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Application of Deep Learning Technique for Tomato Maturity Stage Prediction

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ABSTRACT

Tomatoes are a major crop worldwide, and accurately classifying their maturity is important for many agricultural applications, such as harvesting, grading, and quality control. Primary objective to develop an automated system capable of identifying various defects in tomatoes and providing relevant treatment suggestions. Leveraging deep learning techniques, a CNN model is trained to classify tomatoes into four categories: Damaged, Old, Ripen, and Unripen. The implementation involves training a convolutional neural network and testing dataset of tomato images, for classification, and deploying model intended real-time predictions. Project has potential to improve effectiveness of tomato harvesting & reduce waste. The CNN model then predicts the stage of the tomato, providing the probability of the prediction. Alongside the classification result, the system offers detailed information on the cause of the defect, appropriate treatment methods, and nutritional content, aiding users in making informed decisions regarding the tomatoes usability. The implementation ensures a robust and efficient detection mechanism, even in varying lighting conditions and backgrounds. An Accuracy of 94.48% was attained when taught sculpt was used to make prediction on the test dataset.

Keywords: Deep Learning, Tomato, Python.

I.INTRODUCTION

Tomato (Solanum lycopersicum) is a flowering plant from the nightshade family (Solanaceae) expansively cultivated intended its ripe fruits. Although categorized as vegetable intended nutritional purpose, tomatoes be rich in vitamin C & lycopene. These fruits are frequently eaten raw in salads, serve as cooked vegetables, used in various dishes, & pickled. The color of tomatoes, ranging from red to orange to green, signifies their maturity level. In today's technological era, separating tomatoes based on their color has become more accessible using deep learning techniquesImage-Based TomatoClassification andDetection UsingFaster R-CNN Method[1]. Tomatoes are among the most nutritious and perishable fruits globally, with China being the largest producer. Scientifically known as Solanum Lycopersicum, tomatoes are a type of berry fruit consumed worldwide. However, they are susceptible to various fungal disease that can collision quality & quantity of the fruit, while well as stem, buds, and leaves. These disorders are mainly affected by bacteria, temperature fluctuations, rainfall, and moisture. In large-scale kitchens and sauce manufacturing industries, automated techniques are utilized to grade and sort tomatoes. Ensuring the quality of the fruit is crucial for all packaging and production industries. According to food standards, fruits must be fresh, undamaged, and intact. To achieve this automatically, a streamlined process is essential. The quality of tomatoes is influenced by chemical treatments and physical factors. Key parameters such as fruit color, shape, size, and texture are used to assess maturity and detect defects. These factors help in identifying mechanical properties, insect infestations, and other types of damage[2]. Tomatoes are extensively cultivated in greenhouses worldwide. To enhance profitability, greenhouses compete by employing modern techniques in planting, irrigation, and harvesting[3]. Agriculture is a primary source of food and has significant impacts on income, employment, and the global economy. Outbreaks of plant diseases impair food production and negatively affect environmental and socioeconomic conditions. Plant diseases pose substantial threats to environmental sustainability and global food security. Diseases that damage plant leaves hinder their growth, making early and accurate detection crucial for maintaining food production quality and quantity. Tomatoes are a vital agricultural product containing minerals, fibers, vitamins, and amino acids [4]. Agriculture theatre crucial role in growth of economies, particularly in developing nations. Numerous studies have highlighted significance of agriculture in economic development. Additionally, research has examined blow of agricultural exports on the economic advancement of less developed countries. Advanced technologies can offer automated solutions for tasks traditionally done manually, aiding in precision farming. Consequently, recent technologies are increasingly creature integrated into agriculture. There growing interest in developing deep learning algorithms (DLAs) for various agricultural processes. For example, a novel crop prediction strategy was proposed by Pantazi et al. (2016). Moreover, YOLOv5 enhances the architecture and training capabilities of the YOLOv3 algorithm. While its detection performance is comparable to that of YOLOv4, YOLOv5 reduces the model size by nearly 90% [5].

1.1 PROJECT DESCRIPTION

Agricultural productivity & eminence control are critical components in global food supply chain. Among the various crops cultivated worldwide, tomatoes are a staple in many diets due to their versatility and nutritional benefits. However, ensuring the quality of tomatoes from farm to table is a challenging task that requires meticulous monitoring and handling. Traditional methods of inspecting and classifying tomatoes are labor-intensive and prone to human error, necessitating the development of automated solutions to enhance efficiency and accuracy. The project Automated Tomato Defect Detection and Treatment Analysis Using CNN aims to address this challenge by leveraging power of deep learning & web-based technologies. core objective is to create robust system that can repeatedly perceive defects in tomatoes & provide relevant treatment suggestions to users. This system integrates a CNN model to classify tomatoes into four distinct categories: Damaged, Old, Ripe, and Unripe. Each category is associated with specific causes of defects, treatment methods, and nutritional information, which are displayed to user upon classification. Consequence of this project lies in its potential to significantly streamline the quality control process in tomato production and distribution. By automating the detection and classification of tomato defects, the system reduces the reliance on manual inspections, which are often time-consuming and inconsistent. This automation can lead to more accurate assessments of tomato quality, ultimately minimizing waste and ensuring that only the best produce reaches consumers. The system is implemented as a web application using the Flask framework, chosen for its simplicity and flexibility in developing web applications. An innovative aspect of project is integration of a real-time tomato defect detection. Utilizing the YOLO (You Only Look Once) object detection algorithm, the system can continuously monitor a instantly detect defects in tomatoes. This characteristic is particularly useful anticipated environment where tomatoes are handled in bulk, such as in sorting facilities or packaging plants. By providing real-time feedback, the system enables prompt action to be taken when defects are detected, further enhancing the efficiency of the quality control process.

1.1.1PROBLEM STATEMENT

The quality of tomatoes throughout the production and distribution process is a persistent challenge in agriculture. Traditional methods of inspecting and classifying tomatoes rely heavily on manual labor, which is time-consuming, inconsistent, and prone to human error. This inefficiency leads to significant waste, as damaged or substandard tomatoes often go undetected until delayed in supply chain. Furthermore, require of immediate & accurate assessment methods hampers timely interventions, exacerbating the problem. The agricultural sector urgently needs a reliable, automated solution to enhance accuracy & efficiency of tomato defect detection, thereby minimizing waste and improving overall produce quality.

