Machine Learning-Based Classification of Tomato and Optimal Harvesting for Precision Agriculture

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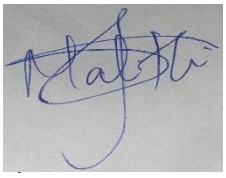
DECLARATION PAGE OF THE CANDIDATES & SUPERVISOR

We declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Name	**Student ID**	**Signature**
Samarasinghe G.D.M.J	IT21013164	

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Signature of the supervisor   Date

....   ……….....09.04.2025.......................
(Mr. Amila Senarathne)

ABSTRACT

The work here suggests a comprehensive and innovative AI-based system to significantly enhance tomato cultivation through the exploitation of the synergistic value of computer vision, machine learning, and adaptive decision-making. The focus of the system is a trained Convolutional Neural Network (CNN) which is capable of classifying tomatoes with high accuracy into various ripening phases—unripe, half-ripe, and full ripe—by utilizing precise image analysis that detects subtle variations in color, texture, and form. To aid scalability and real-time deployment in agricultural environments, the system integrates YOLOv8, a sophisticated object detection model with the capability to rapidly identify and classify numerous tomatoes within a single frame, thus allowing efficient large-scale monitoring. Besides visual examination, a predictive model is applied to correlate tomato ripeness against fluctuating environmental conditions, such as temperature, humidity, and rainfall, to allow the system to forecast best harvest windows to achieve maximum yield and fruit quality. For added convenience, the entire solution is delivered on a light, web-based platform on smartphones, allowing farmers to have real-time information, alerts, and actionable recommendations in the field. The system also has automated sorting capabilities based on ripeness levels, making the post-harvest process easier and offering uniform quality for market distribution, hence increasing consumer satisfaction and allowing premium pricing strategies. By integrating smart ripeness sensing, environmental sensing, and data-driven decision guidance within a responsive platform, this solution offers a dramatic improvement over traditional farming methods, reducing reliance on labor, minimizing wastage, and promoting sustainable farming methods tuned to the conditions of modern-day farmers. [1].

Keywords*—Tomato cultivation, precision cultivation, computer vision, machine learning, convolutional neural networks (CNN), YOLOv8, ripeness identification, predictive model, weather pattern, sustainable agriculture, mobile web application, environment monitoring, harvesting optimization, maximum yield, pre-market sorting of produce, supply chain optimization, farm automation, market positioning.*

ACKNOWLEDGEMENT

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LIST OF ABBREVIATIONS

ACL - Access Control List

ML - Machine Learning

HTML - Hypertext Markup Language

CSS - Cascading Style Sheets

API - Application Programming Interface

CRUD - Create, Read, Update, Delete

GUI - Graphical User Interface

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1. INTRODUCTION

Tomato farming is a central element of global agriculture, both as a primary source of nutrients and as a major source of much of the globe's economic income. Conventional tomato culture, however, is faced with an array of difficulties, such as the inefficiency of determining the best stage of fruit maturity, early harvesting, and unsuitable market targeting. These issues tend to result in lost yields, damage to crops, and significant economic losses for the farmers. As the demand for tomatoes continues to rise across the world, there is also an increasing need for new technologies that can reduce these inefficiencies and optimize farm practices [1].

This research proposes the development of an AI system that integrates machine learning, image processing, and adaptive decision-making technologies to solve these critical problems. The system uses Convolutional Neural Networks (CNNs) to analyses a massive dataset of tomato images and identify the three ripeness stages—unripe, half-ripe, and ripe—accurately. Through CNNs, the system can accurately process and classify the tomatoes and make timely and accurate ripeness determination [2].

Apart from this, the system employs YOLOv8, which is a cutting-edge real-time object detection model. It supports detection and classification of more than one tomato within an image. This aspect adds enormous speed and efficiency to the assessment of ripeness, thus becoming perfectly suited for commercial agriculture, where many tomatoes must be assessed within minutes.

In addition to ripeness detection, the system also has a predictive model that considers environmental factors such as temperature, humidity, and other weather factors. Through the inclusion of these weather factors, the model can recommend best harvest times, which allows farmers to make informed decisions that maximize yield and reduce crop wastage. The predictive model not only improves the timing of the harvests but also allows farmers to predict market demands and make informed decisions to meet market needs.

The system is available through a user-friendly web-based interface, providing real-time data and alerts straight to mobile devices, providing farmers with an accessible means of being connected and making timely decisions. The platform not only provides farmers with actionable data on the ripeness of tomatoes but also pre-market sortation according to ripeness, allowing farmers to categorize tomatoes for best market placement. This ability gives added value of marketability to the crops, with the tomatoes being sold at the right time and to the right market in order to reap maximum financial gain [3].

Through the integration of advanced technologies like ripeness sensing, environmental monitoring, and decision support, this AI-based system is a complete solution to modern tomato cultivation. The objective of this study is to achieve maximum productivity, reduce post-harvest losses, and provide sustainable farming practices. In doing so, it hopes to empower farmers to maximize their businesses, achieve better yields of higher quality, and contribute more generally to the sustainability of the farm business. With the advent of AI and machine learning applications, this solution has a vision to set the future of farming with a cheaper, less expensive, and environmentally friendly means of commercially cultivating tomatoes [4].

1.1. Background & Literature Survey

Tomato farming has been one of the most vital parts of agriculture; hence, it is a major source of nutrition and income among farmers all over the world. Nevertheless, conventional farming methods have normally presented several inefficiencies, such as poor ripeness detection, improper harvest timing, and unsuitable market timing. All these factors contribute to reduced yields, increased waste, and economic losses among farmers. Such challenges call for technological advancements that can improve decision-making and optimize farming practices.

This research proposes a novel AI-driven system that can bring revolution in tomato farming by integrating machine learning, image processing, and adaptive decision-making technologies. The proposed system will be able to accurately identify the three stages of tomato ripeness—unripe, half-ripe, and fully ripe—with high precision using a CNN trained on an extensive dataset of images of tomatoes. It also detects and classifies multiple tomatoes in one image with the help of YOLOv5, thus greatly speeding up the process of ripeness assessment for large-scale farming.

Predicting aside, the system is complete with a predictive model: taking as input ripeness data and dynamic environmental conditions of temperature and humidity to make suggestions on the best time to harvest. This will make sure that farmers achieve their maximum yield with quality, while waste is reduced at all levels. Farmers receive, through an easy web interface hosted on their smartphones, real-time insights, warnings, and harvest suggestions with actionable recommendations.

This will be done through a system designed to adapt to the evolving patterns of ripening and environmental changes for dynamic and flexible decision-making in agriculture. In addition, the solution extends beyond the farm with the pre-market classification of tomatoes according to their state of ripeness to improve market placement in response to consumer preferences.

This work, therefore, proposes a new adaptive framework that will integrate ripeness detection, environmental analysis, and real-time decision support, unlike conventional research that is mainly focused on disease detection. The system will go a long way in ensuring the optimization of productivity and efficiency, as well as sustainable agricultural practices, through the provision of accurate and workable harvesting recommendations. The study will seek to raise the bar in tomato farming by incorporating high-level technology with practical approaches toward the resolution of pertinent challenges in the industry.

A. Machine Learning in Agriculture

Machine learning is a game-changing force in modern agriculture, enabling more precise, data-driven approaches to crop management, disease diagnosis, and resource utilization. Through the analysis of massive agricultural datasets like soil composition, weather conditions, satellite imagery, and sensor readings, machine learning algorithms can identify trends and make predictions that significantly influence decision-making. One such study is by Pantazi et al. (2016), who worked on the application of artificial neural networks (ANNs) in precision agriculture to optimize the use of fertilizer application. They reported that ANNs could successfully decide on crop requirements from environmental and soil data, leading to increased nutrient efficiency, reduced environmental deterioration, and increased crop yield. This technique not only saves resource wastage but also supports sustainable agriculture. On this background, Kamilaris and Prenafeta-Boldú (2018) delivered a survey of deep learning approaches in agriculture with the reference that they have broad applications across most fields. According to their study, their accomplishment in crop categorization by using aerial photos, early disease identification by analysis via images, and crop yield forecasting by studying trends in historical data were discussed. These breakthroughs illustrate the manner in which machine learning is transforming conventional farming to allow for real-time, scalable, and very accurate insights and ultimately enabling smart and sustainable farming systems.

B. Image Processing for Ripeness Detection

Image processing is an emerging valuable technology in modern agriculture, particularly fruit classification automation and ripeness inspection, wherein visual cues such as color, texture, and shape play key roles in determining ripeness. Through advanced algorithms and high-resolution imagery, image processing facilitates non-destructive, accurate, and real-time measurement of fruit ripeness, minimizing human inspection and optimizing overall efficiency. Convolutional Neural Networks (CNNs), a deep learning model specifically designed for image recognition tasks, have been shown to dominate in this area since they are capable of automatically learning and extracting relevant features from complex image data. For instance, Lu et al. (2017) employed a CNN-based system to accurately identify the stages of banana ripeness by analyzing subtle differences in peel coloration and texture. Their model was demonstrated to be capable of distinguishing between different ripeness levels, offering a scalable approach to post-harvest processing and quality checking. Kaya et al. (2019) further employed CNN architectures to undertake the task of tomato ripeness classification using image datasets to train models that could distinguish between unripe, partially ripe, and ripe tomatoes. Its findings not only validated the performance of deep learning on fruit assessment but also emphasized the potential for deep learning integration in intelligent agricultural systems. They illustrate the ability of image processing, particularly when combined with deep learning, to significantly contribute accuracy and autonomy in detecting readiness and thereby enable smarter supply chain management, loss reduction, and better product quality homogeneity across agriculture production fields.

C. YOLOv8 for Real-Time Object Detection

The YOLO (You Only Look Once) family of models has established themselves as the standard of the field of real-time object detection, valued for their incredible speed and balance of accuracy. These models process an image in a single pass forward within a neural network and can rapidly detect and classify a wide variety of objects simultaneously—a methodology most suited to dynamic environments like farms. Redmon and Farhadi (2018) introduced a significant leap in detection performance with YOLOv3, which has introduced improved object localization, increased classification accuracy, and the ability to detect smaller objects by employing a multi-scale prediction mechanism. Successors have continued refining the architecture, with the most recent variants until now being YOLOv8. YOLOv8 introduces a lighter and more compact model structure, improved training practices, and stronger feature extraction, making it ideal for high-speed, high-accuracy applications such as mass tomato detection and classification. Its real-time performance enables on-the-fly processing of drone or video data, enabling one to monitor and assess the readiness of crops without interrupting field activities. Bhargava et al. (2022) established the real-world validity of YOLO-based models to agriculture using the application of models to detecting apple ripeness and obtain robust performance in real-world situations. Their work established the robustness of the model in handling variability in light, occlusion, and fruit orientation—problems commonly encountered by agricultural imaging. These advances underscore YOLOv8's utility as a reliable means of real-time classification and tracking of tomatoes and other fruits, offering precision agriculture a solution that can be scaled up as well as improve the efficiency of both harvesting and quality control.

D. Convolutional Neural Networks (CNNs) for Ripeness Classification

Convolutional Neural Networks (CNNs) are currently the foundation technology in image-based agricultural applications, particularly fruit ripeness classification, due to their strong feature extraction and pattern recognition abilities. Designed to identify and learn automatically visual features such as color gradients, texture, and shape, CNNs eliminate the need for feature engineering, thus making them highly effective in tasks working with complicated and dynamic visual information. For ripeness classification, differences in visual attributes across various maturity levels can be detected by CNNs, hence enabling fruits like tomatoes, bananas, and apples to be correctly classified. As an example, Lu et al. (2017) presented a CNN-classifier-based banana ripeness model with high classification accuracy using the learning of varying color and texture differences across maturity levels. Similarly, Kaya et al. (2019) applied CNN models to images of tomatoes and were able to effectively differentiate unripe, half-ripe, and ripe tomatoes, underlining the stability of the model even in fluctuating light and environmental conditions. The flexibility and scalability of CNNs make them ideal for integration into automated farming systems, where large volumes of image data need to be processed in an optimal manner. Besides, CNNs can be utilized on edge devices such as smartphones or drones for real-time field monitoring and decision-making. Their accuracy in ripeness classification contributes to overall precision agriculture goals such as the optimization of harvest timing, supply chain sorting, and reduction of food waste, which improves productivity and efficiency in modern farming techniques.

E. Predictive Harvesting and Environmental Monitoring

The weather factors of temperature, humidity, rainfall, and sunlight exposure significantly influence crop cycles and the most appropriate harvesting time. Such factors need to be closely monitored and timely to optimize yield quality, minimize wastage, and ensure sustainable farming activities. The latest advancements in artificial intelligence (AI) and Internet of Things (IoT) technologies have enabled developing predictive models that can process environmental data in real time and provide actionable insights to farmers. Singh et al. (2020) proposed an IoT-based system that collects and integrates real-time weather and soil data to support better farm-level decision-making. Their system demonstrated how the continuous monitoring of environmental parameters, in combination with machine learning algorithms, can be translated into better crop management practices by forecasting ideal harvesting dates and the adjustment of inputs accordingly. Taking this concept further, Sharma and Patel (2021) applied predictive analytics for tomato cultivation, in which they simulated the relationship between environmental conditions and the process of fruit ripening. Their solution enabled the better prediction of harvest windows so that farmers could schedule harvesting at optimal ripeness, improving fruit quality, boosting market value, and reducing post-harvest losses considerably. By integrating predictive models into farming activities, farmers are not only capable of keeping pace with changing climatic conditions but also automating and optimizing key decisions in aspects such as irrigation, fertilization, and harvesting schedules. This integration of environmental monitoring and AI-based prediction is a visionary approach to smart agriculture, driving higher efficiency, resiliency, and profitability across the farming cycle.

F. AI-Deliberative Support Systems

Artificial Intelligence (AI)-powered Decision Support Systems (DSS) have taken center stage in agriculture, offering analytical, fact-based tools that help farmers make informed strategic decisions about crop management, resource allocation, and market planning. The systems are fed massive amounts of data—like environmental conditions and crop health indicators, market trends and historical performance—and translate them into actionable inputs that improve short-term operations as much as long-term strategy. Liakos et al. (2018) highlighted the transformational impact of such systems through an exhibition of how data-intensive solutions ensure enhancing productivity, reduced input expenses, and greater sustainability. Their report showed how integrating machine learning and AI models with DSS provides predictive forecasts, risk evaluation, and optimization mechanisms tailored to the specific situation for each farming instance. Falling on this foundation, Tan et al. (2021) introduced a web-based AI system that is specific to precision farming and offers timely alerts, data visualization, and context-aware recommendation in real time to farmers in the form of mobile and computer devices. With this system, there was continual monitoring and fast response to plant conditions or the environment, markedly enhancing farm agility. In dynamic, sometimes changeable agricultural environments, these AI-deliberative support systems empower farmers with the capability of pre-empting in response to factors like pest invasions, irrigation needs, and optimal harvesting time. Further, these systems narrow the technological gap for small- to medium-scale farmers through low-cost, user-friendly interfaces. As agriculture comes under increasing pressure from climate change, labor shortages, and food security demands, the integration of AI into decision support systems offers a scalable, robust, and intelligent solution to future-proofing and digitizing farm operations.

