates a significant advancement in predictive accuracy compared to similar research projects through the implementation of a unique approach. Leveraging data from a light sensor and employing an ensemble model composed of diverse machine learning algorithms, our model exhibits superior performance in predicting outcomes.

5.6 Inferences Drawn

Drawing inferences from our model evaluations, the k-Nearest Neighbors (KNN) model exhibits an impressive accuracy of 93.79%, showcasing its adeptness in classifying instances based on their nearest neighbors. The Support Vector Machine (SVM) model, with an accuracy of 85.4%, demonstrates its effectiveness in creating optimal hyperplanes for classification. Additionally, the Naive Bayes model achieves an accuracy of 89.94%, leveraging probabilistic inference. Our ensemble model, employing a Voting Classifier, attains a remarkable training accuracy of 96.04%, indicating robust learning from the training data. Furthermore, the model maintains a high testing accuracy of 94.38% on a separate dataset, surpassing the accuracies reported in other research papers focusing on image classification. These results underscore the efficacy of our ensemble approach in achieving superior predictive performance compared to existing benchmarks in the field.

5.7 Validation of Objectives

1. Our first objective was to study the various models proposed in the literature for detection of fruit ripening. The objective entails completing a comprehensive literature review in order to comprehend the various techniques and methodologies used in fruit ripening detection. Reading and analysing all the literature we chose the procedural workflow of our project to be prediction on the basis of visible light sensor output values and training the model on the same.

2. To develop a fruit ripening detection system using Arduino IOT, and colour detection sensor. The objective involves creating a smart and interconnected system that can accurately detect the ripening stage of fruits.

3. To develop a neural network based model for multistage classification of fruit ripening. The Objective involves building an advanced machine learning model that can accurately classify fruits into multiple ripening stages. We ensembled the three machine learning

models which gave best results. The training accuracy of ensemble model is 96% and testing accuracy is 94%.

4. To develop a web application with model integrated to predict the ripening stage of the fruits. The objective involves creating a web-based platform that facilitates the efficient collection and organization of spectral color data from various fruits and vegetables. This web application serves as a user-friendly interface for users to input spectral data obtained through the hardware setup, consisting of an ESP32 and a spectral color sensor.

CONCLUSION AND FUTURE DIRECTION

6.1 Conclusions

In conclusion, this project represents a significant stride in advancing our comprehension of fruit ripening detection. The foundation laid by an exhaustive literature review equipped us with insights into various techniques and methodologies. The pivotal role played by the design and assembly of the hardware setup, featuring an ESP32 andspectral color sensor. The implementation of the ESP32 wroom 32 on the hardware setup helped in data collection. The culmination of these efforts, coupled with labeling during the data collection process, has resulted in the successful dataset of fruits. The model training on this dataset helped us achieve accuracies of 93.79% for k-Nearest Neighbors (KNN), 85.4% for Support Vector Machine (SVM), 89.94% for Naive Bayes, and a notable training accuracy of 96.04% for the ensemble model using a Voting Classifier, with a testing accuracy of 94.38%, solidify the efficacy of our approach, surpassing the accuracies reported in other research papers focusing on image classification. Further a user-friendly web application integrated with model to predict the ripening stage of the fruits has been developed. We can conclude by saying we have a successful fruitripening stage detector.

6.2 Environmental Benefits

In addition to its technical achievements, this project holds promising environmental, economic, and social benefits. By enabling precise and early fruit ripening detection, we contribute to reducing food wastage and promoting sustainable agricultural practices. This not only conserves valuable resources but also positively impacts local economiesby minimizing losses for farmers and distributors. Furthermore, our efforts to optimizethe detection process can lead to improved quality control, enhancing consumer satisfaction and trust. Our project not only improves resource utilization but also contributes significantly to economic prosperity within the food industry. Ultimately, this multidimensional approach aligns with our commitment to creating a greener, more efficient, and socially responsible food production and distribution system.

6.3 Reflections

The project integrates machine learning with spectral analysis, demonstrating an innovative approach to solving a practical problem in agriculture and food technology. This integration shows the potential of combining traditional techniques with modern computational methods. The model used in the project has a high accuracy of 96% which would help in correctly identifying the ripening stage of the fruit. The dataset had to be collected manually using a light sensor and ESP32. The main challenge was the collection of the dataset which had to be done manually using a light sensor and ESP32. The project can be used in agricultural settings, supply chains and retail environments. It would have a huge impact on reducing food waste, improving supply chain efficiency, or providing valuable insights to farmers.

