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Intelligent Tomato Sorting Machine With Raspberry Pi And Computer Vision

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Abstract: The Intelligent Tomato Sorting Machine helps sort tomatoes accurately and efficiently, reducing human effort and improving productivity in farming and food industries. A Raspberry Pi camera captures images of tomatoes as they slide down a smooth surface. A Convolutional Neural Network (CNN) is trained to analyse these images and classify tomatoes as ripe or unripe based only on their colour. The model is developed and trained using Google Colab which provides powerful computers for faster learning. Once trained, the model is loaded onto a Raspberry Pi, which processes images in real time. Based on the classification, the Raspberry Pi activates servomotors to push each tomato into the correct bin.

The project has two main steps and the first step is Training the Model in this step we will be Collecting tomato images, training a CNN model in Google Colab and preparing it to classify tomatoes by colour and the second step is Building the Sorting System in this we will Setup a simple sliding surface and a sorting mechanism to move and separate tomatoes based on their classification. This system makes tomato sorting faster, easier, and more reliable, helping industries improve efficiency and quality control.

Index Terms **–** Tomato sorting machine, Raspberry pi camera, CNN model, Ripe and unripe tomatoes, Google colab, Raspberry pi, Real time sorting, Servo motors, Efficiency and quality control.

I. INTRODUCTION

Agriculture and food industries play a crucial role in sustaining human life, and advancements in technology continue to revolutionize these sectors. One such advancement is the automation of sorting processes, which significantly enhances efficiency and reduces manual labour. Among various agricultural products, tomatoes require meticulous sorting to ensure quality and consistency in production. Traditional sorting methods rely heavily on human labour, which can be time-consuming, inconsistent, and prone to errors. To address these challenges, intelligent automation using machine learning and embedded systems presents a promising solution.

The Intelligent Tomato Sorting Machine is an innovative system designed to automate the process of sorting tomatoes based on their ripeness. The system integrates a Raspberry Pi, a camera module, and a Convolutional Neural Network (CNN) model to classify tomatoes as ripe or unripe based on their colour. The implementation of such a system significantly enhances productivity, reduces human intervention, and ensures a standardized quality of tomatoes for agricultural and food processing industries.

This project leverages computer vision and deep learning to analyse tomato images in real-time. A Raspberry Pi camera captures images of tomatoes as they move along a sliding surface, and a CNN model processes these images to determine ripeness. The model is initially trained in Google Colab, where it learns to distinguish ripe and unripe tomatoes based on their colour characteristics. Once trained, the model is deployed on a Raspberry Pi, allowing the system to function autonomously without requiring a continuous internet connection or external computational resources.

Upon classification, the Raspberry Pi controls servomotors to direct each tomato into the appropriate bin. This automated sorting mechanism not only ensures higher accuracy and efficiency but also reduces the reliance on manual labour. By implementing this technology, farmers and food processing industries can achieve better quality control, reduce post-harvest losses, and improve overall productivity.

The adoption of AI-driven automation in agriculture has the potential to transform traditional practices. This project serves as a stepping stone towards smart farming solutions, demonstrating how machine learning and embedded systems can be combined to create cost-effective, scalable, and reliable solutions for the agricultural sector.

II. LITERATURE SURVEY

In recent years, numerous studies have explored automated tomato sorting and classification using a variety of machine learning and deep learning techniques. A hybrid model combining Convolutional Neural Networks (CNN) and Support Vector Machine (SVM) achieved 98.5% accuracy in classifying ripe, unripe, and defective tomatoes. CNN architectures have been widely utilized for fruit classification and have shown high classification accuracy for tomatoes. Color and shape-based classification using CNN has also proven effective in distinguishing between different tomato types. A non-invasive method using MRI was presented to evaluate tomato ripeness based on sugar content and firmness, offering a unique physical property-based classification approach. CNN-based models have also been applied for ripeness detection, while other machine learning techniques have focused on defect detection in agricultural produce.

Further advancements include testing architectures like VGG16, InceptionV3, and ResNet50 for tomato classification, with VGG16 achieving the highest accuracy of 98.75%. Lightweight CNNs like YOLOv4-tiny were used to localize tomatoes on vines, followed by color thresholding for anomaly detection. Earlier systems utilized CCD cameras for size and ripeness-based grading of tomatoes on conveyor belts. Deep learning was also integrated with image processing techniques such as Canny edge detection, and Arduino-driven conveyors were employed for automated sorting. Additional studies explored the use of deep residual networks and fuzzy models to enhance tomato ripeness and disease classification. These diverse approaches highlight the growing impact of deep learning, particularly CNN-based models, in developing efficient and accurate systems for automated tomato sorting in agriculture.