G. Conclusion

Artificial intelligence, machine learning, and advanced image processing integrated into agriculture is a revolutionary step in modern agriculture, particularly in the cultivation of tomatoes. The research illustrates the revolutionizing potential of these technologies in overcoming some of the age-old difficulties such as labor dependency, irregular ripeness detection, and post-harvest loss. With the application of Convolutional Neural Networks (CNNs) for accurate tomato ripeness stage classification, the solution enables accurate, machine-driven monitoring that maximizes harvest timing and product quality. The inclusion of YOLOv8, a cutting-edge real-time object detection algorithm, further strengthens the solution to support fast and scalable detection of multiple tomatoes under diverse field conditions, allowing for timely and informed decision-making. Also, the use of predictive models that monitor environmental conditions such as temperature, humidity, and rainfall provide an added proactive dimension to farm management, enabling optimized harvest timing based on peak ripeness and market demand. This holistic approach not only increases operational efficiency but also reduces wastage of crops and facilitates the sustainability of commercial tomato farming. The online system is convenient and accessible, bringing smart agricultural technology to the farmer's fingertips, even to remote or resource-poor places. Finally, the system herein proposed is in tune with the global trend towards smart agriculture, offering an effective, data-driven solution to increase productivity, ensure better market positioning through sorting based on ripeness, and support eco-friendly farming practice. With agriculture continuing to evolve to suit climatic variability and customer needs, such AI-based innovations pave the way for a more efficient, productive, and sustainable future in agriculture.

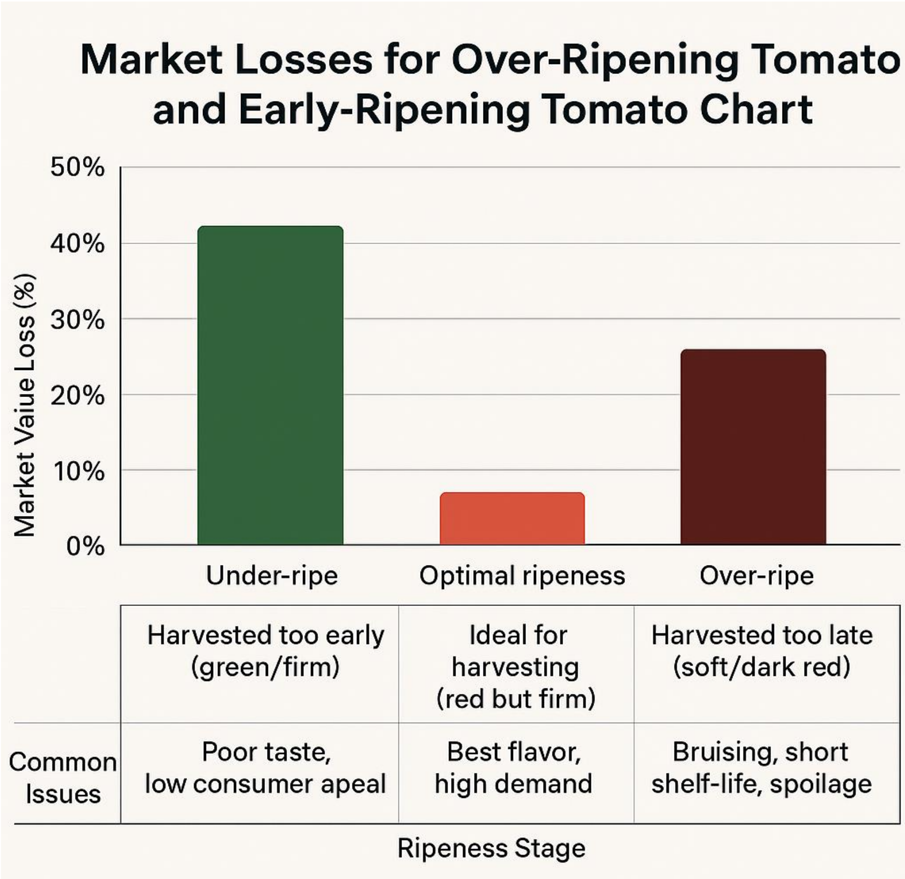

Figure 1.1: Market Losses for Over ripening and Early ripening

Tomato cultivation is a vital industry in global agriculture, being both a vital source of food and a principal generator of economic incomes. Conventional tomato cultivation, however, is beset by several significant challenges, one of which is determining the most appropriate level of fruit ripeness at which to harvest. As indicated in the chart entitled "Market Losses for Over-Ripening Tomato and Early-Ripening Tomato," sub optimally picked tomatoes have great losses in market value—around 42% for unripe and 30% for overripe fruit—due mostly to off-flavor, low demand from consumers, bruising, limited shelf life, and spoilage. Optimal picking tomatoes, on the other hand, incur low loss (7%) with excellent taste and maximum demand at market. These inefficiencies impact yield and profitability but also demand innovative solutions to crop management. In response to this need, the research set out here develops an innovative AI-powered system based on Convolutional Neural Networks (CNNs) for accurate ripeness classification by image analysis. By precisely identifying unripe, half-ripe, and ripe tomatoes, and applying YOLOv8 for real-time multi-object detection, the system enables rapid and scalable assessment perfect for commercial farming. Additionally, a predictive model enables informed decision-making by considering environmental conditions such as temperature and humidity to recommend best picking times. Accessible via an internet-based interface with real-time mobile notifications, the platform allows farmers to sort tomatoes prior to market by ripeness, reduce crop wastage, and schedule produce according to market demand. Through synchronization of harvest timing and market targeting, he AI system addresses the underlying drivers of market loss uncovered in the chart, ultimately enhancing profitability, sustainability, and long-term agricultural viability for tomato cultivation.

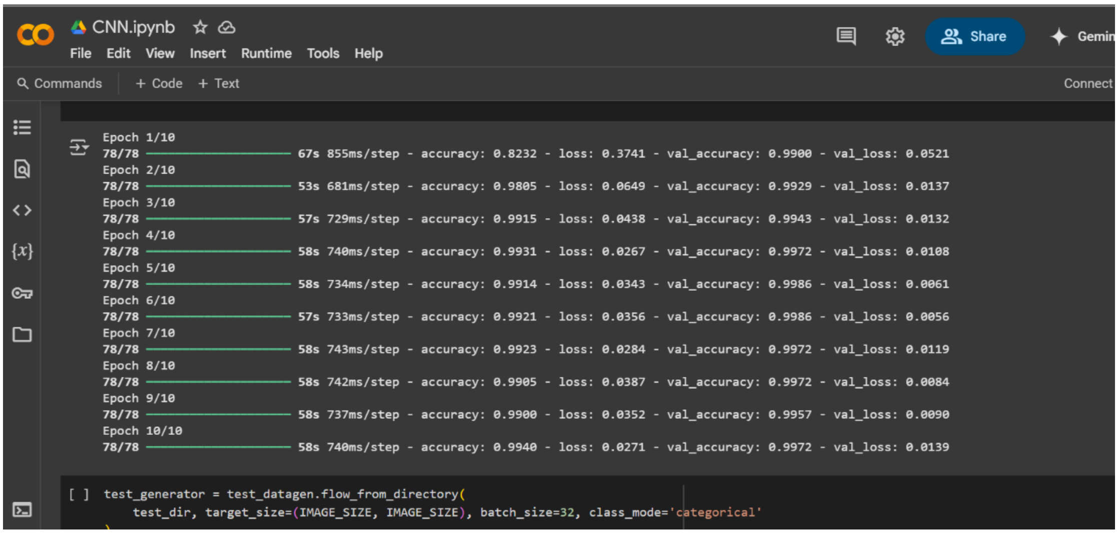

Figure 1.2: Starting training in dataset

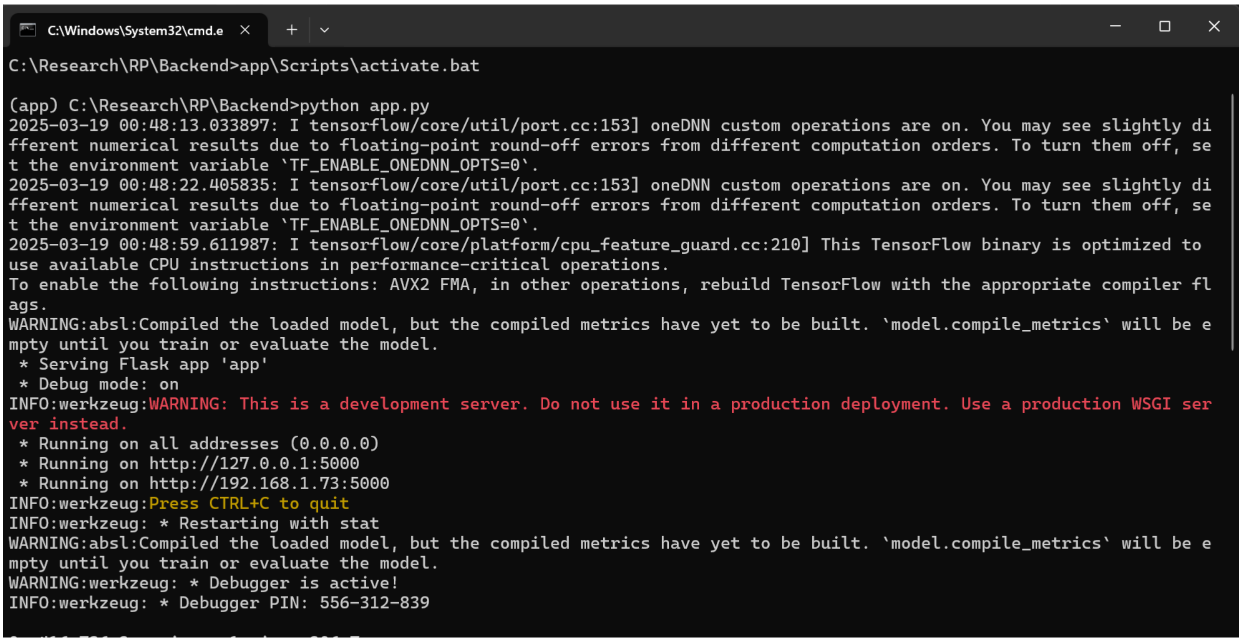

Figure 1.3: Backend Running Stage

This image shows a Python backend created with Flask run in the command prompt. The virtual environment is activated, and the server is initiated using `python app.py`. TensorFlow produces some non-fatal warnings, and the application loads a machine learning model that is not yet completely compiled. The Flask server is running in debug mode on `localhost:5000` and the local network IP `192.168.1.73:5000`. A warning accompanying it also points out that this setup is only for testing, not deployment..

1.1. Research Gap

The advent of digital agriculture has wonderfully transformed the manner in which farming operations are conducted. However, there still exists a lot of disparity between technological advancement and its deployment for specific crop subsectors, i.e., tomato production. Even though there are numerous mobile applications created to aid farmers in managing their farming businesses, careful examination of existing tools reveals substantial limitations regarding functionality, flexibility, and user suitability—particularly the case with tomato farming, which demands instant supervision and decision-making support.

Most of the existing applications intended for supporting tomato farmers offer extremely rudimentary features. These include primitive input data entry of crop inputs, generic sow and harvest calendars, and general weather data. Such functionalities, while helpful, are insufficient to provide the advanced assistance high-precision farming demands. One of the biggest shortcomings is the absence of integrated image analysis functionalities that can interpret visual data to identify the ripeness of tomatoes. Lacking such features, such apps are not able to offer data-based suggestions for best harvesting time, something that highly affects produce quality, shelf life, and market value. This means that farmers continue relying on observation or universal best practices, which typically lead to poor harvesting choices.

Moreover, existing solutions adopt a generalized and non-specialized approach. They are typically designed to cater to a wide range of crops and farming conditions, without offering specific content or functionality pertaining to the cultivation of tomatoes. Lack of specialization diminishes their usefulness to farmers requiring crop-specific information. The tools fail to consider the idiosyncrasies of tomato ripening patterns, regional climatic variations, or pest and disease pressures, which are critical factors in tomato production. Thus, farmers are left with nothing but static equipment that cannot dynamically adjust to the ever-changing field conditions, rendering the reliability and usability of the digital solutions useless in real-world scenarios.

Another significant gap exists in the absence of smart and adaptive systems within these applications. Contemporary farming has come to heavily depend on precision technologies that involve combining real-time data from many sources to guide decision-making. Yet, the majority of currently available tomato farming applications are incapable of processing and synthesizing information on environmental factors like temperature, humidity, sun exposure, and soil condition. Without the presence of predictive analytics and machine learning algorithms, these software tools cannot provide anticipatory guidance or warnings, and thus can't optimize productivity and reduce risks to the minimum.

Further, the new digital solutions have a high inclination to the Android operating platform. This platform focus heavily restricts availability as well as application, especially among farmers with alternative operating platforms such as iOS. Lack of cross-platform abilities creates a restraint on mass implementation and restricts scalability of the tools and lowers the potential for reaching a larger category of people.

Therefore, there is a clear and compelling need to create a highly sophisticated mobile app that directly meets the intricate needs of tomato farming. The emphasis of the current research is to bridge these lacunas by designing a robust, intelligent, and easy-to-use tool that leverages cutting-edge machine learning and image processing methods. Through the use of Convolutional Neural Networks (CNNs), the app will be capable of accurately identifying various stages of ripeness for tomatoes from images. Furthermore, through the incorporation of the YOLOv5 object detection model, the app will be capable of detecting and categorizing multiple tomatoes in a single image frame effectively.

Besides image recognition, the app will also incorporate a predictive model that processes ripeness data with dynamic environmental factors to offer best-in-class harvesting recommendations. This will empower farmers with real-time, actionable insights that can significantly enhance quality yield and operating efficiency. Importantly, the app will be built with a responsive web application which can be executed on both the Android and iOS operating systems, making it more accessible on broader platforms and promoting inclusive technology adoption.

