Analyzing Different Architectures of Convolutional Neural Networks for Tomato Grading System

Abstract

The tomato is a very popular and commonly eaten fruit. Its quality, which affects how people see it, depends a lot on how it looks. Convolutional neural networks, which are advanced computer programs, are great at using deep learning to sort and classify fruits, grains, and vegetables in farming. Right now, there are two ways to classify tomatoes: by eye or by analyzing images. The first method, which involves checking tomatoes by hand, is more accurate but takes longer and costs more. The second method, which uses images, is faster and cheaper but not as precise. In this study, we use a deep learning approach to classify tomato quality, specifically using convolutional neural networks (CNNs). We compared two popular CNN models, ResNet-50 and AlexNet, and tested how well these models automatically find important features in the tomatoes. The success percentage of our suggested strategy in experiments was 99.1%. Our proposed method outperforms existing image-processed tomato quality rating systems on all five of the commonly used evaluation criteria, including accuracy, precision, recall, specificity, and F-score.

Keywords: Machine Learning (ML), Convolutional Neural Network (CNN), Confusion Matrix (CM), Deep Learning (DL), ResNet-50, AlexNet.

1. Introduction

Tomatoes have quickly become one of the fruits and vegetables that are consumed most often all over the world. Tomatoes provide a wealth of minerals, including fiber, vitamins A and C, and the antioxidant vitamin C. Consuming tomatoes on a regular basis might help reduce the chance of developing a range of complex diseases that affect the body, such as cancer, cardiovascular disease, and osteoporosis, among others. As a consequence of the various health benefits that tomatoes offer, they are gaining an ever-increasing amount of favor among consumers of all demographics and socioeconomic levels as an indispensable and extensively distributed fruit around the globe [1].

For this reason, we use tomatoes that are a variety of different stages of ripeness, including green, semi-ripe, rotten and fully ripe. The operation of sorting tomatoes plays a very essential part in the process of supplying ripe tomatoes to the market. The fact that a customer can determine if a tomato is ripe, semi-ripe, or spoiled influences his decision to purchase and stock it. In most cases, we judge the quality of the tomato based on its appearance. That is to say, we determine the quality of the tomato, also known as its grade, by looking at the tomato from the outside. Therefore, we can argue that selecting tomatoes or any other fruit based on their outward appearance is a time-consuming procedure. This holds true for every fruit. A person's involvement is required at every stage of this procedure. A person who is able to determine the quality of tomatoes based only on their appearance is in need of assistance. Therefore, we can conclude that choosing various kinds of tomatoes by hand is a procedure that takes a lot of time, is highly expensive, and is therefore not an appropriate approach. Image-based tomato quality grading is one method that may be utilized for quality selection of tomatoes in order to circumvent the challenges that are inherent in human-based methods. Several distinct kinds of cameras might be brought to the markets and farms in order to acquire these pictures. The buyer is able to verify the actual tomatoes based on the photographs. Therefore, we are able to state that this approach that relies on images can deliver more dependable tomato quality. Recently, deep learning (DL) and, more specifically, convolutional neural networks, have gained outstanding results in the agricultural sector. These results include the classification of various fruits, crops, and leaves; the identification of plant diseases; yield approximation; weed detection; weather prediction; and prediction of soil moisture [2]–[3]. In summary, we proposed a unique system for categorizing tomato grades. Ripe, semi-ripe, green, and rotten tomatoes were the four varieties we used. The market and fields in Tangail, Bangladesh, were the sources of the tomato dataset that was used in the experiment. 1,000 images from four classes were used for the training and testing datasets. Based on the quality of the tomatoes, the training dataset was separated into four categories. Our proposed method is divided into two steps for the training and testing phases. Image acquisition, image preprocessing, and feature extraction complete the training phase. We test the single tomato image in the testing phase using our proposed method. In this study, we used two CNN techniques, ResNet-50 and AlexNet, and examined the performance utilizing those features since the CNN algorithm extracts automated characteristics. We discovered that the accuracy rate of our proposed method is 99.1%. This result clearly shows that the accuracy of our ResNet-50 approach is better than AlexNet's accuracy. The recommended methodology may be applied to any food processing system to evaluate the quality of tomatoes in order to ensure food security.

