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An Automated Tomato Sorting using CNN-ANN based algorithm

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Abstract

Any country's economy is built on agriculture, and one of the most profitable agricultural pursuits in the world is growing tomatoes. Tomatoes are one of the most popular vegetables in the world and areused in a variety of food products. But gathering and inspecting ripening tomatoes by hand is time- consuming and labor-intensive, increasing labor costs and decreasing agricultural productivity.Tomato quality is greatly influenced by their shape, and market value is largely determined by howtomatoes are categorized based on this criterion. Therefore, it becomes necessary to create an automated system that can evaluate and classify tomato quality. This method promises to save time and effort while improving farm sustainability.

Keywords: deep learning, convolutional neural network, agricultural, tomato classification, ripe,unripe, or defective, labor and time savings.

1. Introduction

Because of their broad consumption and economic significance, tomatoes play a crucial role in the agricultural industry in both their cultivation and processing. Because tomatoes are used in so many different food businesses around the world, determining when they are ripe is an important undertaking. Nevertheless, the conventional manual techniques fordetermining the ripeness of tomatoes are labor- intensive, time-consuming, and ineffective.

A crucial factor affecting tomato quality that has a big impact on market value and customer satisfaction is ripeness. The subjective and prone to error nature of manual ripeness assessment results in inconsistent product quality and higher operating costs. Automated techniques that can precisely gauge tomato maturity are needed to address these issues.

Background:

Agricultural automation has been made

possible by the application of artificial intelligence and machine learning. Convolutional neural networks in conjunction with artificial neural networks have shown promise in solving image-based categorizationproblems.

The integration of convolutional neural network - algorithms for tomato maturity assessment has numerous benefits. convolutional neural networks are very good at identifying features from image data, whichenables them to detect minute details and characteristics that indicate ripeness. These methods leverage the hierarchical nature of convolutional neural network s to train discriminative features with high reliability and accuracy.

2. Related Work

In recent years, researchers have made significant strides in the domain of tomato sorting classification, employing various techniques and algorithms to enhance accuracy and robustness.

The research paper 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 witha support vector machine (SVM) to improve the accuracy of tomato sorting. The CNN was trained ona 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.

The research led by Harmandeep Singh Gill et al. [2]. focuses on the classification of different types of fruits, including tomatoes, using a convolutionalneural network (CNN). The results showed that the proposed CNN model was able to achieve highaccuracy in fruit classification, including tomatoes.

In their study, A. Alajrami and Samy S Abu-Naser [3]. utilized a CNN model to classify three types of tomatoes based on their color and shape. Thesestudies demonstrate that the proposed CNN model was able to accurately classify different types of tomatoes.

Lu Zhang and Michael J McCarthy's article [4] presents a non-destructive method for measuring and evaluating tomato maturity using MRI. Thesystem uses MRI images to determine the sugar content and firmness of the tomato, which are indicators of maturity.

To detect tomato ripeness, Myongkyoon Yang and Seong In Cho's research [5] presents a CNN-based fruit classification system. The system uses CNN to classify different types of fruits, including tomatoes.

Xunang Shi,Xuncheng Wu research[6] used to detect defects in agricultural products is primarily illustrated. Automated machine learning technology has grown in importance and potential in a variety of sectors, including the food processing and agriculture industries.

Robert G. de Luna and Elmer P. Dadios [7] The three deep learning models—VGG16, InceptionV3, and ResNet50—are trained, validated, and tested using the images. The experiment's findings indicate that VGG16 performs 95.75-95.92-98.75 in terms of training-validation-testing accuracy percentage.

The work [8] by Sittiporn Tantiborirak and Kanjanapan Sukvichai uses the location of each tomato in tomato vines were identify and localized by using YOLOv4-tiny CNNs model, then, each tomato fruit was cropped. The result showed that YOLOv4-tiny could detect tomato fruits and and the color thresholding successfully detected the tomato anomalies.

The paper [9] by C.A. Gunawardena. The system can route and sort tomatoes to multiple output gradesbased on size and ripeness in a typical application. Produce moving along a conveyor belt with revolving rollers is inspected by a color television camera equipped with a charge-coupled device (CCD).