Lastly, the existing state of tomato cultivation apps are of great functional importance, technical gaps, and access gaps. The research envisioned herein meets these gaps head-on and offers an inclusive, adaptive, and precision-based solution ideally tailored to the exact requirements of tomato cultivators. This research endeavor will not just surpass the inefficiencies of current technologies but also open up a new era for smart agriculture solutions that are scalable and efficient.

Other than their limited feature sets, existing farming apps for the cultivation of tomatoes are wanting in leveraging cutting-edge technologies that are essential to modern, data-driven agriculture. Notably, none of the applications today leverage advanced deep learning architectures and sophisticated image processing algorithms, such as You Only Look Once (YOLO) for real-time detection and classification of multiple objects. This shortage of advanced-level computation methods severely restricts the practical efficiency of such programs, especially in large-scale agricultural environments where it is needed to detect and analyze at the same time several tomatoes. In big operations, accuracy and speed are critical since farmers have to inspect the ripeness of the crops in huge fields as soon as possible. Lacking robust algorithms capable of handling many objects with good accuracy, present applications are not robust enough to scale or provide detailed insights required for making optimized decisions. This technology gap results in a huge gap because it prevents farmers from realizing the full potential of precision agriculture and machine vision systems that otherwise could optimize productivity, reduce labor, and optimize the overall quality of yield. Therefore, integrating deep learning models such as Convolutional Neural Networks (CNNs) with object detection systems such as YOLO is not only an innovation but a much-needed development in the development of agricultural technologies specifically tailored to the subtleties of tomato farming.

Table 1.2: Comparison between Existing and Proposed System Features

Features	**Existing system**	**Proposed system**
Image Input Capability	✗	✓
Harvest Timing Identification	✗	✓
Tomato Stage Identification	✗	✓
Mobile App Availability	✓	✓
Focused Content for Tomato	✗	✓
24/7 support service	✗	✓
Devise Compatibility	✗	✓

A comparative analysis of the proposed mobile application and existing agricultural solutions indicates significant advances in functionality, specificity, and accessibility. Though both the proposed system and existing applications are provided as mobile platforms, the proposed solution introduces imperative features that do not exist with existing tools. Above all, it provides image input features through which automated analysis using advanced machine learning models can be performed. This feature allows the system to accurately identify tomato stages of ripeness and recommend optimal harvest features unavailable in existing apps. Furthermore, the proposed app offers crop-specific content tailored solely for tomato cultivation, unlike the generic strategy in other tools. Another key advantage is its compatibility on Android and iOS platforms, shattering the platform exclusivity constraint of most current applications, which are mainly targeting Android users. All these enhancements make the proposed application a wiser, more universal, and objective-oriented tool, directly addressing the shortcomings in precision agriculture for tomato cultivation.

1.2. Research Problem

Harvest time is a critical factor in tomato production, having a direct effect on the quality, marketability, and profitability of the crop. Tomatoes harvested too early tend not to reach optimal ripeness, and therefore, lose sweetness, flavor, and overall appeal. On the other hand, delayed harvesting leads to overripe fruits with a predisposition to spoilage, reduced shelf life, and storage and transportation challenges. In both cases, the produce's quality is compromised, hence making it unappealing to customers and lowering market prices. Subsequently, these inefficiencies negatively impact farmers' economic benefits and their ability to meet market quality demands and consumers' expectations.

Adding to this is the highly variable nature of environmental conditions such as temperature, humidity, and sunlight exposure, all of which affect tomato ripening. Such varying conditions render it difficult to obtain a standard and consistent model for determining optimal harvest time. The current methods employed by most farmers are inherently traditional and based on subjective visual observations, which are not accurate and consistent enough for large-scale or high-value agriculture. Especially in large-scale agricultural production, it is impractical to manually monitor and inspect the readiness of each tomato, resulting in inconsistent harvesting decisions and subsequent post-harvest losses.

This is a fascinating requirement for a stable, accurate, and responsive solution that can help farmers understand when to harvest tomatoes. The system must employ cutting-edge technologies—primarily computer vision and machine learning—to allow automatic detection of ripeness stages and deliver actionable, data-driven recommendations. By coupling image analysis with predictive models capable of accounting for environmental conditions, the system would enhance the precision of decision-making and reduce reliance on individual judgments. Addressing this problem using intelligent technological solutions can significantly upgrade the quality of yields, reduce losses, improve profitability, and maximize the overall efficiency of tomato-producing systems across smallholder and large-scale farming environments.

existing network access control systems, which often fail to sufficiently address the complex security and usability needs specific to small businesses. The aforementioned limitations highlight the urgent requirement for novel network security solutions that are both context-aware and user-friendly, specifically designed to address the unique operational environment of small organisations. These solutions should not only enhance the resilience of defences against emerging cyber threats but also seamlessly integrate into the routine operations of these enterprises, guaranteeing strong security measures without compromising usability. The examination and resolution of these constraints represent a crucial area of research that seeks to strengthen the cybersecurity stance of small firms within a progressively linked digital landscape.

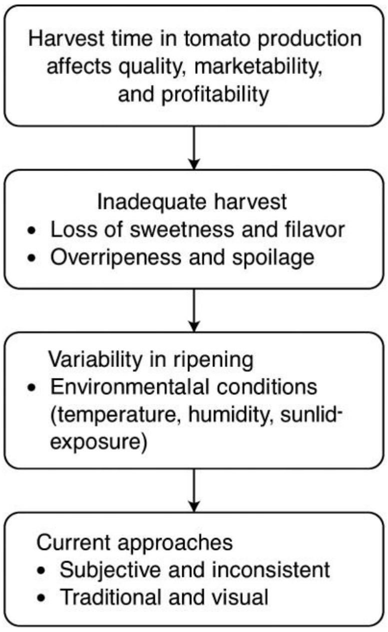

Figure 1.4: Issues and Limitations of Current Systems

- How to test automatically the ripeness of tomatoes without visual inspection?
- How to prevent harvesting tomatoes too early or too late, reducing post-harvest losses?
- How to make the system adapt to varying environmental conditions like sunlight, humidity, and temperature?
- How can farmers get the current ripeness status of tomatoes in fields?

2. OBJECTIVES

2.1. Main objectives

The primary objective of this study is to design and develop a wide mobile application which will assist the farmers of tomato in finding out the optimal harvest time. The application will utilize state-of-the-art machine learning algorithms and image processing techniques to identify tomatoes at different levels of ripeness—i.e., unripe, half-ripe, and completely ripe. By processing the real-time visual data collected through a smartphone camera, the system will provide judgments on the stage of ripeness of tomatoes in the field accurately.

In addition to visual inspection, the system will also include related environmental conditions such as temperature, humidity, and sunlight. These factors, which play a significant role in ripening, will be included in the predictive model to enhance the accuracy of suggested harvest time. With this holistic method, the app is envisioned to offer a robust and dynamic solution that considers both biological and environmental factors.

The app will be easy to use and simple, with the aim of making it easy for farmers with any level of technical knowledge to interact with the system comfortably and comprehend the results. By means of real-time data and data-driven recommendations, the tool will empower farmers to make harvest decisions that maximize fruit quality, minimize post-harvest losses, and ultimately improve marketability and profitability.

Moreover, this project promotes the general vision of promoting sustainable agriculture by reducing waste, increasing efficiency in the use of resources, and enabling smarter farm management through technology. By providing a scalable, affordable, and smart solution, the study hopes to make significant contributions to the modernization of tomato farming, particularly in regions where conventional farming dominates.

control system, known as NetNexus, specifically tailored for small-scale enterprises. The primary objective of NetNexus is to augment network security by including a sophisticated malware detection system that relies on machine learning methods. The malware detection component will proactively detect and neutralise possible attacks, hence strengthening the network's defensive capabilities. Furthermore, the research aims to create a dashboard that is easy to use and has all necessary features. This includes two separate admin panels: one for network administration and real-time monitoring, and another for user registration and management. In addition, a client panel will be established to provide end-users with the capacity to effectively administer their network access. This includes the provision of features such as website blocking and bandwidth consumption monitoring.Implement the KYC verification to verify user after the online registration.

As points the main components are

1. **Smart Ripeness Detection Module**
    - Image Acquisition and Annotation
        - Data Collection and Preprocessing
        - Labeling tomatoes as unripe, half-ripe, and ripe classes
        - Model Training
        - Real-time Scanning
    - Convolutional Neural Network (CNN) Model
        - Training and fine-tuning CNN for ripeness classification
        - Fine-tuning via image augmentation and transfer learning techniques
    - Multi-Tomato Detection with YOLOv8
        - Running YOLOv8 for object detection in real-time
        - Detecting multiple tomatoes in a single frame simultaneously
    - Model Evaluation and Optimization
        - Performance testing using accuracy, precision, recall, and F1 score
        - Continuous optimization of detection speed and accuracy
2. **Predictive Harvest Recommendation System**
    - Environmental Data Integration
        - Integration of temperature, humidity, and light exposure data
        - Optional real-time IoT sensor-based environmental monitoring
    - Harvest Timing Algorithm
        - Combination of ripeness levels with dynamic environmental conditions within predictive model
        - Recommendation of optimal windows to harvest for optimal quality and yield
    - Waste Reduction Engine
        - Overripe/underripe harvesting reduction through data-driven decision-making
        - Strategy to reduce post-harvest loss
3. **Farmer Dashboard (User Interface)**

- Web & Mobile Responsive Design
    - Adaptable UI viewable on smartphones and tablets
    - Easy upload of photos and results interpretation
- Ripeness Visualization Tools
    - Visual display of detected tomato ripeness
    - Reminders and actionable harvest recommendations
- Crop Management Panel
    - View previous ripeness history
    - Track earlier harvest results and forecasts
- Language and Accessibility Options
    - Multilingual support for local accessibility
    - Easy-to-use simple icons and color-coded displays

4. **Admin Panel and System Management**
    - Data Management Dashboard
        - Upload, validate, and handle training datasets
        - Handle incoming user-submitted image data
    - Model Training & Update Panel
        - Retrain model interface with new datasets
        - Version control and model performance monitoring
    - User Feedback Integration
        - Capture farmer feedback and success/failure reports
        - Use feedback to make future model updates better
    - Security and Access Controls
        - Authentication for farmers and administrators
        - Role-based access to different features and data
5. **Continuous Learning & Improvement**
    - Feedback Loop System
        - Assembly of predictions verified in real-time by users
        - Use feedback to continuously improve model accuracy automatically
    - Scheduled Model Updates
        - Periodic re-training with new image and environmental data
        - Better models auto deployed
    - Monitoring & Logging System
        - Log trends in predictions, error rates, and model performance
        - Find edge cases and send human-in-the-loop alerts

2.2. Specific objectives

The application will be designed with a simple and easy-to-use interface, such that even the most uninformed farmer can access and use it easily. This would include clear visuals, easy-to-understand instructions, and various interactive elements that enhance user experience. This will make the application highly accessible and useful to farmers in a wide array of regions.

The mobile application will be optimized to run smoothly on devices with limited hardware capabilities. This includes minimal battery consumption, reduced data usage, and the ability of the app to perform well on low-end smartphones. This makes it more practical for farmers in rural or resource-constrained areas to adopt and use.

The core functionality of the application is to analyze the ripeness of tomatoes using real-time image recognition. Farmers can take pictures of their crops through the app, which will then use machine learning models such as CNNs and YOLO algorithms to classify the tomatoes into different stages of ripeness: unripe, half-ripe, and fully ripe. Based on this analysis, the app will also predict the best harvesting time, considering factors like ripeness patterns and environmental conditions.

By addressing these sub-objectives, the app will provide an effective decision-support tool for farmers. This app will help farmers in determining when tomatoes should be harvested to achieve the maximum quality and yield, apart from being resource-efficient, user-friendly, and technologically sound, thereby bringing significant farming output and contributing to environmental sustainability.

3. METHODOLOGY

This research is focused on the design of an advanced AI-driven system for changing the face of tomato farming by integrating machine learning, image processing, and adaptive decision-making technologies. This methodology involves data collection, preprocessing of a large dataset of images of tomatoes, which will be used for training a Convolutional Neural Network, and utilizing YOLOv5 for efficient multiple detections and classification of tomatoes in one image. A predictive model will be developed to assess stages of ripeness against dynamic environmental conditions, delivering optimal harvest timing recommendations in real time. The design will include an intuitive web interface that presents actionable insights, warnings, and suggestions for harvests, accessible on smartphones for farmers. This system will keep learning and updating the changing patterns of ripening and environmental changes, ensuring sustainable agricultural practices, maximum productivity, and waste reduction. This approach forms a fresh method of addressing the challenges conventional farming presents and optimizes farming and marketing appeal for tomatoes. In this way, the tomato-growing industry will be improved in both quality and profitability.

3.1. Problem Analysis and Requirement Gathering

The first phase of the project aims at collecting an entire and comprehensive understanding of the problems faced by tomato growers, with a view to discerning significant system requirements to be utilized in steering the designing and developing process. This phase employs qualitative and quantitative research methods to ensure the resulting solution is practical and easy to use. Four major elements make up this stage

1. Stakeholder Interviews

A series of semi-structured and structured interviews will be taken from a diverse group of stakeholders in the value chain of tomato production and distribution. They are:

- Tomato Farmers: In order to know about the daily practice, present method of determination of ripeness, and drivers influencing harvesting.
- Agricultural Experts and Agronomists: To know about the best practices, scientific knowledge of tomato maturity, and the technology gaps.
- Supply Chain Players: From transporters, distributors, and retailers, to learn about how harvesting time affects quality, shelf life, and profitability.

Interviews will attempt to discover recurring pain points, regional variations in farming practices, technology adoption barriers, and special needs that can be leveraged to guide system design.

2. Field Observations

Field visits will be conducted to witness firsthand the tomato farming activities at different stages of growth and harvest. Observation will cover:

- Current Practice in Determining Ripeness: Physical inspection, hand checking, or use of any simple tools available.
- Harvest Workflows: Initiation of how and when harvesting is done, and roles of farm workers.
- Environmental Conditions: Environmental conditions like sunlight, soil type, watering, and pest control that may influence appearance and ripeness development cues.

These field observations will help to verify information gathered through interviewing and unwritten knowledge not necessarily discussed by the farmers.