III. METHODOLOGY

In this project, we developed an intelligent tomato sorting system that uses a Convolutional Neural Network (CNN) model integrated with a Raspberry Pi to identify and sort tomatoes into three categories: ripe, unripe, and none (background or non-tomato objects). The methodology includes a comprehensive approach covering both software development and hardware implementation to achieve an efficient and real-time classification and sorting solution.

We began by creating a custom image dataset consisting of 150 images—50 each for ripe, unripe, and none categories. The images were captured manually using a digital camera under different lighting conditions and angles to simulate real-world scenarios. These images were then organized into three separate folders for effective labeling and loading during model training. Pre processing steps such as resizing all images to

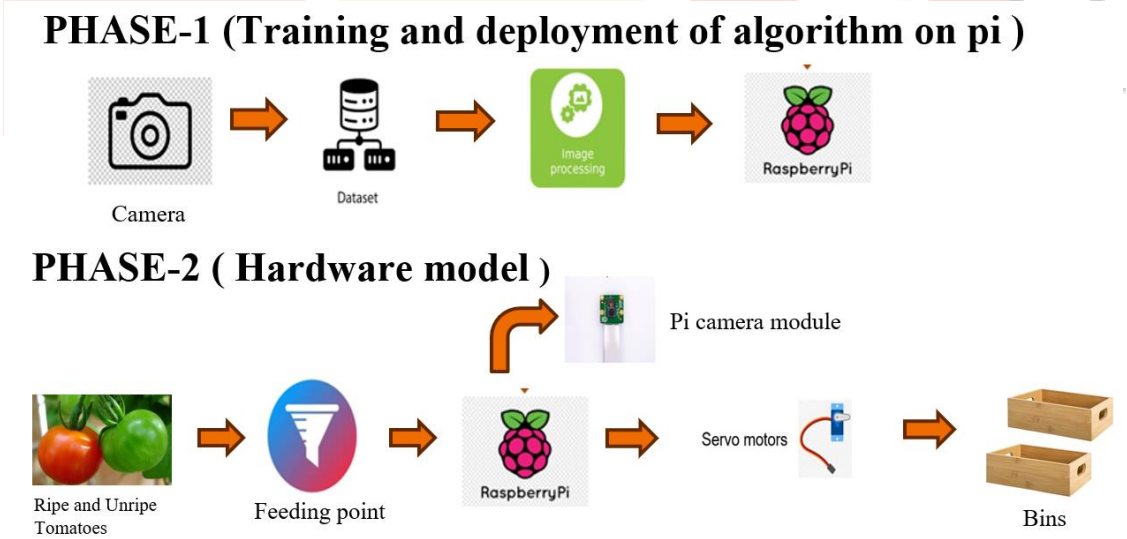
64x64 pixels and normalizing pixel values were applied to maintain consistency and improve model performance.

For the software aspect, we designed a custom CNN architecture using TensorFlow and Keras. The model comprised three convolutional layers followed by max pooling layers to extract essential spatial features. A flatten layer was used to convert the feature maps into a one-dimensional vector, followed by two fully connected dense layers with dropout for regularization. The final softmax layer provided classification output into three categories. The model was trained using categorical crossentropy loss and the Adam optimizer, and the training process was monitored with accuracy and loss plots.

Once the model was trained and validated, it was tested on unseen images to evaluate its performance. The results showed high accuracy across all three categories. The model correctly identified ripe tomatoes with high confidence, accurately classified unripe ones under various conditions, and reliably detected non-tomato images as 'None'. These outcomes were supported by labeled visual outputs, confirming the model's robustness and generalization.

To deploy the system in a real-time environment, the trained model was converted into TensorFlow Lite (.tflite) format and loaded onto a Raspberry Pi 3B+. Using the Thonny IDE, we executed the classification code and used a Pi Camera module to capture live images. Through VNC Viewer, we monitored the Raspberry Pi's terminal, which printed the classification results—ripe, unripe, or none—in real time, confirming successful execution.

On the hardware side, we integrated a servo motor with the Raspberry Pi via GPIO pins. Based on the classification result, the servo motor rotated to a predefined angle: one position for ripe, another for unripe, and a neutral position for none. This enabled an automated physical sorting mechanism where predictions made by the CNN model were translated into real-world actions. The entire setup, including Raspberry Pi,



camera, and servo, was assembled and tested successfully to demonstrate the system's capability in real-time tomato sorting.

Fig.1 : Block Diagram

In Phase 1, the system is trained to identify tomatoes as ripe or unripe based on their color. A camera captures images of various tomatoes, which are then stored in a dataset. These images are processed using machine learning techniques, where a model is trained to recognize color patterns and classify the tomatoes. The training is done in Google Colab, which provides powerful computational resources for faster learning.

Once the model is trained, it is deployed onto a Raspberry Pi, which will later perform real-time classification of tomatoes during the sorting process.