In the study by Justine Fred Bautista [10] The procedure begins with taking a picture of a tomato, which is then processed using image processing techniques like Canny-Edge Detection to classify the size into small, medium, large, and jumbo, and deep learning algorithms to assess the quality. An Arduino microcontroller drives the conveyor, whichmoves the tomatoes to the location where the photoof them is taken.

3. Methodology

Several steps were taken to use convolutional neural network and artificial neural network algorithms to sort tomatoes based on their levelof ripeness. After being gathered, the tomatoesin the dataset were divided into three groups: overripe, ripe, and unripe. After a visual inspection, these tomatoes were divided into therelevant classes. After then, the dataset was split up into training and testing sets. The preprocessing of the dataset involved standardizing image sizes, enhancing datasetvariety through augmentation, and normalizingthe dataset in preparation for the artificial neural network algorithm. The artificial neural network model's architecture was created, typically with input, hidden, and output components strata. Following the creation of architecture, the model underwent training using the training dataset, optimizing learning rate and batch size among other hyperparameters. Following training, the testing dataset was used to analyze the model's performance, and evaluation metrics like accuracy, precision, recall, and F1-score were computed.

Likewise, the convolutional neural network approach involved preprocessing the dataset and adding convolutional layers to identify spatial connections in the images. Fully connected layers were integrated for classification, while pooling layers were used to lower dimensionality. The convolutional neuralnetwork model was trained with the training dataset, and its optimal performance was achieved by optimizing the hyperparameters. The testing dataset was used for evaluation, and assessment metrics were calculated appropriately.

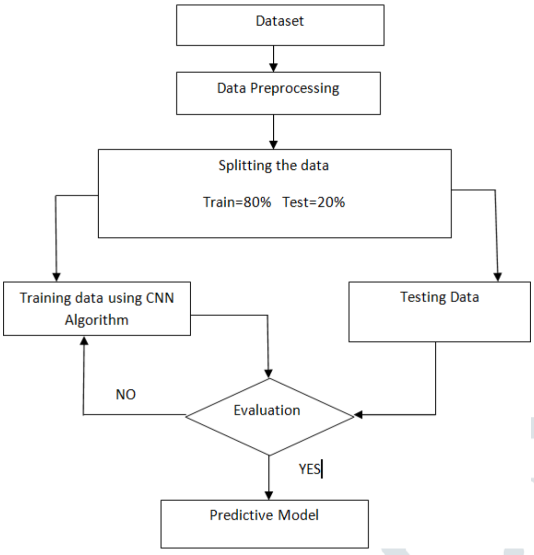
After both algorithms were put into practice, their performance indicators were compared. Itwas shown that convolutional neural network outperformed artificial neural network in tomato ripeness sorting with greater accuracy. This conclusion was drawn from the assessment findings that were discovered when the models were tested using the dataset. convolutional

neural networks improved accuracy was ascribed to its intrinsic capacity to automatically extract complex information from images, which made it useful for image classification

tasks.

In conclusion, the process for classifying tomato maturity included gathering datasets, classifying, preprocessing, designing the modelarchitecture, training, hyperparameter optimization, evaluating, and comparing the convolutional neural network and artificial neural network algorithms' performance metrics.

In summary, the methodology for tomato ripeness sorting encompassed dataset collection, categorization, preprocessing, model architecture design, training, hyperparameter optimization, evaluation, and comparative analysis of performance metrics between ANN and CNN algorithms.



1: Architecturediagram

4. Experimental Setup

Dataset Description: Images of tomatoes that have been prepped for machine learning tasks make up the dataset. Preprocessing processes are applied to every image to improve its suitability for model training and standardize itsformat. First, all of the photos are downsized to

224 by 224 pixels so that the dataset's dimensions are consistent. Since the images' color space is defined as Red,Green,Blue, eachpixel is represented by one of three color channels: red, green, and blue. The photos are then transformed into numerical arrays, which is a prerequisite for utilizing them in machine learning techniques. The arrays' pixel values arenormalized to lie inside the range [0, 1] in orderto aid in learning. The dataset is mainly concentrated on tomato imagery, while the specific content and features of the photographs may differ. A variety of machine learning models, especially deep learning architectures like convolutional neural networks, can be trained using these preprocessed photos as input data. To enable meaningful model training andevaluation, however, associated labels specifying properties like tomato kinds or ripeness levels are crucial for supervised learning applications.