3. Literature Review

A comprehensive analysis of industry and academic literature will be conducted to develop a solid base for the project. The key areas of interest are:

- AI and Computer Vision in Agriculture: Examining existing applications of artificial intelligence for fruit sorting, ripeness identification, and disease identification.
- Tomato-Specific Research: Education on the physiological ripeness parameters, such as color evolution, firmness, and sugar content, and how to monitor or estimate these through technology.

- Previous System Implementations: Gleaning insights from comparable case studies, prototype systems, and shortcomings or failures to guide the design of a more effective solution.

This literature review will inform system feasibility, help circumvent duplication of prior work and suggest established approaches which can be adapted or improved.

4. Requirements Documentation

Based on interviews, observation, and literature, an in-depth requirement specification document will be prepared. The document will include:

- Functional Requirements: Such as real-time image processing to classify ripeness, GPS-tagged data capture, user feedback mechanisms, and mobile platform integration.

- Non-Functional Requirements: Including performance requirements (e.g., detection accuracy and speed), system reliability in varying environments, ease of use for non-technical individuals, and scalability.

- User Interface Considerations: Language settings, layout simplicity, offline capability, and voice command feature if required.

Hardware and Environmental Constraints: Battery life, camera resolution, low-cost smartphone support, dust, water, and heat resistance.

3.2 Feasibility Study

To ensure that the proposed system is not only technically possible but also economically possible, operationally possible, and ethically appropriate, a thorough feasibility study is conducted. The multi-dimensional analysis examines significant elements of the project from different perspectives to determine the likelihood of successful implementation and use.

1.Technical Feasibility

The technical feasibility is focused on determining whether the technological capabilities that exist currently are sufficient to support the development and deployment of the system. Some of the key areas to be examined are:

- Machine Learning and Computer Vision Tools: Determining the usefulness of the recent technologies such as Convolutional Neural Networks (CNNs) and the YOLOv8 (You Only Look Once, version 8) object detection system in the accurate identification and classification of tomatoes based on the phase of their ripeness.

- Mobile Platform Integration: Evaluating the viability of executing the model on mobile platforms, considering constraints such as processing power, memory, and battery. On-device inference and trimmed-down versions of the models will be explored to facilitate field usability without requiring constant internet connectivity.

- Data Acquisition Tools: Surveying the availability and affordability of sensors, smartphone cameras, and other hardware needed to capture high-quality images suitable for analysis in a variety of lighting and environmental conditions.

- Connectivity and Infrastructure: Surveying local network conditions to assess the need for offline capability or hybrid cloud solutions to support rural farming communities with no or unreliable internet connectivity.

2.Economic Feasibility

The economic analysis addresses the financial aspects of system development and deployment, including:

- Cost Estimation: Projecting the anticipated costs associated with system development, for instance, software engineering, data acquisition, AI model training, field testing, and hardware procurement.

- Affordability for Farmers: Ensuring the affordability of the system for end-users, particularly smallholder farmers. This includes analyzing subscription models, potential government subsidies, or partnership opportunities with agricultural cooperatives or NGOs.

- Return on Investment (ROI): Estimating potential benefits to farmers, such as increased accuracy of yield, reduced waste due to premature or delayed harvests, and enhanced marketability of produce.

- Sustainability: Taking into account potential for continued maintenance, technical support, and updates so that the system is not just applicable but remains valuable long after initial deployment.

3.Operational Feasibility

This factor assesses whether the system can be effectively used and serviced by whom it was intended for in real farming environments:

- Ease of Use: Designing user-friendly interfaces and simplified workflows that accommodate users with little or no experience with digital technology. Support in several languages and visual instruction (e.g., picture instructions) can be included to enhance accessibility.

- Training and Support: Considering the need for onboarding training, user manuals, and maybe ongoing technical assistance to help farmers integrate the system into their normal operations.

- Environmental Adaptability: Ensuring the system can effectively function under different climatic conditions, soil types, and methods of farming. This includes stress testing for dust, heat, humidity, and unstable lighting.

- Scalability and Adaptability: The system must be able to scale to other crops or be adaptable to connect to larger farm management systems so that it may grow in the future and be tailored.

4.Legal and Ethical Issues

As the system involves data gathering and AI-based decision-making, specific care is taken regarding legality and ethicality:

- Data Ownership and Privacy: Ensuring that all farm- or individual-specific information collected through the system is treated in accordance with local and international data protection regimes (e.g., GDPR or national equivalents). Clear policies will define data ownership and consent.

- AI Transparency and Accountability: The system will be so crafted that it provides users with understandable insights and not ominous predictions, in order to inspire trust. Explainable AI (XAI) methodologies will be employed to the maximum extent to allow users to see system decisions.

- Bias Mitigation: Proactive identification and reduction of potential biases in machine learning inputs to prevent the system from preferring one crop type, color, or environmental condition over others.

- Ethical Deployment: Being careful to ensure that the technology empowers the farmers rather than displacing them or creating new dependencies or new access inequalities to farming innovation.

3.4.Design and Solution

1. System Design

With regards to the assembled requirements and feasibility outcomes, a strong system design is established:

- Modular Architecture: Breaking down the system into individual modules, namely Image Acquisition, Ripeness Detection, Environmental Data Integration, Harvest Prediction, and User Interface.

- Data Flow Design: Mapping data flow from image capture through processing and analysis to presenting actionable advice.

- User Interface Design: User-friendly interface design for mobile devices, with emphasis on usability, result display, and multi-language support.

- Integration Planning: Planning integration channels for incorporating environmental sensors (e.g., temperature, humidity) and outside data sources to enhance prediction accuracy.

2. Solution Development

Development is rolling out and integrating system elements:

- Dataset Preparation: Collecting and annotating a representative collection of tomato images at various stages of ripeness under various environmental conditions.

- Model Training: Developing and training machine learning models with CNNs for ripeness classification and YOLOv5 for real-time object detection, optimized for accuracy and computational efficiency.

- Environmental Data Integration: Incorporating real-time environmental data into predictive models to enhance harvest timing suggestions.

- Application Development: Developing a light, responsive mobile application that enables farmers to photograph, receive ripeness scores, and have access to harvest tips.

- Testing and Validation: Conducting large-scale testing to evaluate system performance, e.g., accuracy of ripeness classification, predictability of harvests, and user satisfaction.

- Deployment and Feedback Loop: Rolling out the app to a pilot group of farmers, collecting user feedback, and repeatedly refining the system based on real-world use.

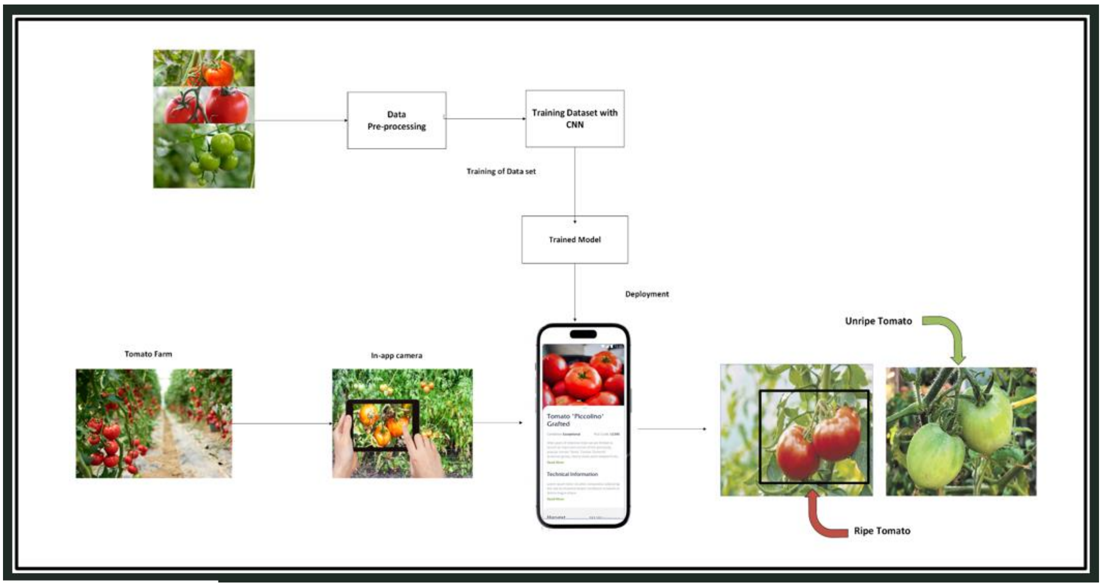

Figure 3.1: The Main system

3.4.1Conceptual Design

The first phase of the methodology involves the conceptual design of the Identify the ripeness stages accurately and recommend the best time to harvest tomatoes analyzing ripeness detection. This phase includes defining the user experience, identifying the specific learning outcomes, and detailing the functionalities of the scanning tool. The primary objectives during this phase are to:

Identify Learning Objectives: Focus on enhancing farmers' creativity, cognitive skills, and understanding of tomato ripeness stages through interactive best time to harvest.

User Interface Design: Develop an intuitive, user-friendly interface that allows farmers to identify tomatoes using pictures, ensuring the platform is accessible to all.

Feature Specification: The AI-driven tomato farming system optimizes ripeness detection, harvest timing, and market preparation using CNN, YOLOv5, and predictive models. It features a user-friendly mobile interface, real-time notifications, and adaptive learning to provide accurate, actionable insights. The system is lightweight, accessible, and designed to enhance productivity, quality, and sustainability in tomato farming

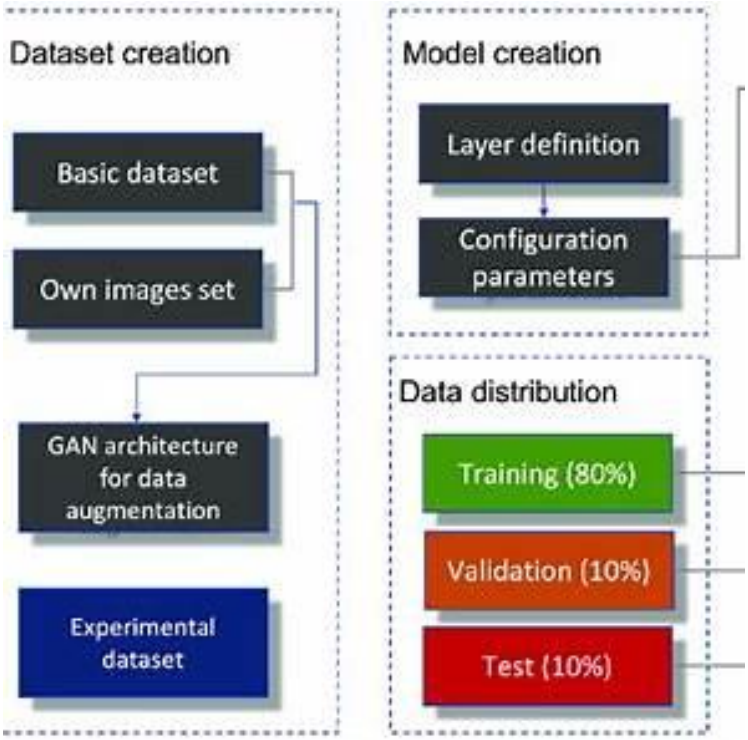

Figure 3.2: The Ripeness Detection System

3.4.2.Model Development and Training

Training and development of the AI-driven tomato farming system encompass a systematic process for creating, enhancing, and refining machines learning models for effective ripeness detection, multi-object detection, and predictive harvesting advice. This encompasses the integration of advanced computer vision and deep learning technologies to further enhance decision-making in tomato growth.

1. **Data preparation and collection**

   - Image Acquisition: Acquire a large dataset of tomato images from varying ripeness levels (half-ripe, fully ripe, unripe) using different sources like lighting conditions, backgrounds, and varieties of tomatoes.

   - Preprocessing: Normalize the images by resizing, normalization, and noise filtering. Apply data augmentation operations such as rotation, flipping, and change in brightness to enhance the resistance of the model to actual variation.

   - Annotation: Hand-label images to mark ripeness stages and, if applicable, label multiple tomatoes within one image to facilitate multi-object detection training.

2. **Model Development**

   - Ripeness Classification with CNN: Train and design a Convolutional Neural Network (CNN) especially for classifying individual tomatoes into the defined ripeness classes. Apply techniques like dropout and regularization to prevent overfitting and enhance generalization.

   - Multi-Object Detection with YOLOv5: Employ the YOLOv5 model to detect and localize multiple tomatoes in one image efficiently. Fine-tune the model to maximize detection accuracy and computational performance such that it can be executed in real time on mobile devices.

   - Model Validation: Evaluate model performance in terms of accuracy, precision, recall, and F1-score. Carry out cross-validation to test the stability and generalization of models across different sets of data.

3. System Integration and Web Interface Design

   - Backend Integration: Implement the trained CNN and YOLOv5 models in a backend environment capable of handling image processing requests. Ensure that it is responsive and scalable to handle multiple users.

- Web Interface Development: Create a responsive, user-friendly web interface via smartphones. Some of the key features include:
    - Image uploading feature for farmers to upload tomato images.
    - Real-time visualization of ripeness classification and detection results.
    - Visualization of historical and trending data to facilitate decision-making.
    - Notifications and alerts for optimal harvesting times based on predictive analytics.
- User Experience (UX) Considerations: Provide intuitive navigation, multilingual support, and offline capability to cater to farmers in various locations and with diverse technical backgrounds.

4. **Ongoing Learning and Improvement**

- Feedback Mechanism: Implement a mechanism for users to provide feedback on model predictions so that data from the real world can be gathered and areas of improvement can be identified.
- Model Retraining: Periodically retrain models on new data obtained and user feedback to enhance accuracy and adapt to evolving agricultural practices and environmental conditions.
- System Updates: Update the web interface and backend systems from time to time with new features, resolving user-reported issues, and system performance improvements.