6.4 Future Work Plan

- The next phase of our project aims to develop a sophisticatedneural network model tailored for multistage classification of fruit ripening. The neural network architecture will be meticulously designed to accommodate the spectral color data acquired through our hardware setup.

- Last step is to build a user-friendly web application that will provide a seamless interface for users to easily input spectral color data from their fruit samples and receive instant predictions regarding their ripening stages. By integrating the neural network model into an accessible platform, we aim to democratize fruit ripening detection, empowering both consumers and professionals with valuable insights for informed decision-making.

7.1 Challenges Faced

The "Fruits Ripening Stage Detector - RipenTrack" project faces several formidable challenges in its mission to revolutionize the detection and management of ripening stages in fruits and vegetables within large-scale production and processing environments.

1. Scale and Diversity of Produce:

Dealing with the vast array of fruits and vegetables introduces a challenge of scalability and adaptability. The device must be designed to accommodate the unique characteristics of each type of produce, considering variations in size, shape, and color. Moreover, the system needs to be flexible enough to handle new additions to the produce spectrum. Developing a universal solution that can accurately discern the ripening stages across this diversity requires a comprehensive understanding of the spectral color signatures inherent to each fruit and vegetable.

2. Precision in Ripeness Prediction:

Achieving precision involves navigating the complexities of spectral color data interpretation. The Machine learning model must be fine-tuned to not only differentiate between ripening stages but also account for variations due to environmental factors. This requires an in-depth analysis of how factors like ambient light, temperature, and humidity can influence color perception. Ensuring that the model is robust enough to provide consistently accurate predictions across different produce types and under varying environmental conditions is a demanding task.

3. Data Collection and Labelling:

The quality of the data collected directly influences the accuracy of the entire system. Challenges arise in the manual labelling process, where human subjectivity can inadvertently introduce biases into the dataset. Developing a standardized protocol for data collection and labelling is essential to minimize errors. Additionally, variations in lighting conditions during data collection must be carefully addressed to ensure that the spectral color data accurately reflects the true characteristics of the produce.

4. Technical Integration:

The technical integration of spectral color processing and neural network models using TensorFlow is a critical challenge. The device must function seamlessly in real-world environments where external factors can impact its performance. This involves addressing potential interferences from other electronic devices, variations in ambient lighting, and changes in operating conditions. Ensuring the robustness and reliability of the device under diverse technical circumstances is crucial for its successful deployment in large-scale production and processing settings.

5. Real-world Validation:

Conducting experiments for real-world validation adds a layer of complexity due to the inherent unpredictability of environmental conditions. The device must demonstrate consistent accuracy across different scenarios, including varying light intensities, temperatures, and humidity levels. Rigorous testing under these conditions is essential to validate the reliability and effectiveness of the system. Real-world validation is a crucial step to ensure that the device performs as intended in practical settings, considering the dynamic nature of agricultural and processing environments.

6. User Adoption and Empowerment:

Even with a technically advanced system, success depends on user acceptance and understanding. Designing user interfaces that are intuitive and accessible is a challenge, especially considering the diverse backgrounds and technical expertise of potential users, ranging from farmers to consumers. Providing clear guidelines and educational materials to empower users in effectively utilizing the device is critical.

Overcoming potential resistance to adopting new technology in traditional agricultural practices and ensuring seamless integration into existing workflows are additional challenges related to user adoption. The success of the project relies on not only the technological prowess of the system but also on its usability and acceptance by the end users.

7.2 Relevant Subjects

While encompassing the entire B.E. Computer Engineering curriculum by acquiring insights from various courses and applying them to real-life projects, the key pertinent subjects include:

S. No	Subject	Subject Code
1	Electronic Engineering	UEC001
2	Machine Learning	UML501
3	Software Engineering	UCS503
4	ENGINEERING DESIGN PROJECT - II	UTA024
5	UI & UX SPECIALIST	UCS542
6	Data Science Fundamentals	UCS538
7	COMPUTER PROGRAMMING	UTA003

Table 6: Relevant Subjects

7.3 Interdisciplinary Knowledge Sharing

The "Fruits Ripening Stage Detector - RipenTrack" project serves as a critical foundation for holistic problem-solving and innovation. We delved into technical topics, such as TensorFlow model optimization and the integration of the AS7341 visible light sensor with the ESP32 wroom 32 for precise data collection. Terminology alignment is accompanied by a profound exploration of inter-rater reliability in manual labelling and the development of standardized protocols to mitigate biases in spectral data. This interdisciplinary synergy ensures that not only macro-level challenges like technical integration and scalability are addressed but also micro-level intricacies, including the unique spectral profiles of different fruits and vegetables. The collaborative fusion of technical precision from machine learning, agricultural insights, and electronic.