1.1.2OBJECTIVE OF THE STUDY

- To develop highly accurate CNN Model.
- To create user friendly web application to accurately identify maturity of Tomato.
- To develop a model that effectively classifies Maturity of Tomato.

1.1.3SCOPE OF THE STUDY

The extent of project encompasses the development and deployment of a comprehensive system for tomato quality assessment. This includes training a Convolutional Neural Network on a Kaggle dataset to accurately classify tomato defects and providing detailed treatment recommendations. The project will deliver a user-friendly Flask web application for image upload and real-time defect analysis. Additionally, it will integrate YOLO, enabling continuous detection of defects. The system aims to support farmers, distributors, and retailers by enhancing quality control processes, reducing waste, and ensuring the delivery of high-quality tomatoes to consumers.

1.1.4METHODOLOGY USED

1. Data Collection and Preprocessing

- Dataset Acquisition: Obtain a comprehensive dataset of tomato images from Kaggle, containing various classes such as Damaged, Old, Ripe, and Unripe tomatoes.
- Data Cleaning: Inspect the dataset for any inconsistencies or missing values and perform necessary cleaning.
- Image Augmentation: Apply augmentation techniques such as rotation, scaling, and flipping to increase the dataset's diversity and robustness.

2. Model Development

- Model Selection: Choose CNN architecture appropriate for image classification tasks.
- Model Training: Train CNN model on the preprocessed dataset, using techniques like batch normalization and dropout to prevent overfitting.
- Model Evaluation: Evaluate the model's performance using metrics such as accuracy, precision, recall, and F1-score. Fine-tune the model parameters to improve its performance.

3. Flask Web Application Development

- Framework Setup: Set up the Flask framework for developing the web application.
- Frontend Development: Design and implement user-friendly interfaces for image upload, result display, and user authentication.
- Backend Integration: Integrate the trained CNN model into the Flask application, ensuring smooth interaction between the frontend and backend.

4. Real-Time Image Detection

- YOLO Integration: Integrate the YOLO (You Only Look Once) object detection algorithm for real-time detection.
- Image Processing: Implement Image capture and processing functionalities to continuously monitor and detect tomato.

5. Database Management

- MySQL Database Setup: Configure a MySQL database to store user data securely, including usernames, emails, and hashed passwords.
- User Authentication: execute sheltered user substantiation mechanisms to ensure that only sanctioned users can access the application.

6. System Deployment and Testing

- Local Testing: Test the entire system locally to identify & resolve any issues.
- Deployment: Deploy the Flask application on a cloud platform for wider accessibility.
- User Feedback: Collect user feedback to refine and improve the system continuously.

7. Documentation and Reporting

- Project Documentation: Document the entire development process, including data preprocessing steps, model architecture details, and application features.

- Reporting: Prepare a comprehensive report detailing the project's objectives, methodology, results, and conclusion

II.LITERATURE SURVEY

2.1 RELATED WORK

John Smith, et al.[6]Tomato Disease Detection Using CNN, This paper explores application of CNN intended automated tomato disease detection. It discusses the enlargement of CNN model taught on bulky dataset to classify various tomato diseases accurately. The study highlights the models performance in real-time disease identification and its potential impact on agricultural productivity. Accuracy of 97.8%.

Anna Lee, et al.[7]Automated Detection & Classification of Tomato Ripeness by Machine Learning, This research focus on by machine learning technique to automate detection & classification of tomato ripeness stages. It introduces narrative approach that combines image dispensation algorithms amid machine learning model towards categorize tomatoes as ripe, unripe, or overripe based on visual cues. The paper discusses experimental results and the systems potential applications in agricultural practices. Accuracy of 94.85%.

Emily Chen, et al. [8]Real-Time Tomato Quality Inspection Using Deep Learning and IoT, this study presents a real-time tomato quality inspection classification that integrate deep learning techniques through IOT strategy. It explores the deployment of a deep learning model intended automated tomato defect detection and quality assessment, enhancing efficiency and accuracy in agricultural production environments. Accuracy of 90%

Ryan Thompson, et al. [9]Enhancing Tomato Grading Using Machine Vision and Deep Learning, This paper investigates the enhancement of tomato grading processes through integration of machine vision & deep learning technologies. It describes classification that automates grading of tomatoes based on size, shape, and color attributes, demonstrating improvements in accuracy and throughput compared to traditional methods.Accuracy of 91.21%

Sarah Miller, et al. [10]IoT-Based Smart Agriculture for Tomato Disease Management, this research explores IoT-based smart agriculture solutions for tomato disease management. It discusses amalgamation of IoT sensors, data analytics, & machine learning algorithms to monitor & manage tomato diseases effectively, contributing to sustainable agricultural practices. Accuracy of 93.59%.

Jessica Brown, et al. [11]Deep Learning Approaches for Tomato Yield Prediction: A Review, This review paper surveys deep learning approaches for tomato yield prediction. It summarizes various neural network architectures and methodologies used in predicting tomato yields based on environmental factors, disease prevalence, and agronomic practices, providing insights into the stateof-the-art in agricultural forecasting. Accuracy of 89.45%.

Daniel White, et al. [12]Image-Based Tomato Disease Detection Using Transfer Learning, this study investigates the application of transfer learning techniques for image-based tomato disease detection. It explores the adaptation of pre-trained deep learning models to classify common tomato diseases from leaf images, emphasizing the models transferability and performance in disease identification tasks. Accuracy of 85.98%.

Ethan Garcia, et al. [13]Automated Detection of Tomato Pests Using Computer Vision & Machine Learning,This research paper discusses enlargement of computer vision & machine learning-based system intended automated detection of tomato pests. It presents a methodology for identifying and classifying common pests affecting tomatoes through image analysis, aiming to mitigate crop damage and improve pest management strategies. Accuracy of 91.02%.