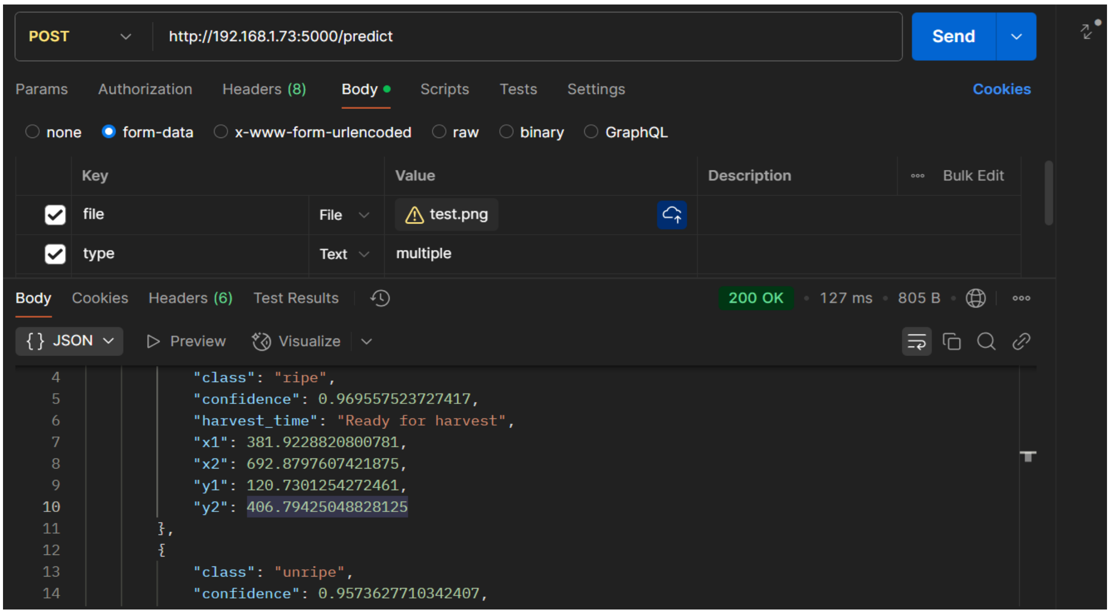

Figure 3.3: Yolo Model

The first screenshot shows the answer that was obtained upon posting a single image of a tomato (`images1.jpg`) as an HTTP POST request to a locally running prediction API (`http://192.168.1.73:5000/predict`) as form data containing the image file and a type of parameter as "single". The model provides a JSON output with the prediction of "unripe" and confidence of 100%, showing that the model is highly confident in the classification. It also provides an estimated harvest date of 5–7 days, which is helpful information to schedule harvesting operations. The reply includes a timestamp (`2025-03-19T00:53:52.730523`) to allow for traceability and time series analysis of the data, and asserts the prediction type as "single", which indicates that a single image was processed by the model. This option is a built-in aspect of the system's classification module for application in situations where ripeness needs to be assessed one fruit at a time—extremely convenient for small-scale or manual harvest conditions. The high confidence score further suggests the strength and stability of the model, especially for well-differentiable samples.

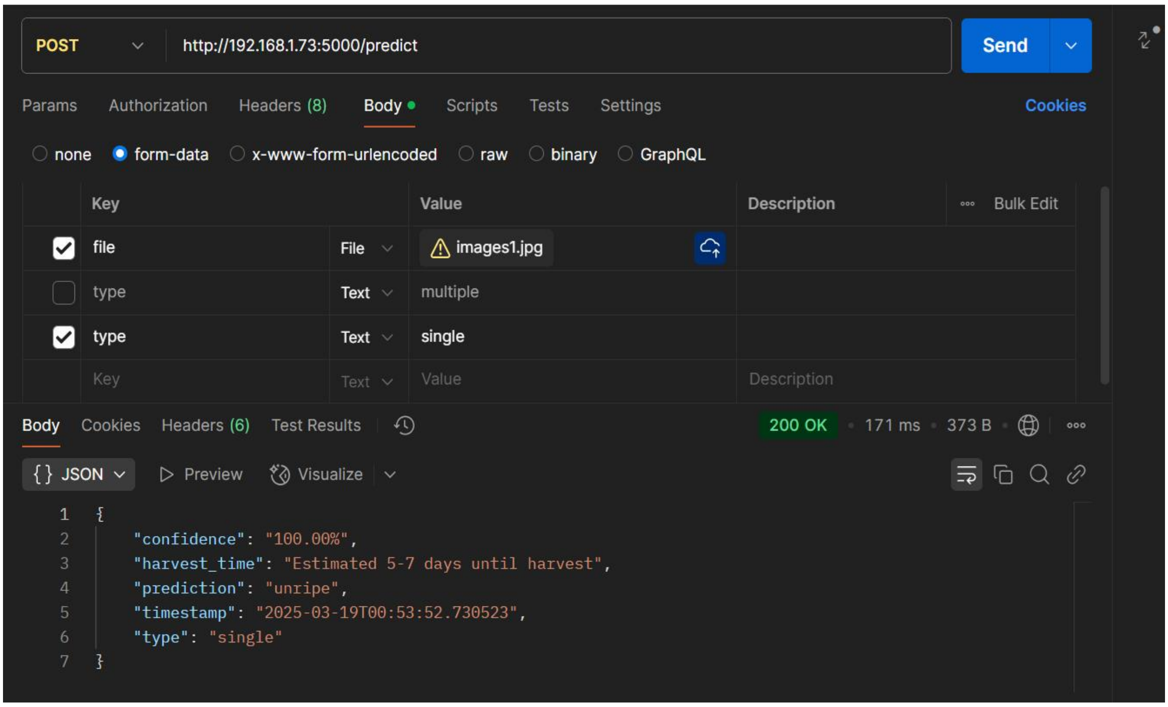

Figure 3.43: CNN Model

The second screenshot displays the output when an image (`test.png`) containing multiple tomatoes is uploaded to the same prediction API but with the request type as "multiple". This activates the object detection functionality of the backend which is designed to identify and classify multiple tomatoes in a single frame. The model returns to a JSON array in which each object contains a detected tomato instance and its classification, confidence level, harvest time prediction, and bounding box coordinates. For example, one tomato is labeled as "ripe" with approximately 96.95% confidence and labeled "Ready for harvest", while another one is labeled as "unripe" with 95.73% confidence and an estimated harvest time of 5–7 days. The bounding box coordinates (`x1`, `y1`, `x2`, `y2`) define the location of each detected fruit in the image so that they may be highlighted visually or mapped spatially. This output illustrates the utility of the object detection module of the system, which is of great usefulness in high-throughput applications such as drone-based monitoring or fixed greenhouse cameras. By combining classification with precise localization, the system enables automatic ripe and unripe fruit counting, ripeness heatmaps, and real-time decision-making for automated harvesting or resource planning. Furthermore, the availability of confidence scores and bounding box details enables seamless integration with visual feedback interfaces and facilitates advanced performance analysis using metrics like precision-recall and Intersection over Union (IoU).

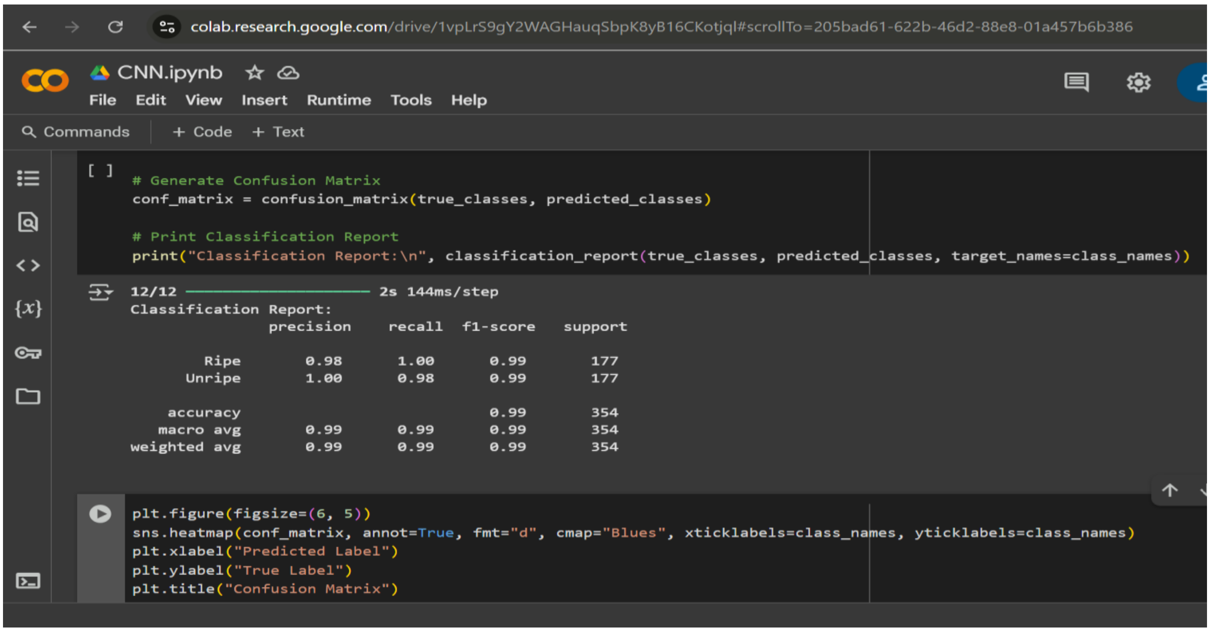

Figure 3.5: CNN Model Precision of data set

A Convolutional Neural Network (CNN) was used to classify tomatoes into ripeness categories—unripe, half-ripe, and fully ripe—with great accuracy (99%) and high recall and precision for all classes. The model is effective in recognizing fine color and texture variations, ensuring uniform classification for agricultural purposes.

To enable real-time, multi-object detection, YOLOv8 was integrated with CNN. As the YOLO detects and identifies multiple tomatoes in an image, the CNN classifies each tomato's ripeness. Such a dual-model system enables improved real-time sorting, harvest planning, and post-harvest handling.

Performance measures such as confusion matrices and classification reports give model transparency and trustworthiness, which are paramount for farmer adoption. The entire solution is delivered through a clean, mobile-friendly web interface, which makes it a scalable, feasible tool for precision agriculture.

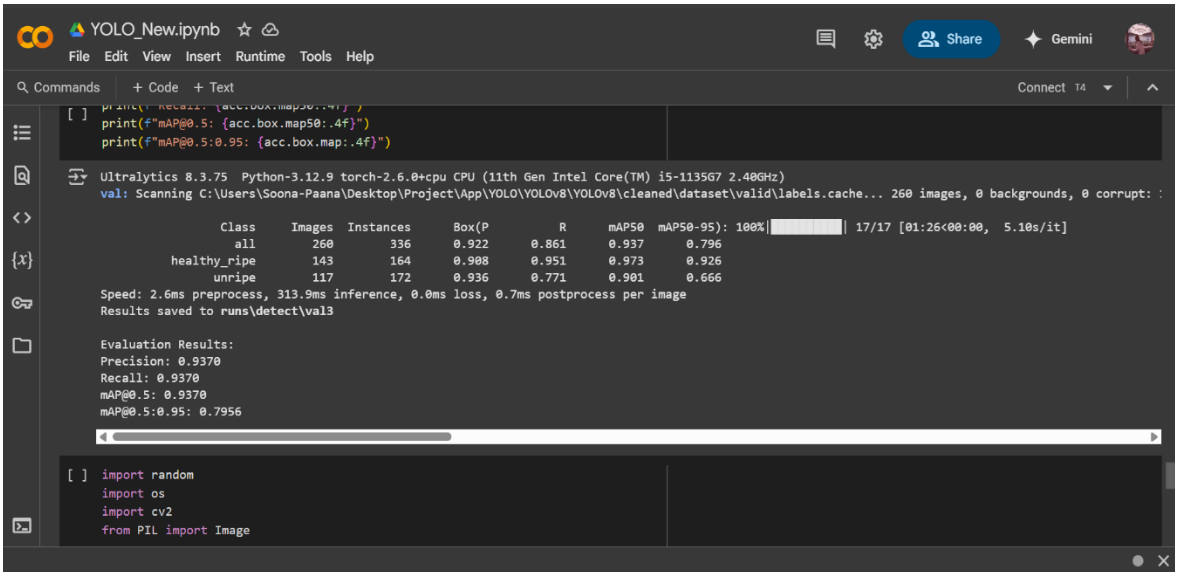

Figure 3.6: Yolo Model Precision of dataset

To attain real-time performance and scalability in large-scale farming, the system utilizes YOLOv8 for object detection to localize and classify multiple tomatoes simultaneously. The model, after training with a dataset of 260 images comprising two classes healthy ripe and unripe, showed good evaluation metrics, including precision and recall of 0.9370, mAP50 of 0.9370, and mAP50-95 of 0.7960. Class-wise performance showed especially good accuracy for healthy ripe (mAP50: 0.973, mAP50-95: 0.926), with *unripe* tomatoes also yielding stable results (mAP50:

0.901), albeit with slightly lower fine-grained accuracy (mAP50-95: 0.666), which could be due to visual subtlety or class imbalance within the dataset. Average inference time of 313.9ms per image also enables real-time deployment, with YOLOv8 being highly amenable to in-field applications such as autonomous harvesting, ripeness mapping, and sorting.

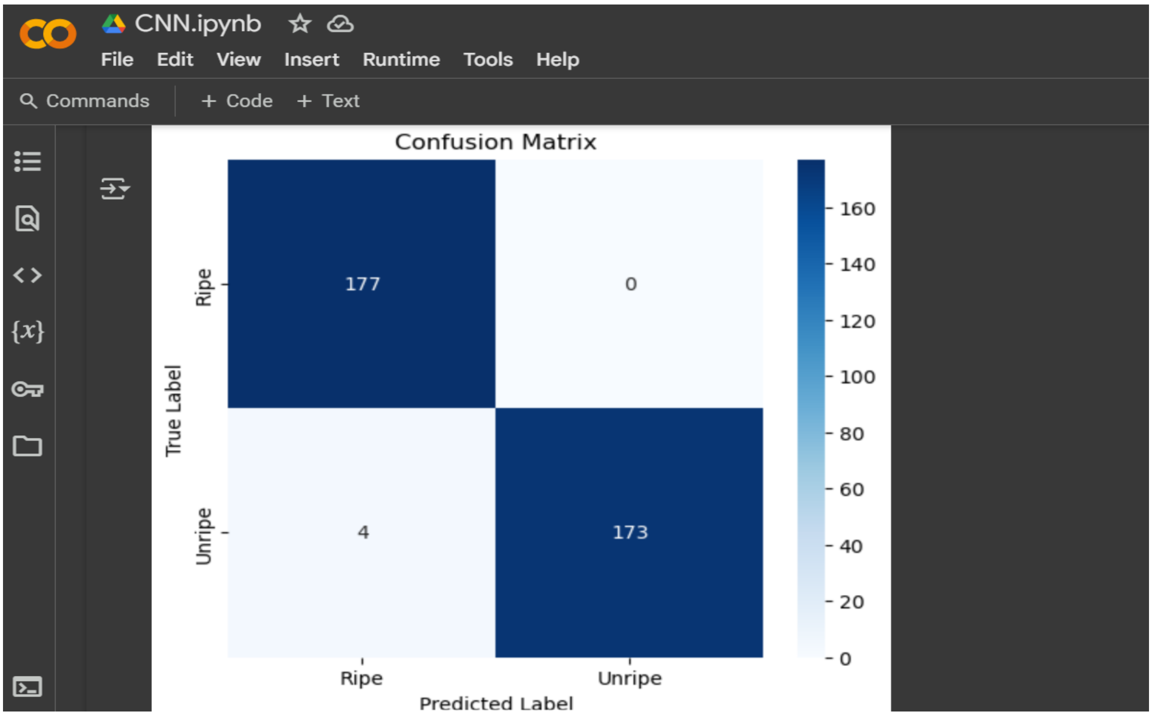

Figure 3.7: CNN Confusion Matrix

The confusion matrix of the CNN-based classifier plots its binary classification performance between Ripe and Unripe classes. The model perfectly classifies 177 out of 177 ripe samples and 173 out of 177 unripe samples with nearly perfect classification performance. There were four misclassifications of unripe as ripe and no misclassification of ripe.