The main contribution of this study is-

• We have hundreds of tomato photos in various grades. These image databases will be made available and can be utilized by other researchers.

• To automatically categorize tomato image predictions, we used deep learning models.

• In order to examine how well Resnet-50 and AlexNet perform, we have employed two different CNN models.

Here is the rest of the article: The literature review is presented in Section 2. Materials and technique are presented in Section 3, followed by the results and discussion in Section 4, and finally, the final thoughts in Section 5.

2. Literature Review

In this section, a variety of methods for sorting and classifying tomatoes have been suggested for consideration. The effectiveness of each of these modern tactics is discussed briefly. To determine the degree of ripeness that fresh tomatoes have attained, K. Choi et al. [4] developed a technique that uses color image analysis. Within their methods, they utilized the following six stages of tomato development: green, breakers, turning, pink, light red, and red. They began by altering the hue, saturation, and intensity (HSI) values of images that were composed of the RGB (Red, Green, and Blue) color spaces. It is anticipated that the TMI (Tomato Maturity Index) will have an accuracy rate of 77.5%. The fundamental shortcoming of this approach is that it only utilized a limited number of photographs and relied solely on RGB color components. Blossom End Rot (BER), also known as Cracks, is one of the many types of tomato flaws that may be detected by a control system that makes use of a neural network (NN). This method was discovered by Rokunuzzaman et al. [5]. In their investigation, color parameters for detecting BER were extracted from high-quality tomatoes, and the shape factor was investigated to differentiate calyx faults from cracks. The control system that was proposed to be used has an accuracy of 87.5%. The fact that just 160 photographs were used in the inquiry is one of the drawbacks associated with their work. S. Srivastava et al. [6] developed an innovative method of vision-sensing for the purpose of categorizing tomatoes according to the quality of the fruit and the severity of any disease present. Only 62 of the 100 tomato pictures that were utilized in their research were of healthy tomatoes, while the other 38 tomato pictures showed tomatoes suffering from a variety of diseases. The technique that was recommended has an accuracy of around 92%. S. Rupanagudi and colleagues [7] developed a complex color model in order to classify the level of ripeness of tomatoes. In their investigation, the researchers classified the six phases of development of tomatoes as follows: green, breaker, changing, pink, light red, and red. The most significant shortcoming of the strategy that they recommend is the absence of any explanation about the number of tomato photographs that were used. In addition, E. Elhariri et al. [8] proposed a revolutionary way to classify the maturation stage of tomatoes into five distinct groups, which they referred to as the SVM: green, changing, pink, pale red, and red. They were given 230 different samples of tomatoes in total from the farm in Minia City, of which 175 were utilized for training and 55 were used for testing. The accuracy of their model, which they suggested, is 92.72%. Their study had a number of limitations, the biggest one being that it only employed 230 samples, which is a very small quantity. The most current method for classifying the various stages of ripeness of tomatoes was created by P. Arakeri and colleagues (9), and it makes use of an artificial neural network. (ANN). They employed 520 different samples of tomatoes for their experiment, splitting them up into four categories: ripe, unripe, defective, and non-defective. With a classification accuracy of 96.47%, they were successful in extracting many color features, contrasts, and connections from photos of tomatoes. In addition, LI ZHANG et al. [10] introduced a unique method for classifying the degrees of tomato maturity by employing deep convolutional neural networks (DCNNs). Their method had an accuracy of 91.9%. The strategy that Avalekar et al. [11] present for evaluating tomatoes is one that is both novel and effective. In their research, the classification of the tomato quality was accomplished through the application of artificial neural networks. After the tomato photo had been scaled, the RGB and HSV color characteristics were obtained. When feeding these characteristics into a neural network, the back-propagation approach is the one that is employed. The strategy that they utilize is accurate 91.6% of the time. In addition, writers in [12] suggested a unique method for classifying the grade of tomatoes by making use of a fuzzy neural network. This method was described as being more accurate. For the purpose of their research, they employed 840 images for the testing portion, and 126 photographs for the training portion. Their technique has a specificity of 83.2%, a sensitivity to classification of 96.50%, a g-mean of 89.40%, and a classification accuracy of 95.5%, each of which may be broken down into their respective percentage ranges. A machine learning (ML) model was created by Wolfgang et al. [13] to forecast the various stages that the tomato will go through. In this particular instance, three different machine learning models were utilized. These models included K-NN (K-Nearest Neighbors), MLP-type neural networks (Multilayer Perceptron), and unsupervised learning approaches such as K-Means. On the basis of the properties of the tomato's color, a number of color parameters that may be used to predict the stages of tomato growth were also obtained. They were able to achieve an accuracy of 90% for K-NN. by combining the ResNet-50, Xception, MobileNet, and ShuffleNet deep learning algorithms, as well as the DenseNet121 Xception method. Hong et al. [14] created a brand new method for determining which illnesses affect tomatoes. The DenseNet121 Xception model, which was the most accurate of the five models, had an average accuracy of around 97.10%, according to their study, which examined these five CNN models using a number of parameters. The study looked at how these five models performed. Last but not least, Hsing-Chung et al. [15] developed a CNN architecture for predicting tomato illnesses based on photographs of leaf lesions. In their investigation to find a cure for tomato illnesses, they made advantage of the most recent version of the AlexNet architecture. It was also discovered that the outputs had an accuracy rate of 98%, which indicates that they are extremely precise.