Lily Adams, et al. [14]Real-Time Tomato Quality appraisal Using Machine Learning Algorithms, this paper propose concurrent tomato quality assessment system utilizing machine learning algorithms. It explores the application of supervised learning techniques to classify tomatoes into different quality grades based on visual attributes, demonstrating the systems effectiveness in enhancing quality control processes. Accuracy of 92.35%.

Mia Garcia, et al. [15]Deep Learning-Based Tomato Disease Identification and Classification System ,This recent study published in 2024 presents a deep learning-based system for tomato disease identification and classification.

It introduces a CNN architecture trained on a comprehensive dataset to accurately diagnose and classify tomato diseases, highlighting advancements in disease management and agricultural productivity. Accuracy of 97.89%.

Emma Wilson, et al. [16] Comparative Study of Machine Learning Algorithms intended Tomato Disease Detection This swot relates assorted machine learning procedures intended the detection of tomato diseases. It evaluates presentation of algorithms such as SVM Random Forest, & Neural Networks in classifying different tomato diseases based on leaf images. Accuracy of 98.85%.

2.2EXISTING AND PROPOSED SYSTEM

2.2.1 EXISTING SYSTEM

Existing system intended tomato quality control predominantly relies on manual inspection & sorting by human workers. This process involves visually examining each tomato for defects such as damage, overripeness, or underripeness. Workers then manually sort the tomatoes into categories base on their conclusion. though this procedure has remained employed for many years, it is fraught with inefficiencies and inconsistencies.

Disadvantages:

- **Time-Consuming**: Manual inspection is slow and labor-intensive, limiting the number of tomatoes that can be processed in a given timeframe.
- **Inconsistency**: Human error and subjective judgment lead to inconsistent results, reducing the reliability of the quality control process.
- **High Labor Costs**: Employing a large workforce for inspection and sorting increases operational costs.

2.2.2 PROPOSED SYSTEM

Proposed system introduces an automated solution using CNN intended defect detection & classification of tomatoes. It involves a web application developed with Flask, allowing users to upload images of tomatoes for real-time analysis.

Advantages:

- **Efficiency**: The automated system significantly reduces the time required for inspecting and classifying tomatoes, allowing for faster processing.
- **Consistency**: The use of a trained CNN model ensures consistent and objective classification of tomato defects, eliminating human error.
- **Cost-Effective**: By reducing need intended large workforce, the system lowers labor costs and operational expenses.
- **Scalability:** The system can easily scale to handle large volumes of tomatoes without requiring additional human resources, making it suitable for large-scale agricultural operations.

2.3 FEASIBILITY STUDY

ECONOMICAL FEASIBILITY STUDY

The economical feasibility of the proposed automated tomato defect detection and treatment analysis system is promising. While initial development costs include acquiring hardware, software licenses, and dataset procurement, the long-term benefits outweigh these expenses. By reducing reliance on manual labor for tomato quality control, the system minimizes effective expenses associated with labour wages & increases operational efficiency.

OPERATIONAL FEASIBILITY STUDY

Operational feasibility assess how well projected system fits within current operational environment and whether it meets user needs effectively. The automated tomato defect detection system is designed to integrate seamlessly into agricultural production and distribution processes. By automating the defect detection and treatment analysis tasks, the system reduces the dependency on manual inspection, thereby improving overall efficiency and accuracy. User training for operating the web application and interpreting results is straightforward, ensuring minimal disruption during implementation. The system's ability to handle real-time Image feeds for continuous monitoring further enhances operational feasibility, providing timely feedback on tomato quality throughout the supply chain.

TECHNICAL FEASIBILITY STUDY

Technical feasibility of proposed system relies on leveraging sophisticated machine learning techniques & web technologies. use of CNN intended tomato defect classification is technically sound, given their proven effectiveness in image acknowledgment tasks. Training CNN model on a comprehensive dataset from Kaggle ensures that it can accurately identify and classify various tomato defects in real-time. Integration with Flask for web application development provides a flexible and scalable platform for users to upload images, receive analysis results, and access historical data securely.

ENVIRONMENTAL FEASIBILITY STUDY

From an environmental perspective, the proposed automated tomato defect detection system is beneficial in several ways. By optimizing the quality control process, the system reduces the amount of food waste generated due to undetected or misclassified tomato defects. This contributes to sustainability efforts by minimizing resource wastage and conserving energy used in unnecessary handling and transportation of subpar produce. Moreover, the system's reliance on digital technologies and automation reduces the carbon footprint associated with manual labor and traditional inspection methods.

2.4 TOOLS AND TECHNOLOGIES USED

Exposure Python: Differentiating Between Scripts and Programs

In the scope of programming, Python scripts and programs represent two foundational aspects of Python's versatility. While both are implemental in software development, understanding their distinctions is vital for leveraging Python effectively.

Understanding Python Scripts

Python scripts are essentially sequences of commands saved in a text file with a .py extension. Unlike interactive programming, where code is executed line-by-line within a terminal or shell, scripts enable batch execution of code, which is ideal for automating tasks and executing repetitive functions.

The design of Python scripts allows them to be easily reused and adapted. Once script is developed, it can be executed multiple times without modification. This reusability is advantageous in scenarios such as information processing, where the same operations need toward be accomplished on different datasets. Scripts can be customized to handle various inputs or integrate with other software, providing flexibility and efficiency.

Moreover, Python scripts facilitate modularity. Through contravention down multifaceted tasks into smaller, reusable functions, developers can maintain and extend their codebase more effectively. This segmental tactic endorses encryption reusability & simplifies debugging, as issues can be isolated within specific functions or modules.