Evaluation Metrics:

Common criteria necessary for binary classification tasks are used to assess the tomato ripeness detection model. Precision, recall, andF1-score are important measures that show howwell the model can identify tomato ripeness occurrences while lowering false positives.

1. Accuracy: The model's overall predictionability.

TP + TN / TP + TN + FP + FN equals accuracy.

2. Precision: the percentage of correctly predicted phishing incidents to all of the incidents that were forecasted. Repeatability = TP / TP + FP

1. Recall (Sensitivity or True Positive Rate): The percentage of accurately anticipated phishing attacks that actually occurred. TP / TP + FN = Recall.

2. F1 Score: The harmonic mean of recall and precision

is used to create a balanced statistic. F1score is equal to 2 × (precision x recall) / (precision + recall.

Whereas,

The number of accurately anticipated positive events is known as True Positives.The number of accurately predicted negative cases is known as True Negatives.False Positives, are the quantity of positivecases that were mis predicted. The amount of negative events that were mis predicted is known as False Negatives. These metrics are often used to evaluate the performance of classification models.

5. Results

This section displays the evaluation results of various machine learning techniques for the dataset's tomato ripeness detection. Tomato ripeness was categorized using techniques fromartificial neural and convolutional neural networks . The algorithms performance was evaluated in terms of support, F1 score, recall, accuracy, and precision.

Confusion Matrix

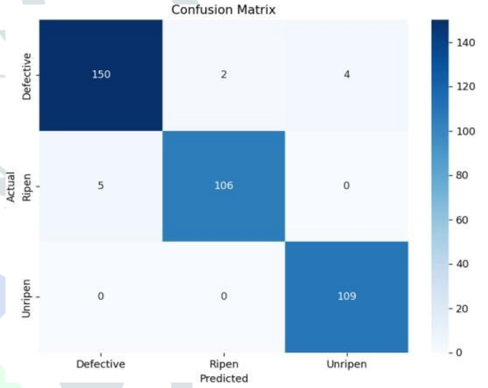
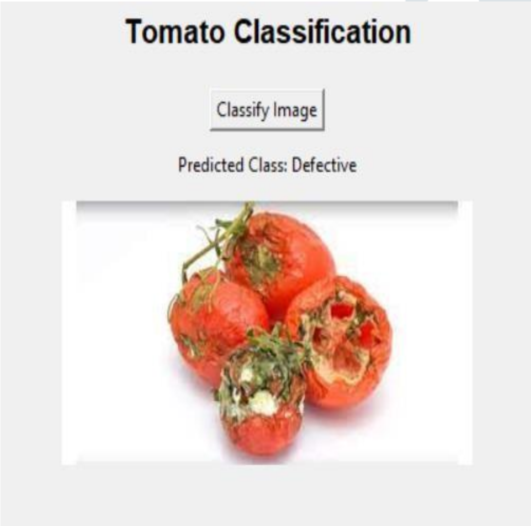


Table1: Model Evaluation Results

	Precision	Recall	F1-score	Support
ANN	0.95	0.95	0.95	376
CNN	0.97	0.97	0.97	376



6. Discussion and Analysis

In comparison to the artificial neural network model, the convolutional neural network modelperforms better in all classes in terms of precision, recall, and F1-score. Accordingly, the convolutional neural network model performs a better job of recognizing and categorizing tomatoes according to their level of ripeness. Additionally, the convolutional neural network model's total accuracy is higherthan the artificial neural network model's, indicating that it outperforms the latter on thisarticular classification task. In conclusion, theconvolutional neural network model appears tobe more dependable and efficient for the particular tomato ripeness classification task.

7. Conclusion

The convolutional neural network model outperforms the artificial neural network modelin terms of precision, recall, and F1-score in every class, according to the experimental findings. Accordingly, the convolutional neuralnetwork model performs a better job of recognizing and categorizing tomatoes according to their level of ripeness. For ripe, unripe, and faulty tomatoes, the accuracy was approximately 97%. Additionally, the convolutional neural network model's total accuracy is higher than the artificial neural network model's, indicating that it outperformsthe latter on this particular classification task.

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