An Experimental Based Tomato Classification Using Deep Learning Algorithm

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Abstract- *Agriculture plays a vital role in the economy of any country, and tomato farming is one of the most profitable crop productions in the world. Tomatoes are one of the most extensively consumed vegetables globally and are used in the food industry for various purposes. However, the inspection and harvesting of ripening tomatoes can be time-consuming and labor-intensive, leading to higher labor costs and reduced farm productivity. The quality of tomatoes is determined by their shape, and the classification of tomatoes based on their shape is crucial for determining their market value. Therefore, it is essential to develop an automated system for tomato quality assessment and classification, which can save time and labor and improve farm sustainability.*

Keywords- Tomato classification, ripe, unripe, or defective,deep learning, convolutional neural network, agriculture, save time and labor.

I. INTRODUCTION

Machine learning is a growing technology that enables computers to learn automatically from past data. To construct mathematical models and make predictions based on historical data or information, machine learning relies on diverse algorithms. At present, machine learning is utilized for numerous tasks, including but not limited to image recognition, speech recognition, email filtering, Facebook auto-tagging, recommender systems, and more.

Deep Learning is a subset of Machine Learning that uses mathematical functions to map the input to the output. These functions can extract non-redundant information or patterns from the data, which enables them to form a relationship between the input and the output. This is known as learning, and the process of learning is called training. Deep Learning has revolutionized the field of computer vision, enabling computers to recognize and classify objects in images.

II. LITERATUREREVIEW

Tomato classification is an important task in the agriculture and food processing industries. In recent years, the use of deep learning techniques, particularly convolutional neural networks (CNNs), has gained popularity for tomato classification due to their ability to automatically learn features from raw data.

A study by Mayar Haggag et al. (2019) proposed an intelligent hybrid experimental-based deep learning algorithm for tomato sorting controllers [1]. The algorithm combined a CNN with a support vector machine (SVM) to improve the accuracy of tomato sorting. The CNN was trained on a dataset of tomato images and used to extract features, which were then fed into the SVM for classification. The proposed algorithm achieved an accuracy of 98.5% in sorting ripe, unripe, and defective tomatoes, outperforming other state-of-the-art algorithms.

Similarly, in a study by Harmandeep Singh Gill et al. (2021), the use of deep learning for fruit image classification was investigated [2]. The study focused on the classification of different types of fruits, including tomatoes, using a convolutional neural network (CNN). The results showed that the proposed CNN model was able to achieve high accuracy in fruit classification, including tomatoes.

In another study, A. Alajrami and Samy S. Abu-Naser (2019) proposed a type of tomato classification using deep learning [3]. The study utilized a CNN model to classify three types of tomatoes based on their color and shape. These studies demonstrate that the proposed CNN model was able to accurately classify different types of tomatoes.

Lu Zhang and Michael J McCarthy's article "Measurement and Evaluation of Tomato Maturity using MRI" (2012) presents a non-destructive method for measuring and evaluating tomato maturity using MRI [4]. The system uses MRI images to determine the sugar content and firmness of the tomato, which are indicators of maturity.

Myongkyoon Yang and Seong In Cho's article "Fruit Classification using Convolutional Neural Network (CNN)"

(2021) presents a CNN-based fruit classification system [5]. The system uses CNN to classify different types of fruits, including tomatoes.

Overall, these studies show that CNN-based approaches can achieve high accuracy in tomato classification, even in the presence of various lighting conditions and defects. Some studies also utilized support vector machines (SVMs) and MRI images to improve the accuracy of tomato sorting and evaluate tomato maturity, respectively. The studies demonstrate the effectiveness of CNNs for tomato classification and grading tasks.

III. EXISTINGSYSTEM

- The current methods for tomato classification suffer from several limitations. Manual inspection by humans is one such method, which is time-consuming and labor-intensive, leading to increased costs for farmers and producers. Moreover, this method is prone to errors, resulting in a high risk of misclassifying tomatoes.
- Traditional image processing techniques without machine learning algorithms can also be inaccurate and less robust than more advanced techniques. Additionally, using only basic algorithms like K-Nearest Neighbors or SVM may not be sufficient to capture the complexity and diversity of tomato characteristics, leading to lower accuracy in classification.
- Finally, systems that require high-end hardware or specialized sensors may not be practical or affordable for small farmers or producers, further limiting the availability and adoption of such systems.