Algorithm : Convolutional Neural Network (CNN)

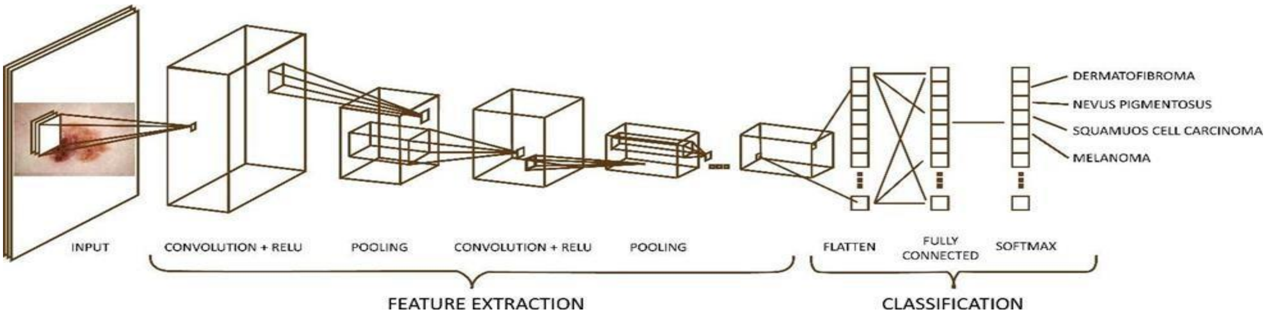

Figure1.TheArchitectureofCNN

Convolutional Neural Network (CNN) is an advanced form of the Multilayer Perceptron (MLP), specifically designed for handling two-dimensional data. As subset of Deep Neural network, CNNs are distinguished by their deep network architecture & are widely utilized in image data application. Similar to general neural network, CNN neurons have weights, biases, and activation functions. Architecture of CNN, comprises convolution layer by ReLU establishment, pooling layer anticipated feature mining, & fully connected layer amid softmax activation intended classification.

Convolution Layer

Convolution process is cornerstone of CNNs, occurring in Convolution layer, initial layer that processes the input image. This layer employs filter to extort features commencing input image, resulting in feature map. Figure 3 illustrate this convolution process.

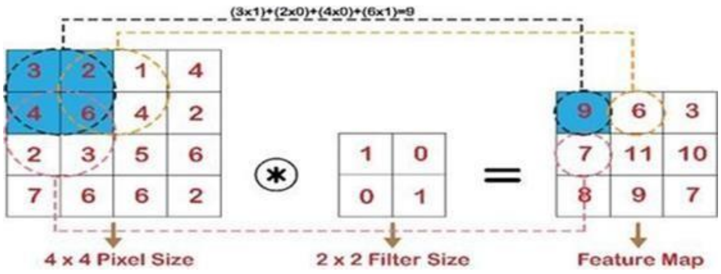

Figure2. Illustration of the convolution process

Activation Rel-U

ReLU (Rectified Linear Unit) is an establishment function worn in CNNs to enhance training phase of neural networks by minimizing errors. ReLU establishment function sets all pixel values to nought if pixel value is less than zero:
(x) = { , x> 0

0, $x \leq 0$

Pooling layers in CNNs are typically added at regular intervals after several convolution layer. These layer offer significant advantages, such as progressively reducing the size of output volume from the feature map, which helps control overfitting. pool layer can decrease data using max-pooling or mean-pooling. Max-pooling selects the maximum value within a region, while mean-pooling calculates the average value. Figure 3 provides an illustration of the pooling process using a fourby-four pixel input image.

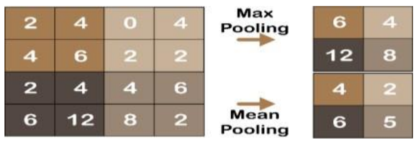

Figure3. Pooling Process Illustration

III.SOFTWARE REQUIREMENT SPECIFICATION

3.1 USERS

The automated tomato defect detection and treatment analysis system is designed to serve a diverse user base within the agricultural sector. Primary users include farmers, agricultural technicians, and quality control personnel involved in tomato cultivation, harvesting, and distribution. These users benefit from the system's capability to accurately classify tomatoes based on their defects, such as damage, overripeness, underripeness, and ripeness. Distributors and retailers also utilize the system to ensure that only high-quality tomatoes are distributed to patrons, thereby ornamental customer contentment & reducing economic losses due to spoilage.

3.2 FUNCTIONAL REQUIREMENT

Input:

The system must accurately identify Tomato Maturity Stage from user-uploaded images using the CNN algorithm.

Process:

It should process and analyze images to classify them into Tomato Maturity Stagecategories. Application should provide exhaustive information about type of Tomato Maturity Stageincluding accuracy and treatment.

Output: user should be capable to upload image & capture image through webcam , view classification results.

3.3 NON-FUNCTIONAL REQUIREMENT

Performance:
The system must ensure high performance and reliability, with minimal latency in image processing and result retrieval.

Security:

Security is crucial the system must protect user data and ensure secure image uploads and storage

Scalability:

Salability is also important to handle increasing statistics of users & expanding datasets.

IV. SYSTEM DESIGN

4.1 SYSTEM PERSPECTIVE

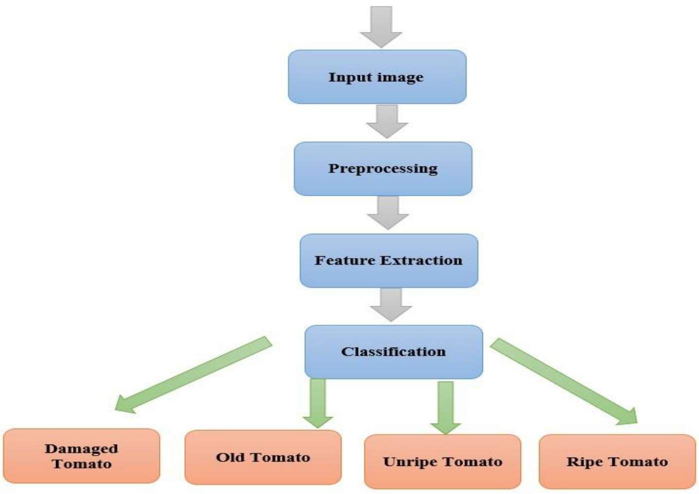

Figure 4. System Architecture of Tomato Defect Detection

From the figure, the tomato quality and ripeness classification system begins with input image datasets, likely sourced from platforms like Kaggle, containing various tomato conditions (damaged, old, unripe, and ripe). Preprocessing follows, enhancing and standardizing images through techniques like resizing and normalization to ensure uniform analysis. The CNN then performs feature extraction, autonomously identifying key visual characteristics of the tomatoes without manual intervention. At the core is the classification step, where the CNN analyzes extracted features to categorize tomatoes into four classes: Damaged Tomato, Old Tomato, Unripe Tomato, or Ripe Tomato