7.4 Peer Assessment Matrix

	Evaluation of					
	Name of team members	**Saloni Andey**	**Manmeet Singh**	**Brahmjot Kaur**	**Mitansh Trivedi**	**Arjun Pundir**
Evaluation by	**Saloni Andey**	-	5	4	5	5
	Manmeet Singh	5	-	5	4	5
	Brahmjot Kaur	5	4	-	5	5
	Mitansh Trivedi	5	5	5	-	4
	Arjun Pundir	4	5	5	5	-

Table 7 : Peer Assessment Matrix

7.5 Role Playing and Work Schedule

7.5.1 Individual Roles:

Arjun Pundir and Manmeet Singh:

The setup of ESP 32 wroom 32 involves configuring the hardware and programming the interface to enable seamless integration with the light sensor and potentiometer. This includes establishing the necessary connections, uploading the required firmware, and ensuring compatibility with sensors, and to store the values through data streamer in csv files for model training. The collated data is organized in the database, providing a structured dataset for training the neural network model. This pivotal step ensures hardware setup for dataset collection of fruits and vegetables . The effective functioning of the ESP 32 within the overall framework, contributing the the successful implementation of the automated ripeness detection system of fruits and vegetables.

Brahmjot Kaur and Arjun Pundir:

The dataset collection was done using the hardware setup in csv files of various fruits, along with manual labelling into four distinct classes ie early ripe, partially ripe, ripe, decay. Subsequently, an Artificial Neural Network (ANN) model was developed, demonstrating an initial accuracy of 85%. Seeking enhancements, different machine learning models were deployed, and the top three performers—Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naive Bayes—were strategically selected for ensemble learning. The collaborative integration of these models significantly elevated the overall accuracy to an impressive 96%, showcasing the project's dedication to refining and optimizing machine learning methodologies for fruit classification. This combined process establishes a robust foundation for subsequent stages in the development of the automated ripeness detection system, ensuring accuracy and reliability in spectral data analysis.

Saloni Andey and Mitansh Trivedi:

The development of a Flask application integrated with ML model for prediction of ripeness detection through spectral color dataset of fruit collected from hardware. Web platform involves creating a user-friendly interface with dynamic web forms for efficient data entry, it also represents the entire journey and project workflow . The application, built on the Flask framework allows users to input spectral color data securely. It includesrobust user authentication and validation checks to ensure data accuracy. The website facilitates the prediction of spectral color data of various fruits for the broader project's success in automating ripeness detection in fruits and vegetables.