Table 1. Summary of approach and analysis between studies for prediction tomato sorting.

Authors	Year	No.of Classes	No.of Images	ML models	Measures	Claim Accuracy
K.Choi et al[4]	1994	6 class	120	TMI	Accuracy	77.5%
Rokunuzzaman et al[5]	2013	4 class	160	NN	Accuracy	87.7%
S.Srivastava et al[6]	2014	4 class	100	Vision-sensor	Accuracy	92%
S.Rupanagudi et al[7]	2014	6 class	Undefined	color model.	Accuracy	98%
E.Elhariri et al[8]	2014	5 class	175	SVM	Accuracy	92.72%
P.Arakeri et al[9]	2016	4 class	520	ANN	Accuracy	96.47%
LI ZHANG et al[10]	2018	5 class	200	CNN	Accuracy	91.9%
Avalekar et al[11]	2018	6 class	180	ANN	Accuracy	91.66
Authors in[12]	2018	6 class	926	Fuzzy NN	Sensitivity, specificity, g-mean, Accuracy	95.5%.
Wolfgang et al[13]	2019	6 class	600	K-NN, MLP K-Mean	Accuracy, Precision, Sensitivity, Specificity	90%
H. Hong et al[14]	2020	9 class	13112	CNN Models	Accuracy	97.10%
Hsing-Chung et al[15]	2022	9 class	18345	AlexNet	Accuracy, Strictness, Recall, F1-Count	98%

3. Methodology

This section provides a definition of the deep learning algorithm that was used in this research to grade tomatoes. The primary focus of this investigation is to identify the pre-trained CNN model that is most suited for the categorization of tomatoes.

3.1 Proposed System

Within the scope of this investigation, the proposed system is partitioned into two parts: one pertaining to training, and the other to evaluation. Both parts are broken down into five core processes, which will be covered in more detail below. These processes are as follows: image capture, image pre-processing, feature extraction, feeding CNN models, and image classification at the end. The image should be broken up into a training set and a testing set. Seventy percent of the images were used for instructional purposes, while thirty percent were used for testing. The primary components of the system that we have proposed are shown in Figure1.