IV. PROPOSEDSYSTEM

In this paper, we propose a custom CNN model for tomato quality assessment and classification. The tomatoes in the dataset are first segmented and labeled as ripe, unripe, or defective. The dataset is then split into three sets: a training set, a validation set, and a testing set, sourced from various resources. The proposed model uses size, shape, color, and ripeness to extract features and classify tomatoes.

The research methodology comprises five main components: image input, preprocessing, segmentation, feature extraction, and classification. Experimental findings suggest that the proposed model accurately classifies tomato species, reducing the need for manual classification labor. The proposed model has the potential to enhance the use of digital horticulture resources for farming, improving farm sustainability by reducing labor costs and increasing productivity.

DATA COLLECTION

When collecting data, it is important to ensure that it is unbiased and collected in sufficient quantities to accurately predict the performance of the system. A larger amount of data generally leads to more accurate algorithms. If the training data for the proposed system is limited, it may not support the necessary model complexity to solve the problem. Improper data collection can lead to reduced accuracy and predictive ability of machine learning models. In this study, a total of 180 images were used for tomato classification, consisting of 60 images each of ripe, unripe, and defective tomatoes. This dataset size was relatively small and influenced the selection of the adopted network and model training techniques. The dataset was split into a training set consisting of 70% of the data (126 images), a validation set consisting of 15% of the data (27 images), and a testing set consisting of 15% of the data (27 images).

Figure1: Dataset

CUSTOM TOMATO CNN

The first approach was to create and train a custom from scratch CNN. Multiple combinations have been tried, in order toachieve the highest possible accuracy, while reducing the loss.

The final configuration of the network consists of:

- 16 layers
- Conv2D: Convolutional layers with 32, 64, 128, 256, and 512 filters, respectively.
- MaxPooling2D: Max pooling layers with a pool size of (2, 2).
- Flatten: A layer that flattens the output of the previous layer**.**
- Dense: Fully connected layers with 512, 256, 128, and number of classes (3) neurons, respectively.
- Dropout: Dropout layers with drop probabilities of 0.5, 0.3, and 0.2, respectively.
- Activation: Rectified Linear Unit (ReLU)activation functions for all hidden layers and SoftMax activation for the output layer.
- The model is compiled with the Adam optimizer, a learning rate of 0.001, and categorical cross-entropy loss.

- During training, the model is fed augmented image data generated by Image Data Generator, with various transformations such as rotation, shift, shear, and flip applied.

Figure 2:Flowchart diagram

Figure 3:Ripened Tomato

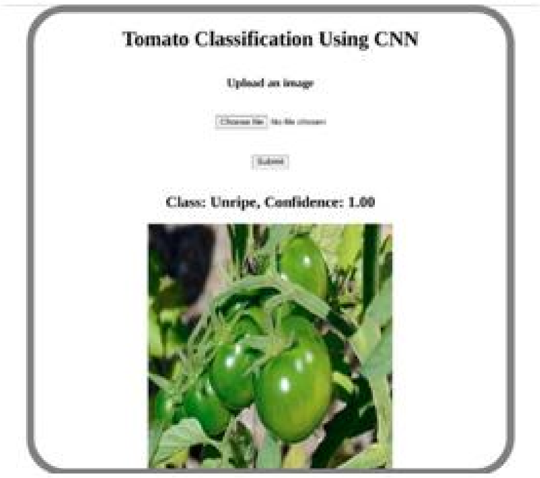

Figure4: Unripened Tomato

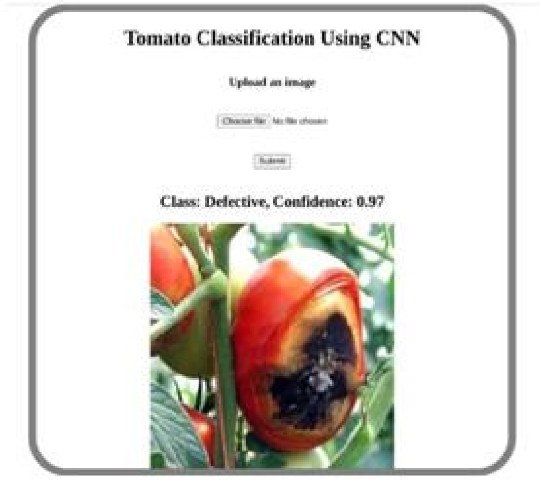

Figure5: Defective Tomato

V. CONCLUSION

Based on the experimental results, CNN was employed to classify different classes of tomatoes, namely ripe, unripe, and defective based on their maturity level. These tomatoes were different from the ones used for training and validation. The accuracy for ripe, unripe, and defective tomatoes was around 95%.

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