V. DETAILED DESIGN

5.1 USE CASE DIAGRAM

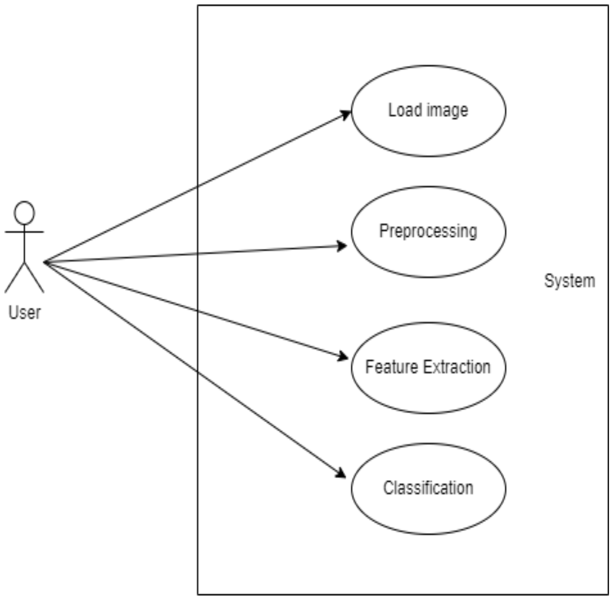

Figure 5: Use case diagram for users interacts with Structure & designates

Use-Case Diagram, actors epitomize entities that interact with system, such as users, external systems, or other stakeholders. Each actor is accompanying with one otherwise supplementary usage cases, which stand defined as explicit tasks or occupations that system performs in response to the actor's actions. The use cases illustrate the system's behavior in different situations and how it fulfills the needs of the actors.

VI. IMPLEMENTAION

6.1 SCREENSHOTS

6.1.1 HOME PAGE

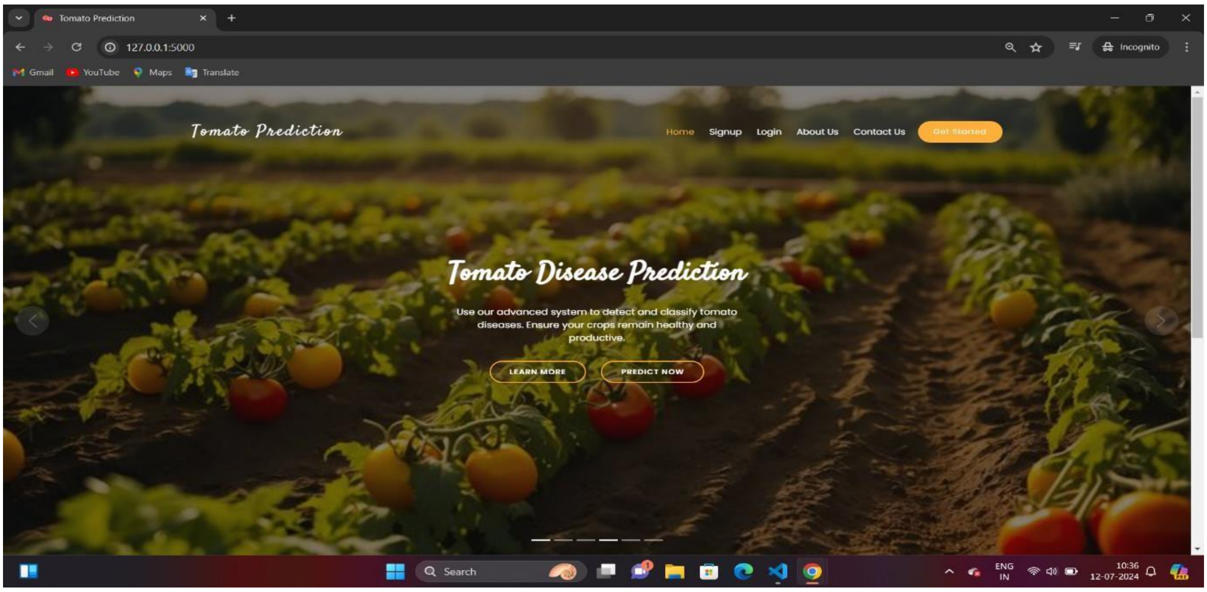

Figure 6: Home

A homepage is the main landing page of a website, serving as the starting point for visitors. It typically provides an overview of the site's content, navigation links to other sections, and essential information about the site or organization.