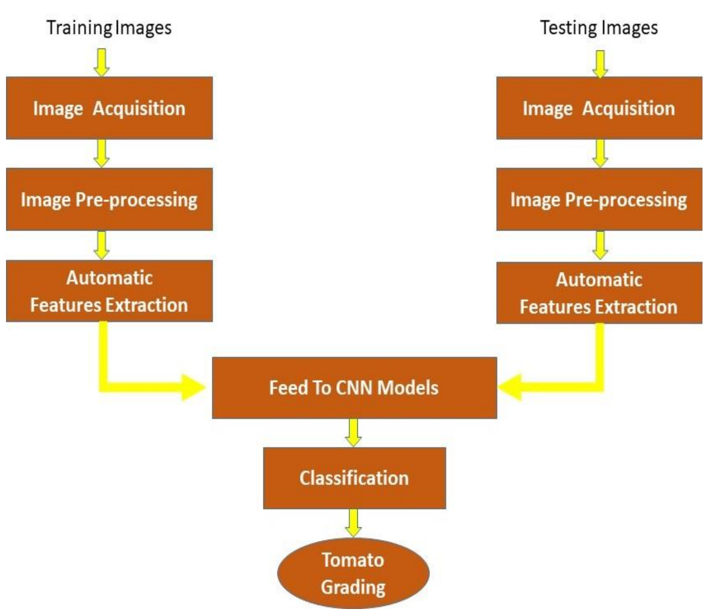

Figure 1. Proposed System Architecture for Tomato Grading.

3.1.1 Image Acquisition

The majority of the tomato samples in this study were obtained from various locations such as agriculture fields and local marketplaces in Bangladesh's Tangail district. These tomato images were taken on a Samsung smartphone, and just a few tomato images were taken from an internet tomato image library.

Figure 2. Tomato Grading Sample (Green, Semi-ripe, Ripe, Rotten).

Tomatoes are classified into four types: ripe, semi-ripe, green, and rotten. Each class in this tomato dataset has 250 images. As a result, the early tomato dataset has 4×250 = 1000 images.

Table 2. Dataset details.

Tomato Grade	Description	No. Tomato samples
Green	The surface of the tomato is fully green.	250
Semi Ripe	50% red and yellow color of tomato surface.	250
Ripe	More than 90% surface of the tomato is aggregated and displays red color.	250
Rotten	If any part of the green, ripe, or semi-ripe tomato surface is rotten, the tomato is said to be rotten.	250
	Total Tomato samples	1000

3.1.2 Image Pre-processing

In this stage, we prepared the tomato image data for categorization. We have compiled a sizable collection of tomato images in varying resolutions and noise levels from various places. As a result, since the initially captured image could contain different noises and sizes, images preprocessing is necessary. However, the CNN models demand input images of 224 × 224 by 3 dimensions. Our proposed CNN models automatically resize and convert RGB (red, green, and blue) images into grayscale images prior to receiving input from the network. Figures 3, 4, and 5 display the original RGB image, the 224-224-3 image after preprocessing, and the grayscale image.

Figure 3. Original Image

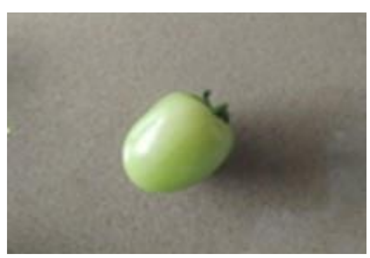

Figure 4. Pre-processing Image 224-224-3

Figure 5. Grayscale Image

3.1.3 Automatic Features Extraction

In the process of classifying photos, one of the most important steps is the automated extraction of features. The CNN model extracts essential information from the images that are fed into it. CNN takes use of these derived feature signals in order to classify images [16]. Figure 6 was displayed by the automated extract features in the application.

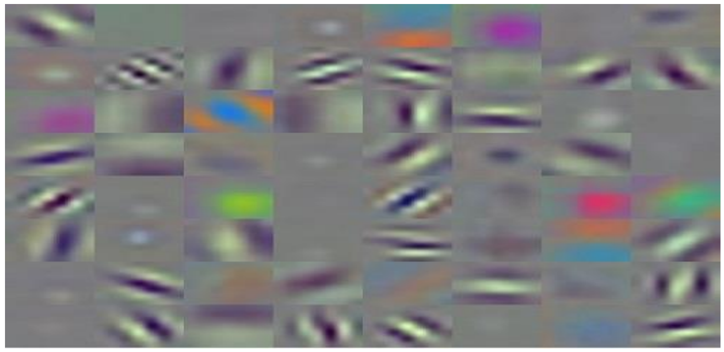

Figure 6. Automatic Feature Extraction

3.1.4 AlexNet

AlexNet, one of the most widely used CNN designs, has around 650,000 neurons and 60 million parameters. AlexNet also has three fully linked layers and five convolutional layers. The first layer, the picture input layer, requires an input image that is 227 by 227 by 3 (where 3 represents the RGB channel). More than a million photos were used to train, and over a thousand distinct items were discovered. This AlexNet model has been pre-trained to extract some of the most essential attributes from the input pictures. A softmax layer, a wholly linked layer, and a classification output layer are the last three layers.