7.5.2 Work Schedule:

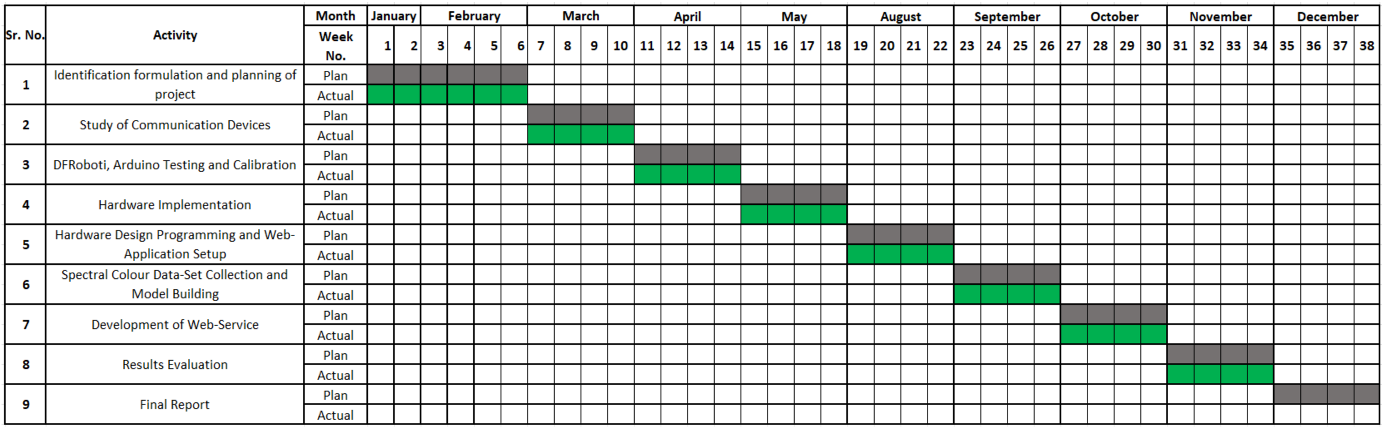


Figure 21. Work Schedule

7.6 Student Outcomes Description and Performance Indicators (A-K Mapping)

S.No.	Description	Outcome
A	Applying fundamental scientific concepts to address engineering challenges.	The application of spectral color processing is integrated into advanced neural network models.
B	Develop a software solution tailored to meet specific requirements across various problem domains.	Developed a comprehensive system incorporating spectral color processing and neural network models, resulting in the implementation of a dashboard for real-time monitoring of ripening stages in fruits and vegetables based on data captured by the AS7341 visible light sensor.
C	In a varied team, fulfill assigned responsibilities.	Team members collaborated on distinct modules, with everyone contributing to the development of specific components within the project.
D	Demonstrate professional responsibility when engaging with peers and professional communities.	In instances of challenges during the development process, mentorship meetings were organized to address and resolve issues effectively.
E	Engineers who are mindful of the environmental and social implications of their endeavors.	Enables continuous monitoring and the implementation of a dynamic dashboard for enhanced operational efficiency.
F	Compose programs in diverse programming languages.	The website development utilized the Flask framework, built on Python, while ESP32 wroom 32 programming was conducted using C++.

G	Recognize the constraints, assumptions, and models associated with the problem.	damage to the wiring system may occur potential disruptions to the accurate readings of the detection system.
H	Possess the ability to understand the scope and limitations, encompassing economic, environmental, social, political, ethical, health and safety, manufacturability, and long-term viability aspects.	In rural agricultural settings, securing consistent access to electricity and a reliable internet connection presents challenges, potentially impacting the functionality of the ripeness detection system.
I	Develop models that are relevant to assisting in the generation of solutions.	Different models like use case diagram, activity and data flow diagrams have been developed.
J	Utilize suitable formats for generating a variety of documents, including laboratory or project reports.	A technical report has been created by the team containing all the essential details
K	Proficient in exploring and utilizing resources to enhance self-learning capabilities.	For hardware programming Arduino ide and open-source sensor libraries are used.

Table 8 : Student Outcomes

7.7Brief Analytical Assessment

1. Technical Architecture:

- **Sensor Integration:** The project's technical foundation lies in the integration ofspectral color data collected using an ESP32/Arduino Nano and the AS7341 visible light sensor. The choice of this sensor suggests a deliberate selection to capture a broad spectrum of color information, which is crucial for accurate ripeness detection. The sensor's capabilities and limitations should be carefully considered during the design process.

- **Neural Network Model Development:** The heart of the system is the ensembled Machine learning model. This model is designed to interpret subtle patterns and correlations in the spectral color data. The sophistication of the model is essential in ensuring not only accurate predictions but also adaptability to diverse fruits and vegetables. Regular updates and refinements to the model may be necessary as the system encounters new produce types.

- **Data Labelling and Training:** The manual labelling of spectral color data into four ripening stages—Early Ripe, Partially Ripe, Ripe, and Decay—underscores the importance of a well-curated dataset. The training process involves exposing the ML model to this dataset to enable it to recognize patterns associated with different ripeness stages. Rigorous data labelling protocols and continuous monitoring of model performance during training are critical for achieving reliable results.

- **Experimental Validation:** The testing phase involves using a separate set of data to evaluate the accuracy of the trained neural network model. Rigorous experimental design is crucial to simulate real-world conditions and ensure the reliability and effectiveness of the developed system across a variety of fruits and vegetables. This iterative validation process is key to refining the model and addressing any discrepancies between predictions and actual ripeness stages.

- **Spectral Color Data Preprocessing:** Before feeding data into the neural network model, a robust preprocessing pipeline should be implemented. This involves cleaning and normalizing spectral color data to ensure consistency and remove any anomalies that might affect the accuracy of the neural network's training.