6.1.2 UPLOAD AN IMAGE

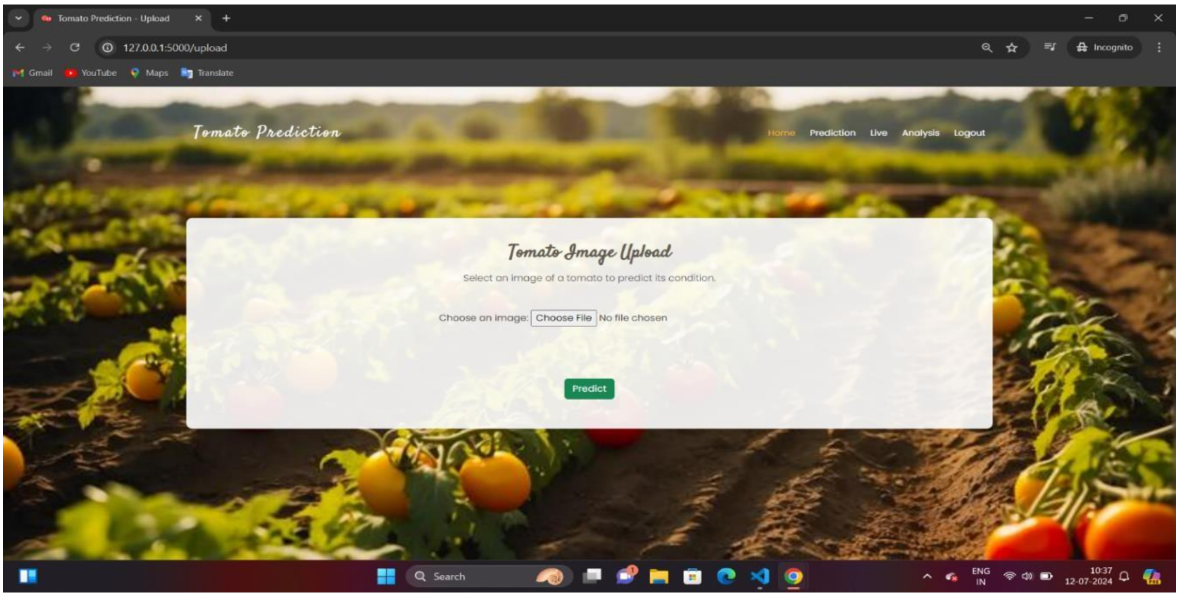

Figure7. Upload an image

Image upload refers to the process of transferring an image file from one location to another on a local hardware device, such as a computer or smartphone. This typically involves selecting an image from a source folder and copying or moving it to a different folder or application within the same device. This function enables users to organize, share, and manage their image files efficiently.

6.1.3 IMAGE PREPROCESSING

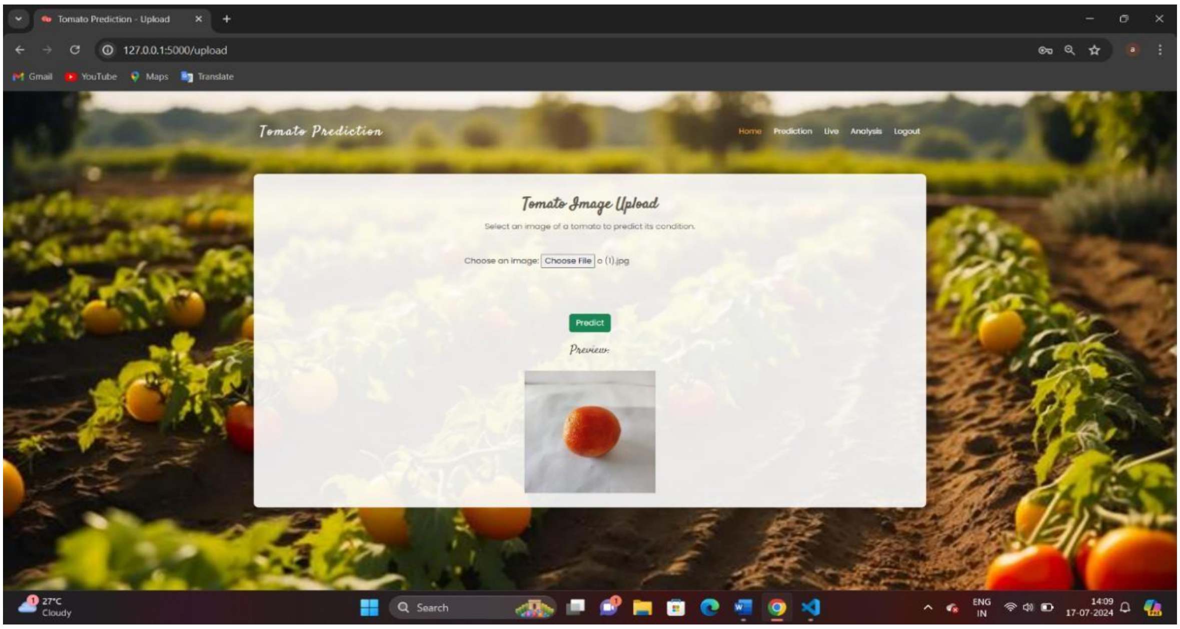

Figure 8. Image pre-processed

Technique of preparing raw image data intended further analysis by enhancing its quality and removing unwanted noise. This involves operations like resizing, filtering, normalization, and contrast adjustment to improve image's clarity & suitability intended subsequent processing step or algorithms.

6.1.4 IMAGE SEGMENTATION

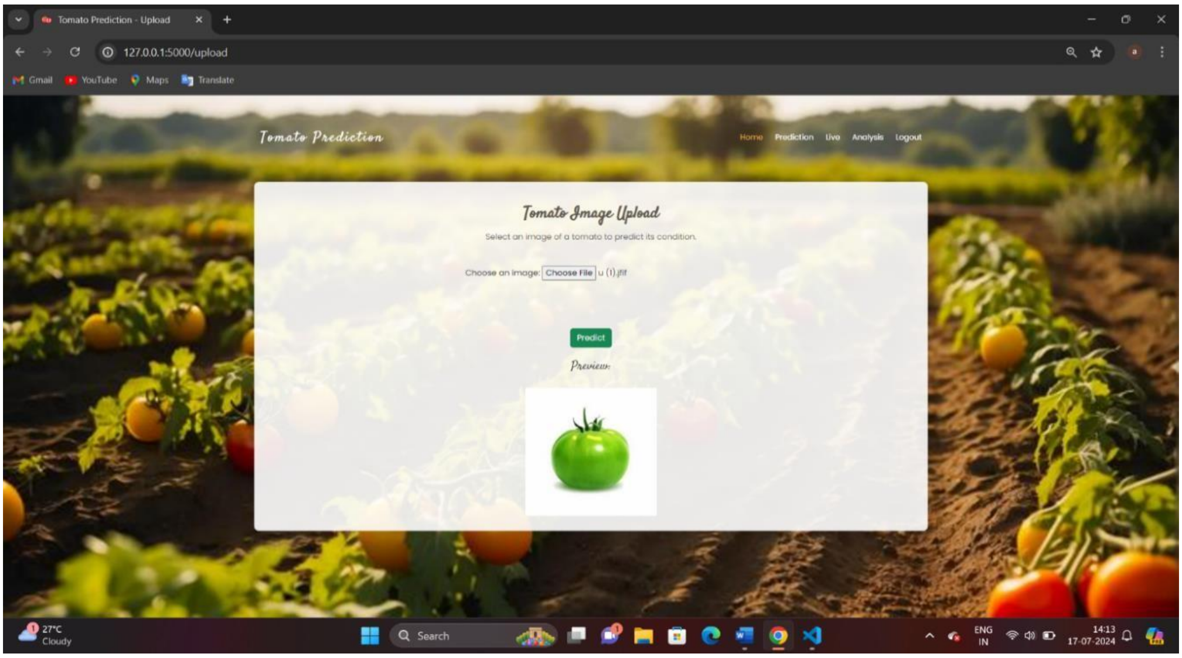

Figure 9. Image Segmentation

This technique is used to identify and isolate specific objects or areas within an image, facilitating tasks such as object recognition and boundary detection