3.1.5 Residual Network (ResNet-50)

The pre-trained Residual Network is a different 50-layer convolutional neural network architecture. This network can classify images into 1,000 distinct item categories, including several varieties of fruits, vegetables, and animals. A 224 x 224-pixel picture input is required for this network. This deep network can extract incredibly specific information from input photos since it has been trained beforehand [17]. After 49 convolutional layers, the ResNet 50 model features a fully connected layer at the network's core. In order to save computing resources and training time, ResNet-50 was ultimately chosen to pursue this study.

3.1.6 CNN Setting

An example of an artificial neural network (ANN) is a convolutional neural network (CNN). It has hundreds of layers, each of which gains the ability to directly extract certain visual elements. Manual feature extraction is also prevented because a lot of important attributes are immediately learnt from training and test images. A variety of resolution filters are applied to each training image, and the output of each convolutional layer is utilized as the input for the following layer. The filters can start by extracting basic features like brightness and edge detection before moving on to item-specific attributes. Figure 7 graphically illustrates the general layout of the CNN algorithm [18]. Its common elements include the input layer, convolution layers, pooling layer, fully connected layer, and output layer, which displays the result after the image characteristics reach the completely connected layer.

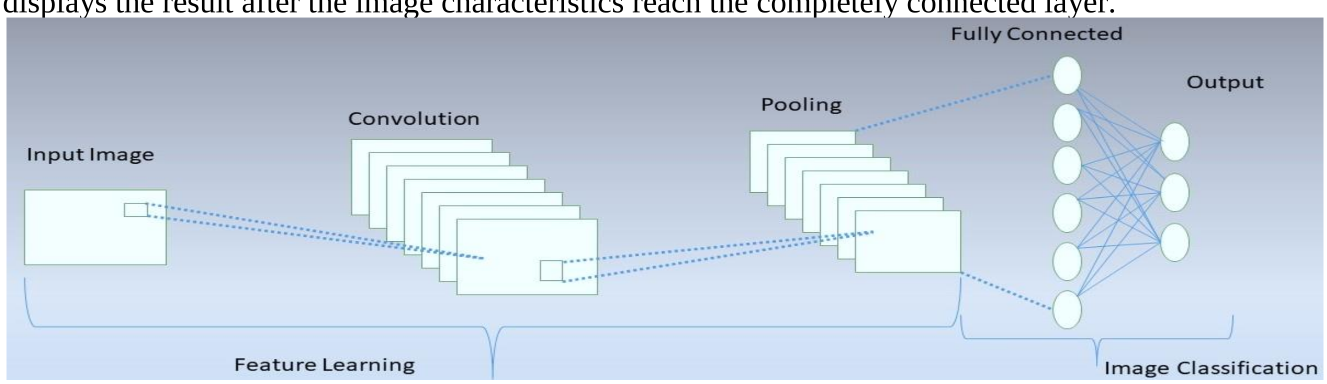

Figure 7. Display the architecture of a convolutional neural network (CNN).

On that account, the attributes of the convolutional neural network (CNN) architectures used are explained in Table 3.

Table 3. Synopsis of the utilized architectures.

Network Architectures	Depth Layers	Parameters (Millions)	Image Input Size
AlexNet	8	60	227-by-227-by-3
ResNet-50	50	25.6	224-by-224-by-3

3.1.7 Tomato Classification

Following the completion of automated feature extraction, CNN algorithms are trained using images of tomatoes with varying degrees of ripeness. After the training has been completed, we test our system with a single image of a tomato taken from the testing dataset. The tomato varietals that will be harvested in the future are predicted by the algorithm that we have suggested. As a direct result of this, we used conventional methods of assessment, such as group interpretation (3.1.8), to evaluate the pre-trained model that we had provided.