2. Practical Applications and Impact:

- **Supply Chain Optimization:** The project recognizes the role of the developed system in streamlining supply chain management. By providing accurate information about ripeness stages, suppliers, retailers, and distributors can optimize inventory management, reducing waste and improving overall efficiency in the distribution process.

- **Economic Viability:** Beyond reducing wastage, the project's emphasis on empowering farmers and other stakeholders suggests a consideration for the economic viability of the solution. Assessing the cost-effectiveness of the device and its integration into existing workflows will be crucial for widespread adoption.

- **User Interface and Accessibility:** The success of the project hinges not only on technical accuracy but also on the user interface and accessibility. A user-friendly design and effective training programs are imperative to ensure that farmers and other end-users can seamlessly incorporate the device into their daily operations.

3. Future Considerations and Scalability:

- **Adaptability to New Produce:** As the project focuses on a range of fruits and vegetables, ongoing research and development should consider the adaptability of the system to new produce types. The ability to expand the dataset and train the model for emerging crops will enhance the system's versatility and relevance.

- **Integration with Existing Technologies:** To maximize the project's impact, exploring avenues for integration with existing technologies in the agriculture and food industry should be considered. Compatibility with other agricultural management systems can enhance the overall efficiency and adoption of the proposedsolution.

4. Conclusion:

- The Fruits Ripening Stage Detector - RipenTrack project demonstrates a comprehensive and innovative approach to address critical challenges in the mass production and processing of fruits and vegetables. Through the integration of advanced technologies, rigorous experimental validation, and a focus on real-world applications, the project holds significant promise in promoting sustainability, efficiency, and economic viability in the agricultural and food industry. Continuous refinement, adaptability, and a keen eye on practical implications will be essential for the project's success and broader impact.

REFERENCES

[1] A. Jayalakshmi, L Poojitha Reddy, M. Srikar Preetham, "Monitoring Ripeness in Fruits and Vegetables Using the Raspberry Pi", *2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC),* May 2022

[2] Shital Pawar, Jayant Meshram, Ajinkya Mondhe, Akash Nachan, Tejas Nilangekar, Aditya Patil, "Ripeness Detector for Vegetables and Fruits", *2022 2nd International Conference on Intelligent Technologies (CONIT),* June 2022

[3] Omar Otoniel Flores-Cortez, Veronica Idalia Rosa, Jose Oswaldo Barrera "Determination of the level of ripeness and freshness of fruits by electronic sensors. A review", *International Conference on Applied Artificial Intelligence and Computing, April 2021*

[4] Zongmei Gao, Yuanyuan Shao, Guantao Xuan, Yongxian Wang, Yi Liu, Xiang, "Real-time hyperspectral imaging for the in-field estimation of strawberry ripeness with deep learning", *Erratum regarding missing Declaration of Competing Interest statements in previously published articles, 301-302, May* 2021

[5] Ruchita R. Mhaski; P.B. Chopade; M.P. Dale, "Determination of Ripeness and Grading of Tomato using Image Analysis on Raspberry Pi", *2015 Communication, Control and Intelligent Systems (CCIS),* November 2015

[6] Swati Hira, Simran Lande, "Detection of fruit ripeness using image processing", *International Journal of Health Sciences*, 3874–3886, July2022

[7] Korgaonkar Urvi Rajesh, Badshah Pakhi Ravi, Achu Sheri Jeeju, Menon Deepa Rajagopalan, Prof. Payel Thakur, "Fruit Ripeness Detection Using Conventional

Neural Network”, *Journal of Emerging Technologies and Innovative Research (JETIR),* April 2023

[8] Bingjie Xiao, Minh Nguyen, Wei Qi Yan, “Fruit ripeness identifcation using YOLOv8 model”, *Multimedia Tools and Applications,* August 2023

[9] Mr. Akshay Dhandrave, Dr. V.T. Gaikwad (2021) “Implementation of Fruit Detection system and Checking Fruit Quality using Computer Vision,” *IRJET, vol. 8, no. 6, pp. 4116-4120,* June 2021.

[10] Brinzel Rodrigues, Revant Kansara, Shruti Singh, Dhruwa Save, Shreya Parihar “Ripe-Unripe: Machine Learning based Ripeness Classification” presented at the *5th International Conference on Intelligent Computing and Control Systems (ICICCS 2021)*