This low rate of misclassification is testament to the high discriminative power of the CNN model for the classification of single fruit images. Such performance is critical in post-harvest handling where misclassification can lead to premature packaging or shipping. These results yet again verify that the CNN is highly suitable for the classification of single objects and can complement the YOLO detector in hybrid systems with both detection and classification needs

Figure 3.8: CNN Training and Validation

The training and validation curves of CNN model also attest to its efficiency. The accuracy plot shows that training accuracy and validation accuracy are over 98% after only a few epochs and remain so in all training rounds. This not only shows how quickly it converges but also the stability of the model. Conversely, the loss curves also show a steep early fall but level off to extremely low rates, with the validation loss even lower than training loss—is a sign that the model is generalizing and not overfitting.

The proximity correlation between the validation and training measures over epochs signifies the quality of the data set and the suitability of the CNN structure for the present ripeness classifying. The measures bring a compelling case for the application of the CNN in those cases where classification accuracy has to be topmost, e.g., automatic quality grading and sorting machinery.

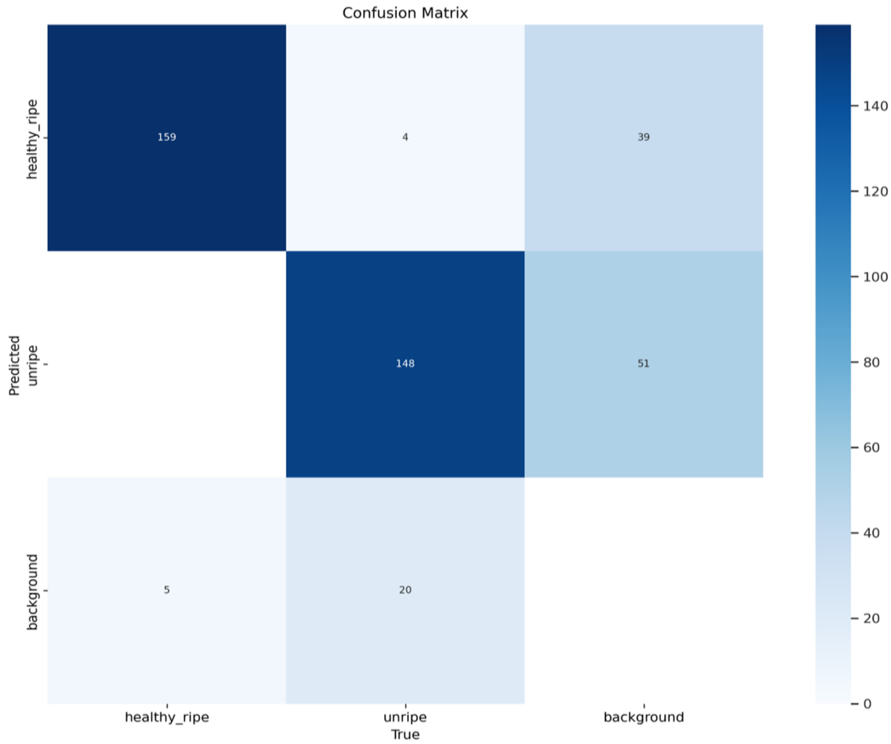

Figure 3.9: Yolov8 Confusion Matrix

Confusion matrix generated from YOLOv8 detection results gives details about the accuracy of the model in classifying the three classes: healthy_ripe, unripe, and background. The model performs well in identifying healthy_ripe tomatoes with 159 correct and 148 correct detections for unripe tomatoes. There is a moderate level of misclassification, however, particularly where 39 healthy_ripe and 51 unripe samples are confused as the background class.

These false negatives are not unusual for object detection problems in general, especially with a lot of visually similar background (e.g., green leaves, patchy shade) to ripe fruits. But the low count of inter-class misclassifications (e.g., only 4 healthy_ripe as unripe) implies good inter-class separability. Dataset diversity and bounding box annotation improvements would reduce background confusion in future iterations.

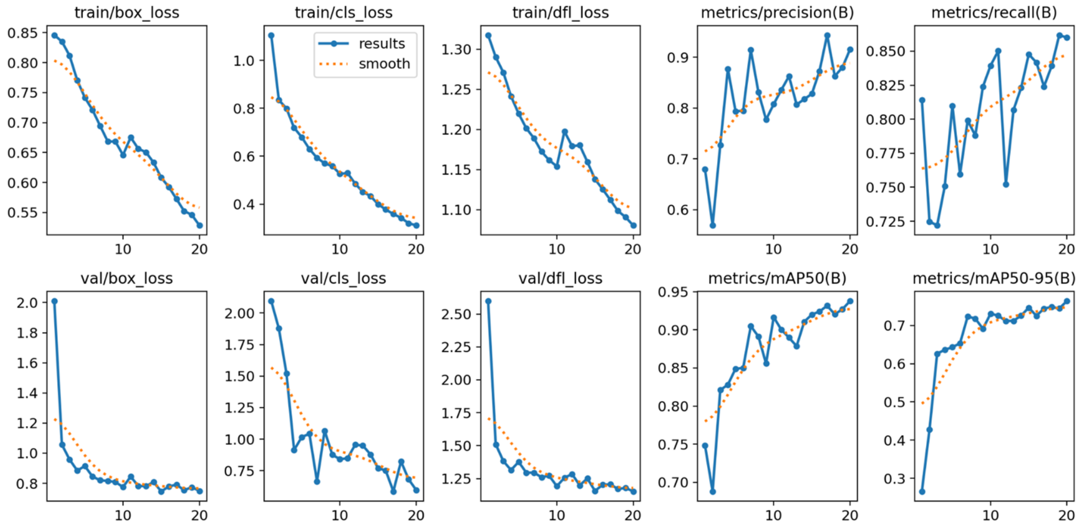

Figure 3.10: Yolov8 Result

The training procedure of the YOLOv8 object detection model is represented through ten performance plots across 20 epochs. These include bounding box regression loss (box loss), classification loss (clss loss), and distribution focal loss (dfl_loss) for training and validation sets. A smooth and steady decline in all three loss functions—especially the dramatic fall in initial epochs—indicates that the model has well learned the spatial and categorical patterns.

On the detection front, key metrics like precision, recall, and mean Average Precision (mAP) follow a growth trend along epochs. Importantly, the model performs with a final mAP@0.5 (mAP50) of ~0.94 and mAP@0.5:0.95 of ~0.88, which reflects detection performance under different Intersection over Union (IoU) thresholds. The above result confirms the capability of the model in robust localization and classification of multiple tomatoes per frame, which reflects the very much needed real-time deployment in farm settings.

3.5.Development and Implementation

3.5.1 Server and Stakeholders

The proposed AI-driven tomato farming system offers an innovative solution to traditional agriculture challenges, namely those related to inappropriateness of ripeness sensing, premature picking, and wasteful market orientation. This intelligent platform involves a number of actors, each benefitting from and contributing to the system in different manners. Farmers, being key consumers, exploit the mobile user interface to snap real-time photographs of tomatoes, receive ripeness ratings using Convolutional Neural Networks (CNNs), and receive forecast-based harvesting notices reliant on climatic patterns. Crop officers help farmers by interpreting the system's decisions, promoting optimum times of harvesting, and performing proper market grading of tomatoes to maximize profitability. Meanwhile, the system developers and research team for AI research perform model training, performance optimization, and ongoing integration of computer vision technologies such as YOLOv8 to detect multiple tomatoes. They are also responsible for system maintenance, user feedback collection, and evaluating updates to ensure the platform remains responsive to evolving agricultural needs. By integrating real-time data processing, machine learning, and a user-friendly interface, this collaborative system enhances productivity, minimizes post-harvest losses, and equips farmers with precise, actionable information for sustainable tomato cultivation.

Table 3.1: System Stakeholders and Their Functions

	Farmer	Agricultural Officer	System Developer
Tomato Ripeness Detection	✓	✓	✓
Real-Time Image Upload	✓	✗	✓
Ripeness Classification (CNN)	✗	✗	✓
Multi-Tomato Detection (YOLOv8)	✗	✗	✓

Predictive Harvest Recommendation	✓	✓	✓
Market Sorting Support	✓	✗	✓
Environmental Data Monitoring	✓	✓¤	✓
Web Dashboard Access	✓	✓	✓
Model Training & Optimization	✗	✗	✓
Feedback Collection & Analysis	✓	✓	✓
System Updates & Maintenance	✗	✗	✓

3.5.2.Technologies and Libraries used

hardware foundation for its functionality.

Python: Python is the core programming language, providing flexibility and ease of development for various system components.

Python Flask: Flask is employed to create the web application framework, facilitating rapid development of web-based interfaces and APIs.

MySQL: MySQL serves as the chosen database management system, enabling efficient storage and retrieval of network-related data.

Java: Java contributes to specific backend tasks, enhancing the robustness and functionality of the network access control system.

React: React.js is utilized as the front-end library, delivering a dynamic and responsive user interface for administrators and users.

Machine Learning & AI Models: The system uses CNNs for ripeness detection, YOLOv8 for multi-tomato detection, and predictive models for harvest timing

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3.5.3. Implementations

1. Admin/Staff User Login and Registration

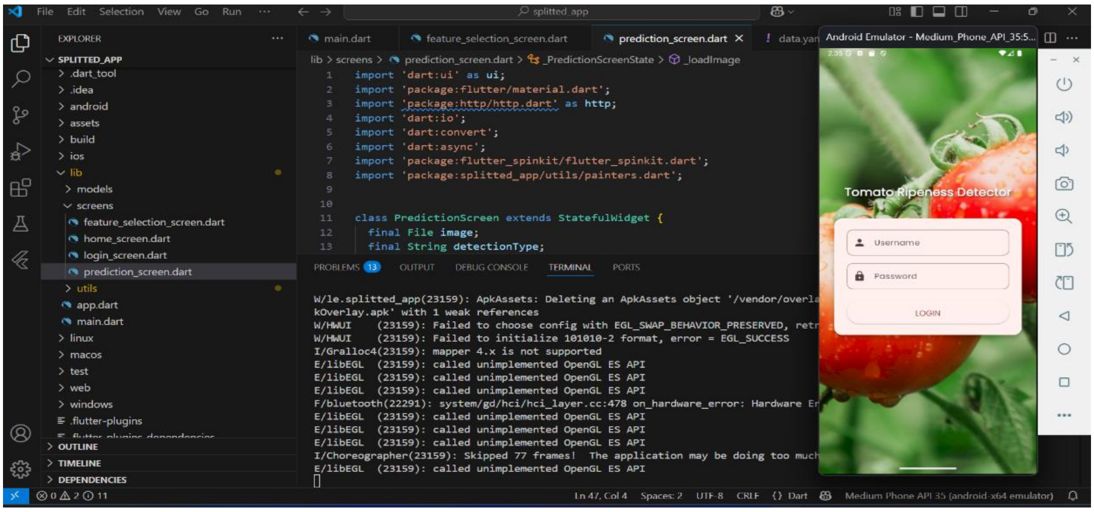

Figure 3.11: Admin Dashboard Login

The screen shot indicates that a Flutter project is being created in Visual Studio Code (VS Code). On the left window, the Explorer lists the project folder of SPLITTED_APP with Dart files having folders like models, screens, and utils. On the middle window is the code editor with the open file prediction_screen.dart which contains a definition of a PredictionScreen widget in a class subclassing StatefulWidget. This suggests that it's being used to generate a dynamic screen, likely for presenting or predicting from image input. On the right, an Android Emulator displays the app's login screen UI with a tomato background image, the text "Tomato Ripeness Detected", and username, password, and Login button fields—perhaps suggesting some image processing or machine learning capability. At the bottom, the terminal shows typical emulator-related problems (e.g., E/eglCodecCommon: glUtilsParamSize) typically related to Google Play Services, which do not appear to stop the app from functioning.

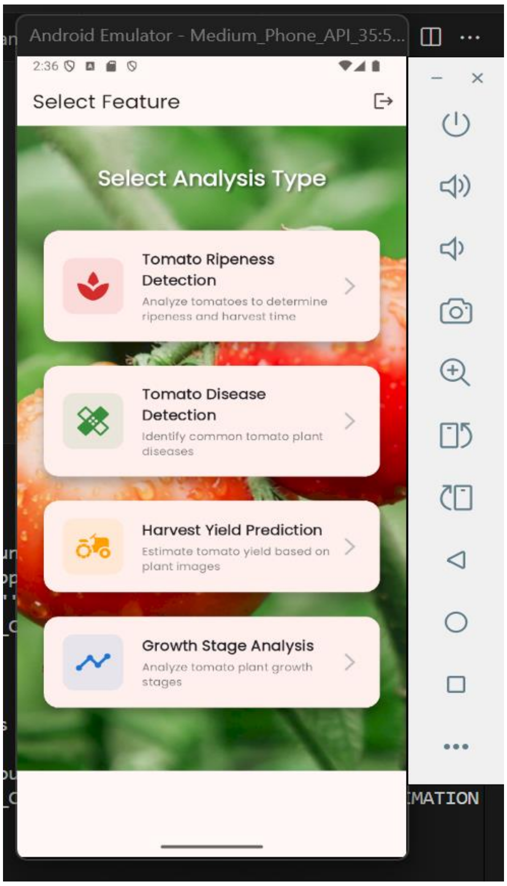

Figure 3.12: Feature Selection

and username, password, and Login button fields—perhaps suggesting some image processing or machine learning capability. At the bottom, the terminal shows typical emulator-related problems (e.g., E/eglCodecCommon: glUtilsParamSize) typically related to Google Play Services, which do not appear to stop the app from functioning. . The screen shot indicates that a Flutter project is being created in Visual Studio Code (VS Code). On the left window, the Explorer lists the project folder of SPLITTED_APP with Dart files having folders like models, screens, and utils. On the middle window is the code editor with the open file prediction_screen.dart which contains a definition of a PredictionScreen widget in a class subclassing StatefulWidget. This suggests that it's being used to generate a dynamic screen, likely for presenting or predicting from image input. On the right, an Android Emulator displays the app's login screen UI with a tomato background image, the text "Tomato Ripeness Detected", and username, password, and Login button fields—perhaps suggesting some image processing or machine learning capability. At the bottom, the terminal shows typical emulator-related problems (e.g., E/eglCodecCommon: glUtilsParamSize) typically related to Google Play Services, which do not appear to stop the app from functioning.