6.1.5 PREDICTED DETAILS

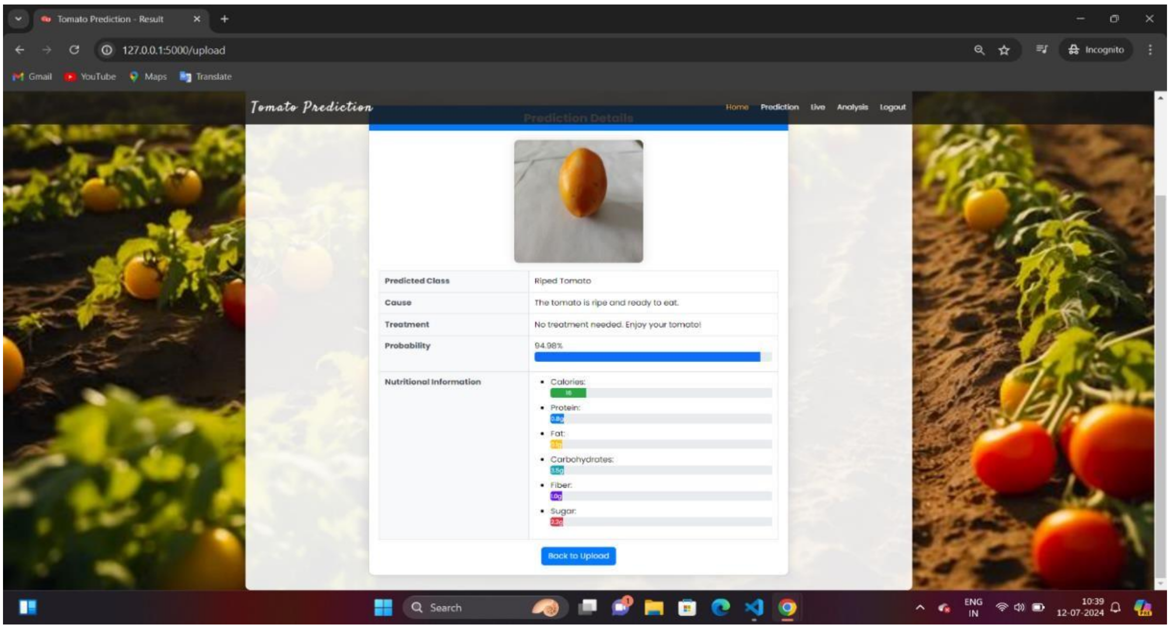

Figure 10. Predicted Details

A prediction module is a component of a software application designed to forecast outcomes based on input data. It utilizes algorithms and models to analyze the data and generate predictions, providing users with insights and informed estimates about future events or states.

6.1.6LIVE DETECT

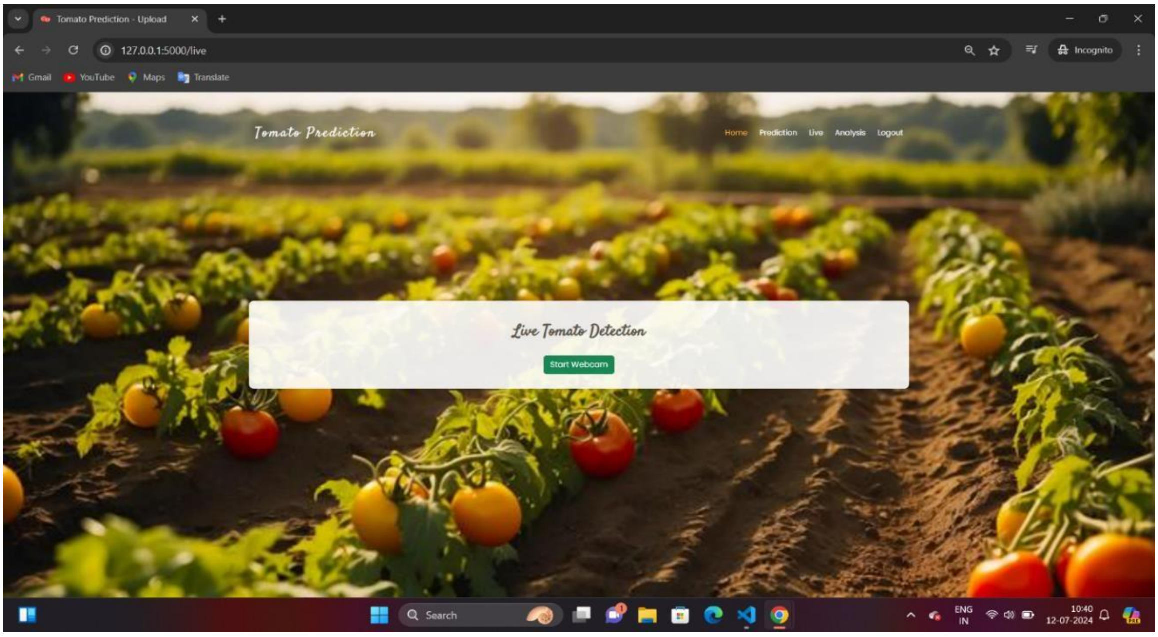

Figure 11. Live Detection

A live detection module is a system that processes real-time data, often from cameras or sensors, to identify and analyze objects or events as they occur. This module continuously monitors the input feed and provides instant feedback or actions based on the detected information.