In Phase 2, the hardware system is set up to automate the sorting process. The tomatoes, both ripe and unripe, are placed at a feeding point, where they start moving through the sorting mechanism. A Raspberry Pi camera module captures images of each tomato as it moves along the surface. The Raspberry Pi processes the image using the trained model and determines whether the tomato is ripe or unripe. Based on the classification, servo motors are activated to push the tomatoes into the appropriate bins—one for ripe tomatoes and another for unripe ones.

IV. RESULTS AND DISCUSSION

The Intelligent Tomato Sorting Machine was successfully tested through multiple phases, from model training to real-time deployment using Raspberry Pi. Below are the detailed results recorded during each stage of development and execution:

CNN Model Training Results

The CNN model was trained using a dataset of 150 images, 50 each for ripe, unripe, and none. The training was carried out on Google Colab using Python and TensorFlow libraries.

Training Log Output

The training log displayed accuracy and loss values for each epoch. The model showed consistent improvement with reduced loss and increased accuracy, indicating successful learning.

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class s
  self._warn_if_super_not_called()
Epoch 1/25
2/2 ━━━━━━━━━━━━━━━━━━━━ 9s 5s/step - accuracy: 0.5291 - loss: 1.0893 - val_accuracy: 1.0000 - val_loss: 1.0317
Epoch 2/25
2/2 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.7543 - loss: 1.0258 - val_accuracy: 0.9286 - val_loss: 0.9637
Epoch 3/25
2/2 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.8566 - loss: 0.9509 - val_accuracy: 0.9286 - val_loss: 0.8768
Epoch 4/25
2/2 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.8358 - loss: 0.8665 - val_accuracy: 1.0000 - val_loss: 0.7831
Epoch 5/25
2/2 ━━━━━━━━━━━━━━━━━━━━ 4s 2s/step - accuracy: 0.8150 - loss: 0.7825 - val_accuracy: 0.9286 - val_loss: 0.7086
Epoch 6/25
2/2 ━━━━━━━━━━━━━━━━━━━━ 4s 1s/step - accuracy: 0.9349 - loss: 0.6817 - val_accuracy: 1.0000 - val_loss: 0.5531
Epoch 7/25
2/2 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.8575 - loss: 0.6086 - val_accuracy: 1.0000 - val_loss: 0.4830
Epoch 8/25
2/2 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.9661 - loss: 0.5111 - val_accuracy: 1.0000 - val_loss: 0.3670
```

Fig.2 : Training output

The model started with a training accuracy of 52.91% and a loss of 1.0893, indicating that it was the patterns in the dataset. As training progressed, accuracy increased significantly, reaching 93.49% by epoch 6 and 96.61% by epoch 8, with a steady decline in loss. The validation accuracy consistently remained high, reaching 100% by epoch 6, suggesting that the model was generalizing well on unseen data.

Training Graph:

Accuracy and loss graphs were plotted to monitor training behavior. These graphs show that the model effectively learned to differentiate between ripe, unripe, and none categories, with minimal signs of overfitting.

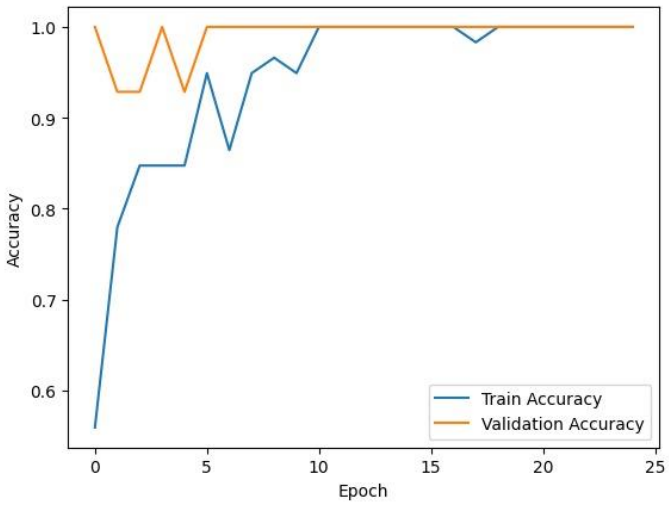


Fig.3 : Training Graph

The accuracy graph visually represents the model's learning progress. The blue line (training accuracy) started low but showed a sharp increase, reaching near 100% by epoch 12, indicating that the model learned effectively over time. The orange line (validation accuracy) fluctuated slightly in the beginning but remained consistently high, suggesting that the model was not overfitting. The graph clearly shows that after a few initial epochs, both training and validation accuracies stabilized at high values, ensuring strong performance.