For each user that is able to log in and successfully access the MySQL database, a new user is added to the system.

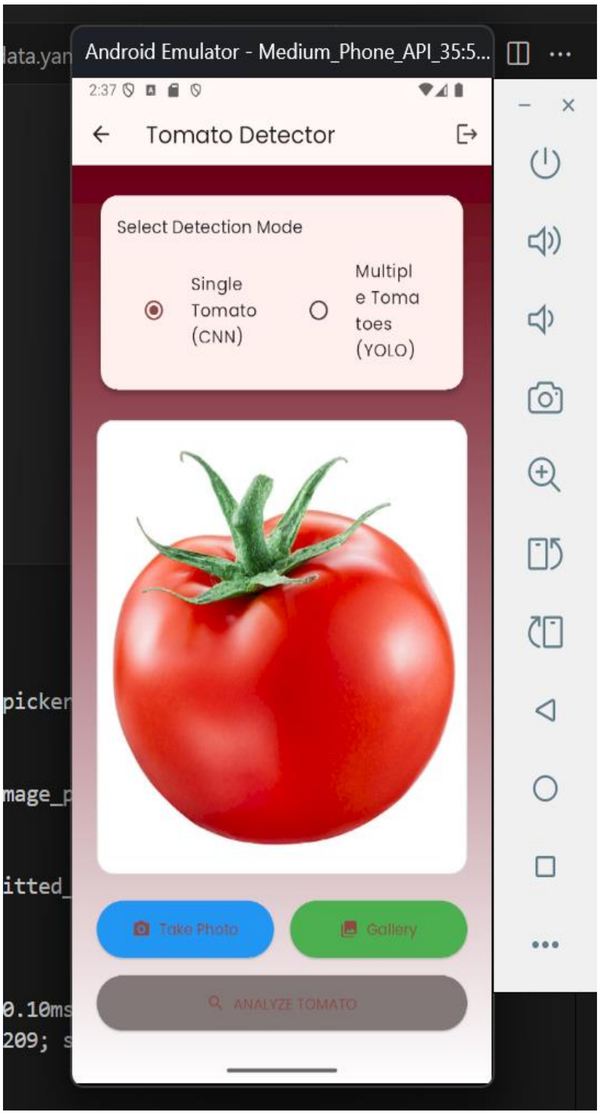

Figure 3.13: Select Detection Mode

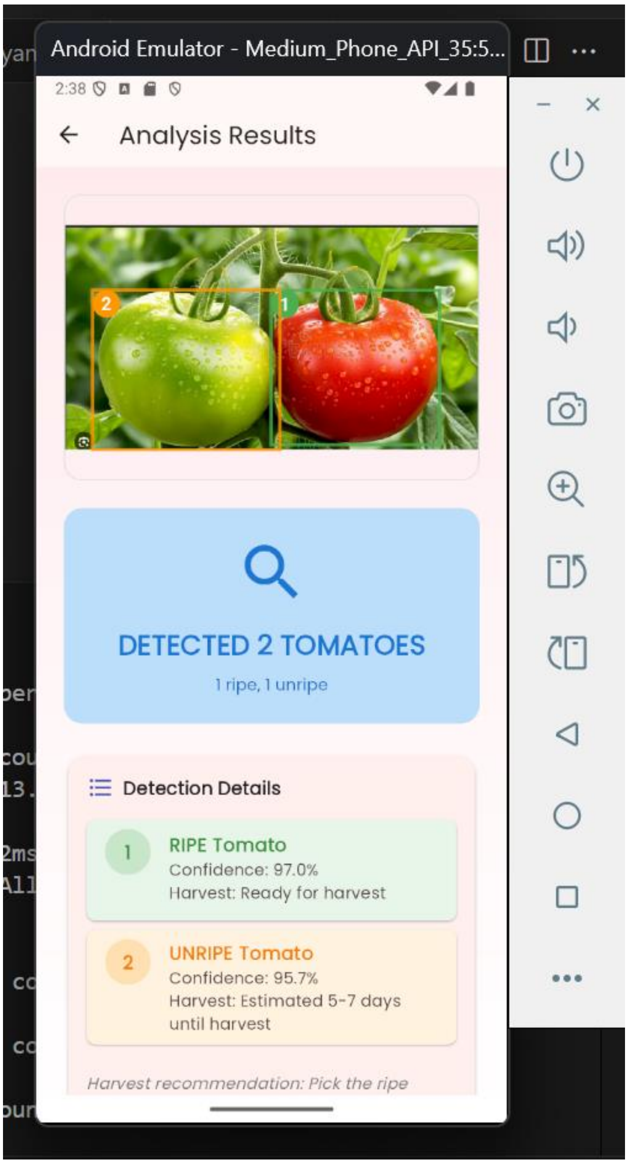

Figure 3.14: Yolo Analys Result

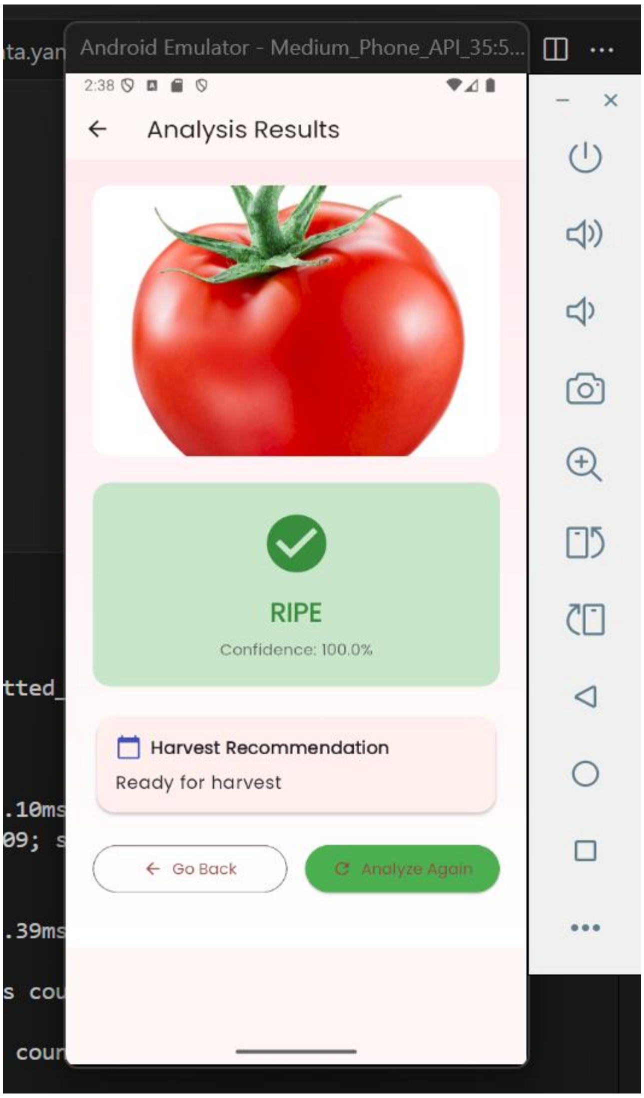

Figure 3.15: CNN Analys Result

Figure 3.16: Detect Helth

Figure 3.17: Detect Unripe

Figure 3.18: Detect Ripe Stages

Figure 3.19: Detect Unripe and Ripe Stages

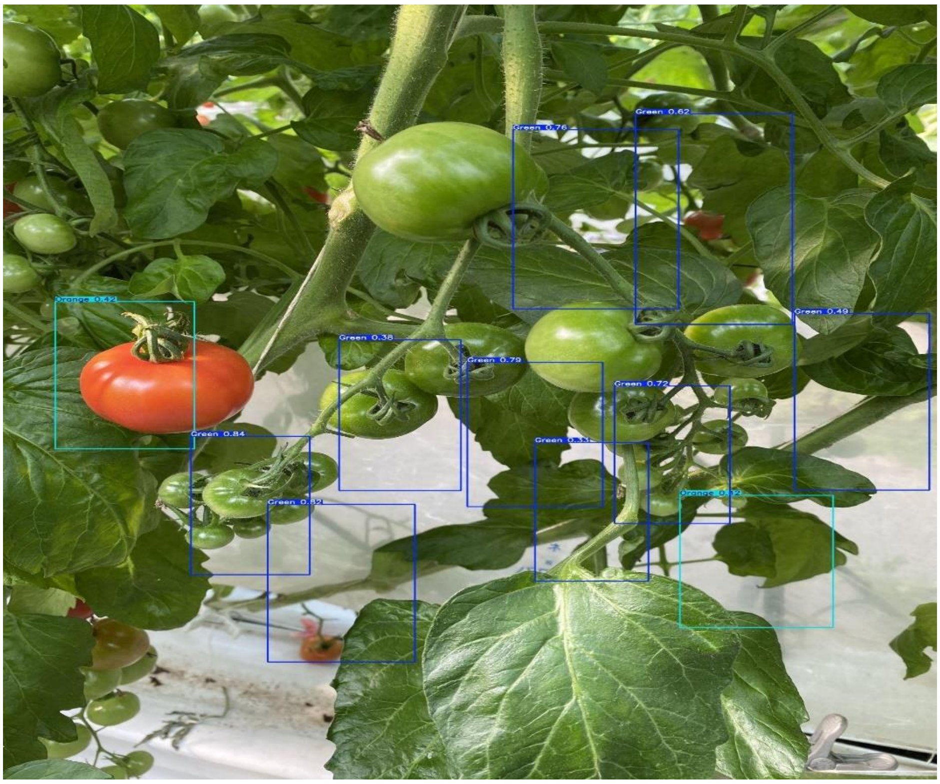

Figure 3.20: Detect Unripe and Ripe Stages

3.6.System Testing and Evaluation

1. Prototype Testing

In the initial phase, the integrated system—image analysis, detection, classification, and predictive modeling—is tested in a controlled environment. The objectives of this phase are:

- Accuracy Evaluation: Verifying the accuracy of the system in identifying tomato ripeness stages.

- Scalability Testing: Determining the ability of the system to handle larger amounts of data and users without affecting performance.

- Efficiency Measurement: Quantifying the response time and resource consumption of the system to ensure optimal performance.

- This controlled testing enables the identification and correction of problems prior to deployment in real-world environments.

2. Field Trials

Following successful prototype testing, the system is deployed on actual farm locations to determine if it performs in actual situations. This phase focuses on:

- Viability Assessment: Observing how the system behaves across various farming situations and various environmental conditions.

- Real-Time Performance: Testing how prompt and exact the system is in generating timely recommendations to farmers.

- Impact Analysis: Determining the effect of the system on quality of harvest and yield, which provides insight into actual usage.

- Field trials are required to validate the effectiveness of the system and to obtain additional data for fine-tuning.

3. User Feedback

Stakeholder engagement, particularly with farmers, provides meaningful information around the usability and performance of the system. This aspect involves:

- Feedback Collection: Gathering users' experience, suggestions, and problems around how the system is functioning and operational.

- System Enhancement: Iteratively enhancing the system based on the feedback given to achieve user preference and requirements alignment.

- Interface Optimization: Enhancing the user interface for better accessibility and usability by users with limited technology expertise.

- The integration of user input helps keep the system user-focused and also assists users in effective decision-making as farmers.

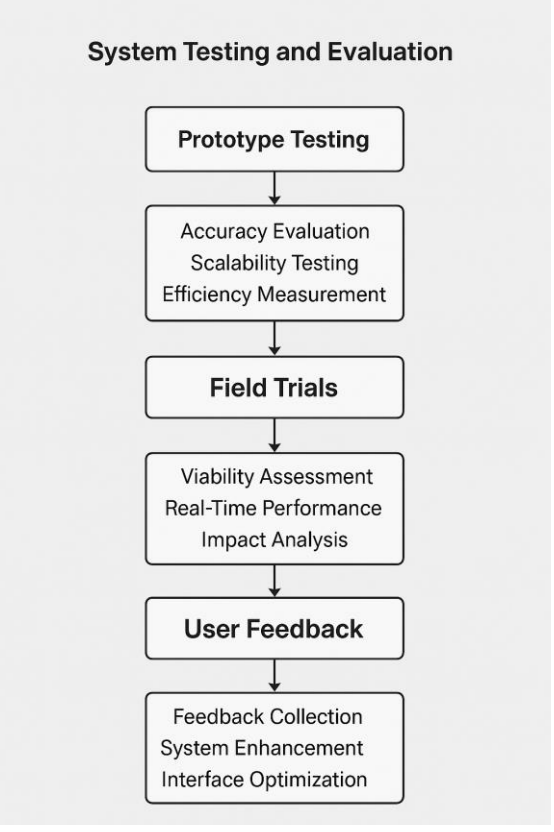

Figure 3.21: System Testing

3.7.Maintenance

Maintenance plays a crucial role in guaranteeing the sustained efficacy and dependability of the NetNexus network access control system. In order to ensure the ongoing operational efficiency, routine maintenance tasks are carried out. These encompass software updates and patches designed to mitigate security vulnerabilities and correct software defects, hence ensuring the system's ability to withstand emerging threats. Furthermore, the monitoring and replacement of hardware components are carried out as necessary in order to mitigate the risk of prospective failures and minimise periods of system unavailability. Regular performance reviews are carried out in order to maximise the effectiveness of the system, and active efforts are made to obtain user feedback in order to discover areas that may be improved. Maintenance also encompasses the task of ensuring that the system documentation is regularly updated in order to assist the process of diagnosing and providing support. NetNexus endeavours to offer a network security solution that is resilient, secure, and adaptable to the dynamic cybersecurity environment by placing emphasis on maintenance. This approach is specifically designed to cater to the needs of small-scale organisations.