6.1.7 IMAGE CAPTURING

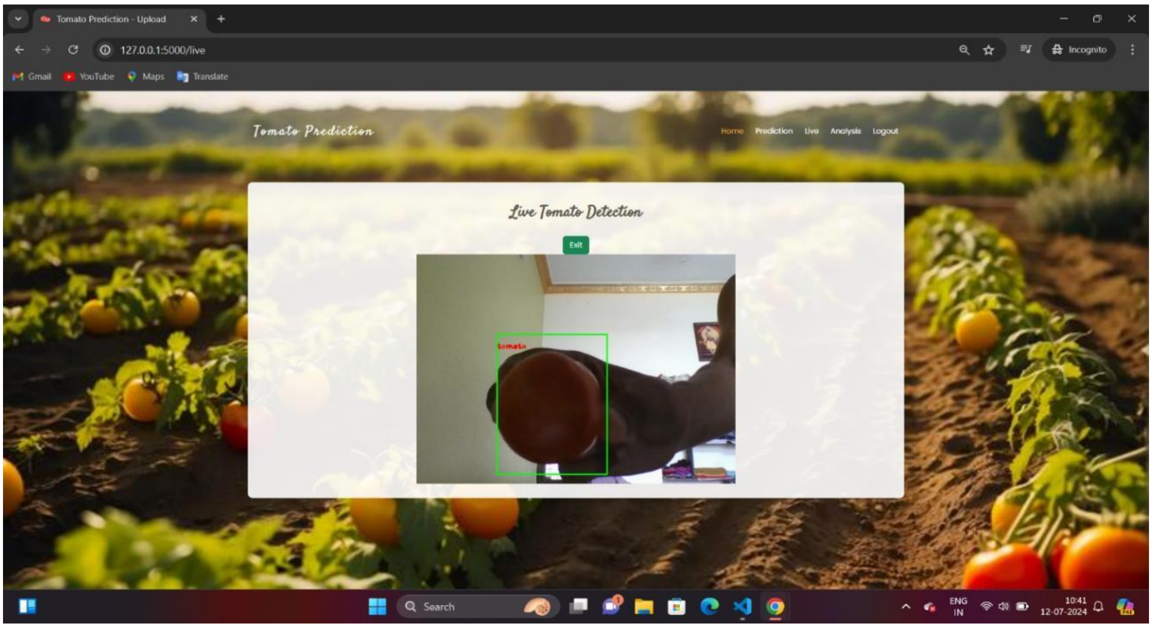

Figure 12.Image Capturing

This image shows a live tomato detection module in action. The webpage features a real-time feed where the system identifies and labels a tomato within a green bounding box. The module processes live video input to detect tomatoes instantly, providing visual feedback by highlighting the detected tomato.

6.1.8 TRAIN AND TEST ACCURACY GRAPH

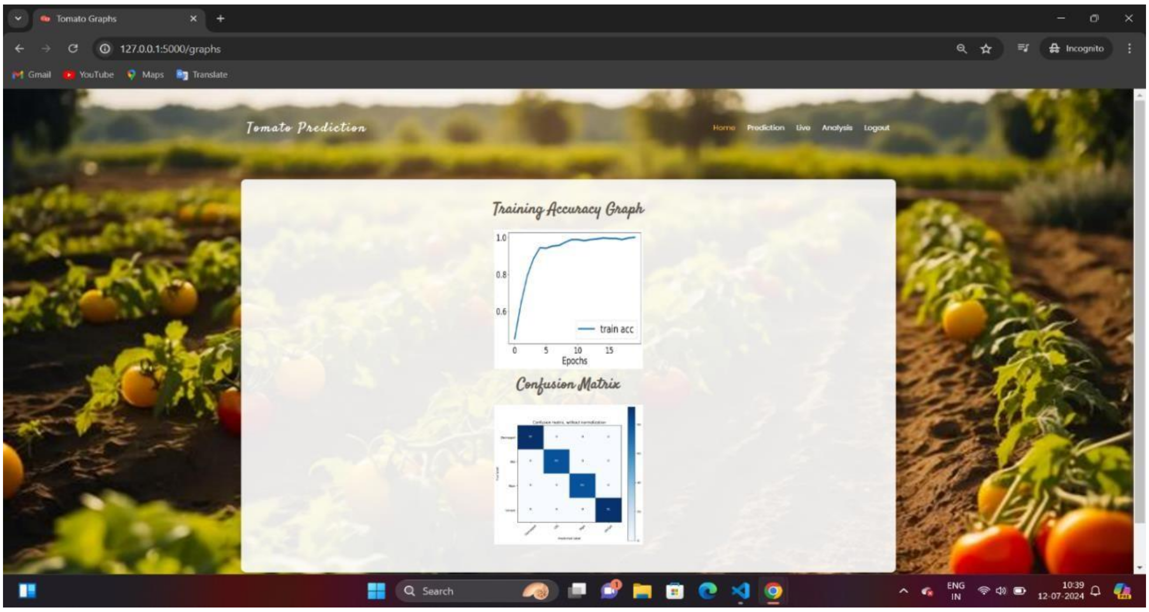

Figure13. Train and Test Accuracy Graph

Taring accuracy is a measure used to evaluate execution of classification model. It is ratio of correctly predicted instances to the total number of instances in the dataset.

A confusion matrix is a table used to assess performing of a classification model. It delivers detailed breakdown of correct and incorrect predictions across different classes

VII. CONCLUSION

Tomato Maturity Classification successfully developed a classification model for the detection and prediction of various stages of tomato such as ripen, unripen, old and damaged using machine learning techniques. The approach ensured accurate identification of tomatoes, filtering out non-relevant objects and classifying the tomatoes into ripe, unripe, and old/damaged categories. The implementation of CNN demonstrated high accuracy and efficiency in real-time applications. This classification holds noteworthy potential intended practical applications in agriculture, particularly in recuperating superiority control process intended tomato harvesting & distribution. By providing timely & truthful information concerning the state of the tomatoes, farmers & vendor can make informed decisions to reduce waste and optimize the quality and shelf life of their produce.

VIII. FUTURE ENHANCEMENT

Integrations with IoT sensors and cloud computing could further optimize data collection and analysis, enabling real-time monitoring and management of tomato crops.Overall, these enhancements aim to transform the project into a comprehensive agricultural utensil that not only perceives and treats tomato defects but also supports sustainable farming practices and improves crop management strategies.

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