Testing Outputs:

The trained model was evaluated on unseen test images, and the classification results were recorded.

Ripe Tomato Classification Output:

The model correctly identified ripe tomatoes with high confidence. The prediction was visually verified using labeled outputs.

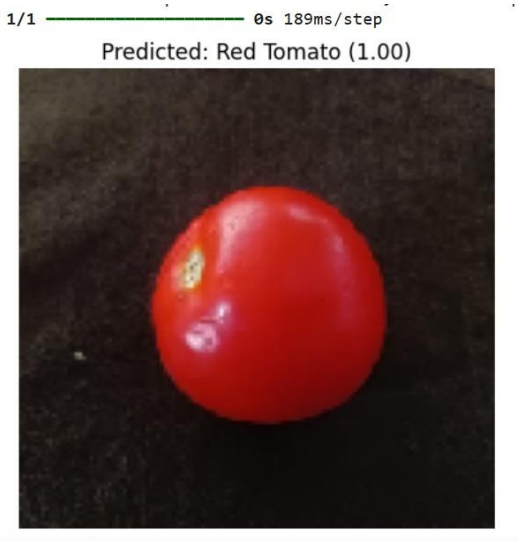


Fig.4 : Prediction of Ripe tomato

Unripe Tomato Classification Output:

Images of unripe tomatoes were accurately classified, even under varying angles and lighting.

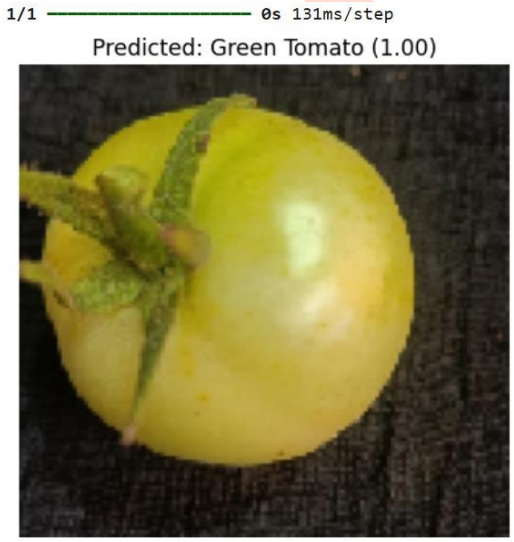


Fig.5 : Prediction of Unripe tomato

None Tomato Classification Output:

Non-tomato or background images were effectively recognized as 'None', showing the model's robustness

to irrelevant or noisy inputs.

Fig.6: Prediction of None tomato

Deployment on Raspberry Pi (Real-Time Execution) Outputs:

The trained model was converted to a lightweight format (.tflite) and deployed on Raspberry Pi 3B+ using the Thonny IDE.

VNC Viewer Outputs:

Using VNC, we monitored the Raspberry Pi's execution. When an image was captured using the Pi Camera, the classification result (Ripe/Unripe/None) was printed on the terminal in real time.

VNC Output for Ripe

This image shows the Raspberry Pi terminal after identifying a ripe tomato. The prediction is displayed in real time as the image is captured by the Pi Camera.

Fig.7: VNC output for ripe

VNC Output for Unripe

This image confirms the real-time detection of an unripe tomato by the Raspberry Pi. The result appears instantly in the terminal, validating our deployment.

Fig.8 : VNC output for unripe

VNC Output for None

This image shows the Raspberry Pi terminal after identifying a ripe tomato. The prediction is displayed in real time as the image is captured by the Pi Camera.

Fig.9 : VNC output for None

Final Hardware Setup

This image shows the complete hardware arrangement of the Intelligent Tomato Sorting Machine. It includes the Raspberry Pi, Pi Camera, servo motor, and power connections, all integrated to perform real-time sorting efficiently.

Fig.10 : Hardware setup

V. CONCLUSION

This project successfully demonstrates the development and deployment of an intelligent tomato sorting system that combines deep learning with embedded hardware. By building a custom dataset of ripe, unripe, and background (none) images and designing a tailored CNN architecture, we achieved accurate classification of tomato types under various real-world conditions. The use of image pre processing, well-structured model training, and testing phases ensured that the network learned effective features for robust prediction.

Furthermore, converting the trained model into TensorFlow Lite format enabled seamless deployment on a Raspberry Pi 3B+ for real-time execution. The integration with a Pi Camera and monitoring through VNC Viewer validated the system's performance in identifying tomato types on live inputs. The servo motor-controlled physical sorting mechanism based on CNN predictions provided a practical and automated solution, showcasing the potential of AI-driven systems in agricultural applications.

Overall, the project not only highlights the potential of computer vision in automating quality control and classification in the agricultural sector but also proves the feasibility of low-cost hardware-based real-time solutions. Future work can enhance this system by expanding the dataset, incorporating multi-class sorting, and adding object detection capabilities for more complex agricultural sorting tasks.

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