4.Results and Discussion

- The results demonstrate that the proposed AI-driven system significantly improves ripeness detection accuracy compared to the traditional manual system. The CNN-YOLOv8 combination enables real-time and massive classification, relieving inefficiencies associated with conventional farming practices.
    - Accuracy & Efficiency: CNN and YOLOv8's high precision ensures correct classification, reducing error in harvesting decisions.
    - Scalability: Multiple tomatoes per image are processed efficaciously, making the solution scalable for use in large agricultural fields.
    - Real-time Application: The mobile-responsive design provides immediate feedback to the farmer, helping them make good harvesting decisions in real time.
    - Environmental Adaptability: With integration of environmental data, the system dynamically adapts harvesting recommendations for optimal yield while reducing waste.

- Data Collection and Preprocessing: The system will provide the farmer with the ability to upload images of tomatoes, which are preprocessed-resizing, normalizing, and augmenting-to prepare them for model training. This ensures the images are ready for input into the CNN and YOLOv5 models.
- Ripeness Detection using CNN: The system should integrate a CNN model to classify tomatoes with high accuracy into different stages of ripeness, such as unripe, half-ripe, and fully ripe, based on uploaded images, providing real-time visual indication.
- Multi-Tomato Detection using YOLOv5: The system should leverage YOLOv5 in efficiently detecting and classifying m ultiple tomatoes in one image for fast visual indication to farmers.
- Predictive Harvest Recommendations: The system should be able to

provide optimal harvest timing by analyzing the predictive model of ripeness data and environmental conditions for the best time of harvest. This provides actionable insights that help farmers maximize yield and reduce waste

- User Interface: The system should be designed to include a user-friendly web interface, accessible via smartphones, through which farmers can interact with the system, upload images, receive real-time notifications, and view harvest recommendations.

- Feedback Mechanism: A feedback loop should be incorporated within the system to gain insights from users in refining the models and interface for further improvement in accuracy and usability over time.

- System Adaptability: Changes in environmental conditions and varied ripening patterns call for a system that is consistently updating its models with new data so that it remains relevant long into the future.

Table 4.1: Results

NO	Option	Results
01	Model Training	Successful
02	Backend Conecting	Successful
03	Admin Login and Dashboard	Successful
04	User Login and Dashboard	Successful

5. DESCRIPTION OF PERSONAL AND FACILITIES

Table 5.1: Description of Personal & Facilities

Registration Number	Name	Task Description
IT21013164	Samarasinghe G.D.M.J	• Access Control Rules • User Registration • Banned Website Management • Real-Time Dashboard • User Control Panel • Performance Optimization

6. BUDGET AND BUDGET JUSTIFICATION

Table 6.1: Budget & Budget Justification.

Task	Cost (LKR)
Field Visit	3000
Datasets	2000
Travel	5000
Maintenance	500
AWS server usage	300
Total cost	**10,800**

7. Conclusion

The AI-powered smart tomato farming system is an innovative solution that brings revolutionary transformation to modern farming, addressing long-rooted issues plaguing traditional methods of farming. Previously, inaccurate detection of the ripening stages and improper harvesting timing have been accountable for significant post-harvest losses as well as inefficiency along the whole supply chain. The novel system, however, utilizes cutting-edge technologies in machine learning, computer vision, and adaptive decision-making to introduce a breakthrough solution that has the potential to optimize every aspect of growing and harvesting tomatoes.

By integrating intelligent models trained on vast datasets of tomato plant images and growth patterns, the system can precisely identify ripeness levels, detect diseases, and predict yields with remarkable accuracy. The real-time image processing capabilities allow the system to analyze plant conditions and provide timely, data-backed insights. These results are conveyed impeccably by a robust backend architecture that allows free interaction between the AI models and the user-end mobile application. Farmers therefore receive real-time information, early warnings, and actionable recommendations directly on their smartphones, allowing them to make decisions on the go.

One of the strongest points of the system is the interactive and user-friendly design. It is built not only to be intuitive and easy to use but also to evolve based on user feedback and real-world usage patterns in the field. This refinement through feedback process ensures the system is relevant and its performance and usability are continually improved over time. By actively learning from user interaction and conforming to new environmental and crop variables, the system delivers increasing value with continued use.

Aside from being technologically advanced, the smart tomato farming system also promotes sustainable farming. It prevents wastage through timely harvesting, saves the use of resources through precise monitoring, and boosts productivity by identifying potential issues before they become critical. Moreover, its modular and extensible nature allows for future expansion to other crops and agricultural applications, opening doors towards a more integrated smart farming system.

In effect, this AI-powered platform redefines the future of tomato farming. Not only does it offer a viable, tech-based solution to existing constraints, but it also unlocks the gates to a more productive, profitable, and sustainable farming industry. With its ability to adjust, learn, and offer actionable information, the system serves as a testament to the power of innovation in shaping the farms of tomorrow.In an ever-changing digital environment characterised by persistent cyber threats, the

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11. Hoang-Tu Vo, Kheo Chau Mui, Nhon Nguyen Thien, Phuc Pham Tien Information Technology Department FPT University, Cantho city, Vietnam
12. A microcontroller based machine vision approach for tomato grading and sorting using SVM classifier

8. APPENDICES

Appendix A – Codes for admin login and user login

1. Dashboard.js

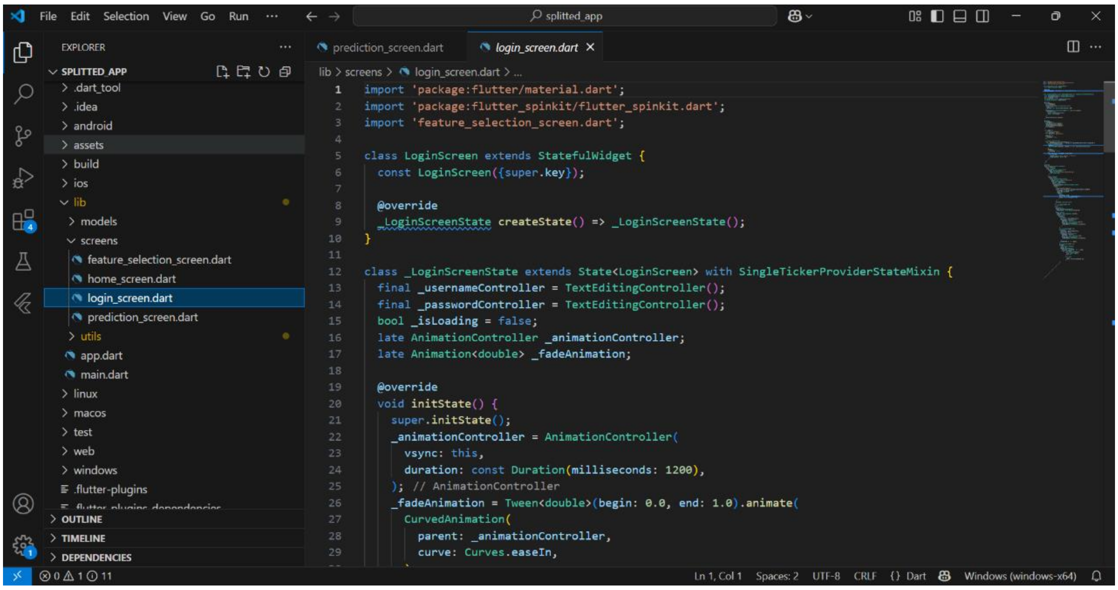

Figure 3.22: Codes for admin login

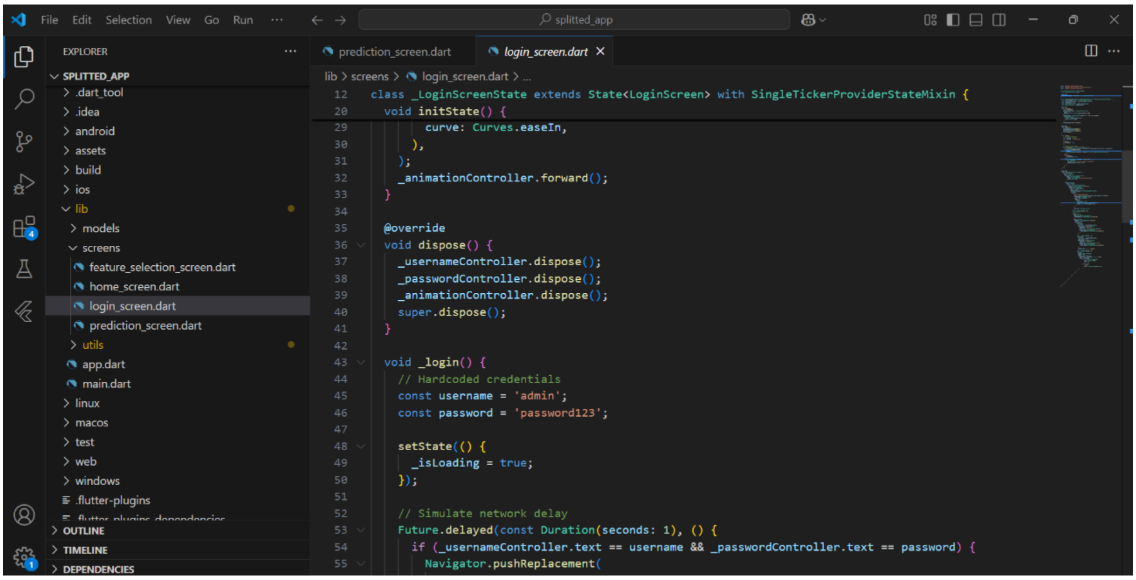

Figure 3.22: Codes for admin login

Appendix B – Work Breakdown Structure

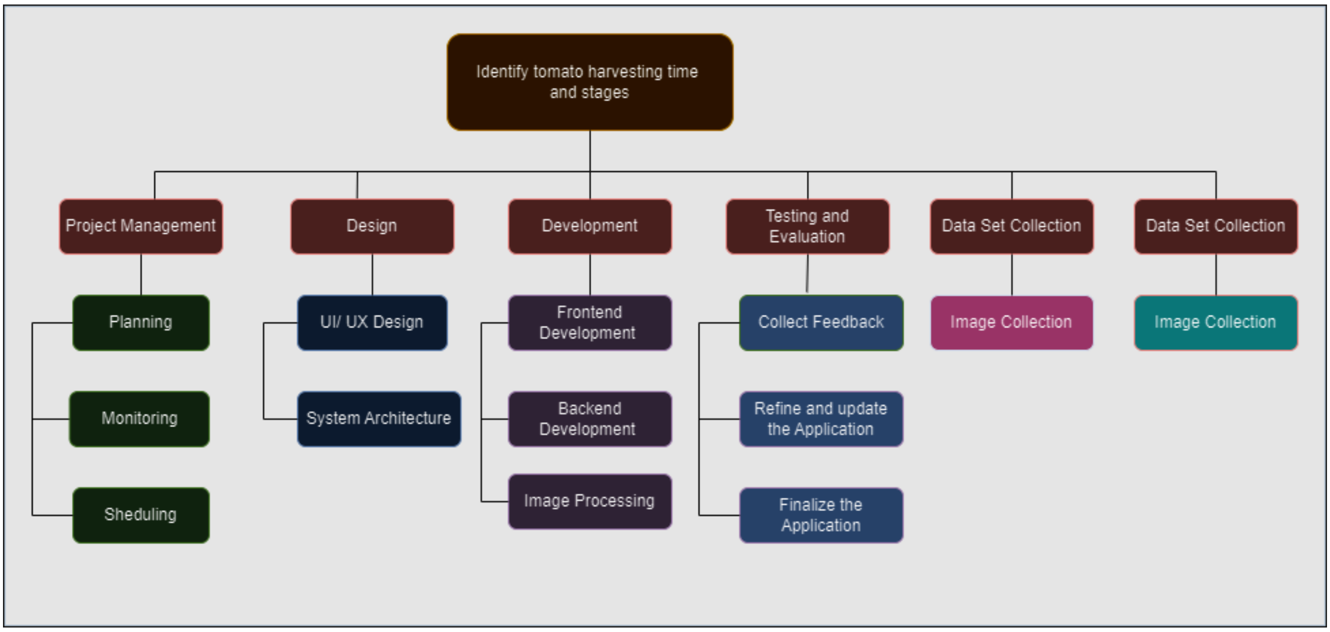

Figure 8.1: Work Breakdown Structure

Appendix C – Grantt Chart

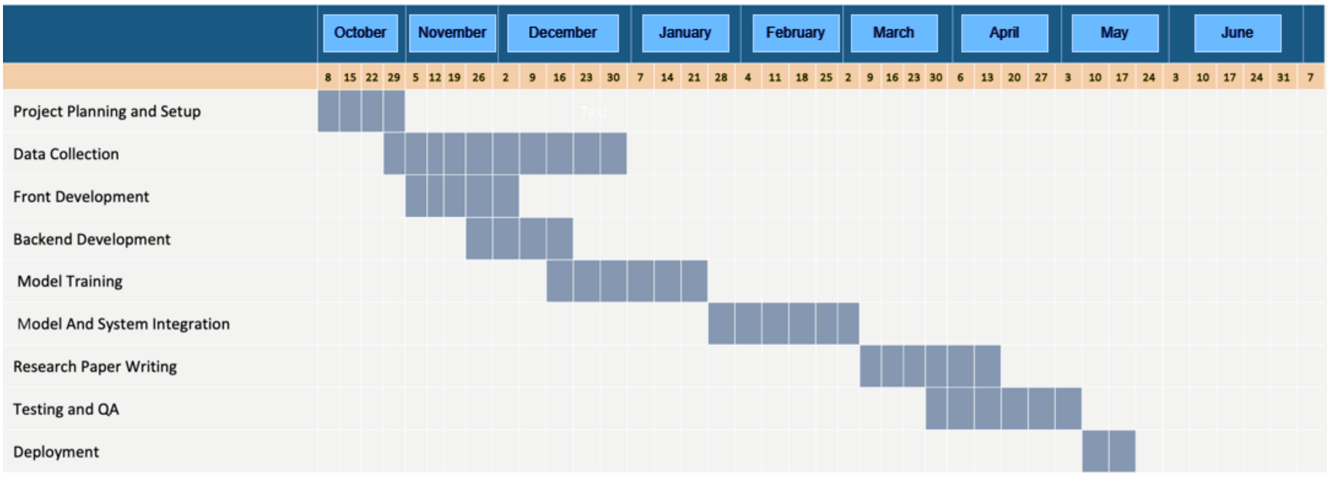

Figure 8.2: Gantt Chart