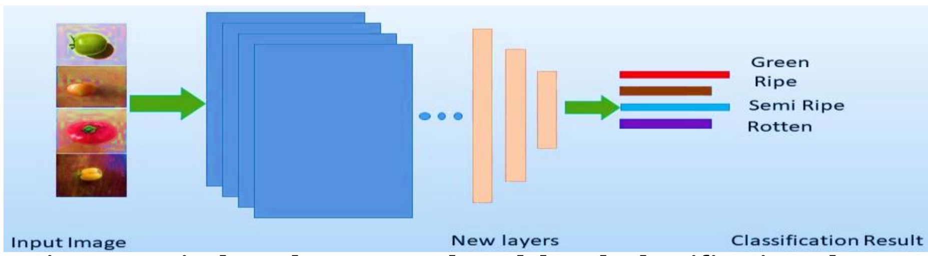

Figure 8. Displays the proposed model and Classification Phase.

3.1.8 Evaluation

Comparisons were made between five popular measures, including accuracy, precision, sensitivity, and specificity, as well as an F-score, in order to evaluate the performance of the model that we proposed. The primary way that is used to evaluate the quality of training models is by observing how well the model's function when applied to test data. A mathematical equation that explains the aforementioned five quality rating indications has now been presented by us.

Accuracy: In general, we have evaluated the model's performance using an accuracy metric. Ten iterations were used to gauge the model's accuracy throughout the analysis phase. Equation displays the accuracy metric's calculated proportion of correctly identified samples (1). Mathematically,

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad \textbf{(Eq.1)}$$

Where TP stands for "true positive cases," meaning "the number of instances correctly classified," TN for "true negative cases," meaning "the number of instances incorrectly classified," FP for "false positive cases," meaning "the number of instances correctly classified," and FN for "false negative cases," meaning "the number of instances incorrectly classified the number of instances."

Precision: It is the ratio of accurately predicted true positive observations divided by the total positive observations. It also describes the correctness of the model. Statistically,

$$Precision = \frac{TP}{TP+FP} \qquad \textbf{(Eq.2)}$$

Sensitivity: In general, the ability to determine the number of positive instances is correctly classified. It also describes the perfectness of the model. Statistically,

$$Sensitivity\ or\ Recall = \frac{TP}{TP+FN} \qquad \textbf{(Eq.3)}$$

Specificity: In general, the ability to determine the number of negative instances is incorrectly classified. It also describes the effectiveness of the model. Statistically

$$\text{Specificity} = \frac{TN}{TN+FP} \qquad \textbf{(Eq.4)}$$

F-Score: F-Score measures the harmonic mean of precision and recall. Statistically,

$$F - Score = \frac{2*(recall*precision)}{recall+precision} \qquad \textbf{(Eq.5)}$$

4. Result Analysis

The accuracy of pre-trained models that were constructed for the prediction of tomato quality grading based on images was investigated and assessed in this work. A comparison of several CNN models was carried out in order to ascertain accuracy, precision, sensitivity, specificity, F-scores, convergence, and accuracy, precision, sensitivity, and specificity, respectively. The research's performance findings are presented in an easily digestible manner in Table 4, which summarizes the findings of the investigation.

Table 4. The performance measured for the pre-trained model.

Performance Evaluation	Reset-50 model	AlexNet model
Accuracy	99.1%	98.6%
Precision	98.2%	95.2%
Recall	99.1%	99.0%
Specificity	99.1%	98.4%
F-Score	98.6%	97.1%

Table 4 reveals that the outcomes of the two models are essentially comparable, with statistically significant outcomes and almost identical behavior. The similarities between the two models are striking. The performance of all of the important metrics of the Resnet-50 evaluation was exceptional. These metrics included accuracy, precision, recall, specificity, and F-score, which all had respective values of 99.1, 98.4, 99.1, and 99.6. As a result of this, AlexNet had a performance that was inferior to that of ResNet-50.

Figure 9. Performance outcome for each model

In this study, we evaluated the performance of two pre-trained CNN models, ResNet-50 and AlexNet, using five standard measures: accuracy, precision, sensitivity, and specificity. The overall performance of the ResNet-50 model is shown in a confusion matrix in Figure 10. According to this confusion matrix, ResNet-50 significantly outperformed the AlexNet model, demonstrating the best effectiveness among the evaluated metrics.

Figure 10. Confusion Matrix of Resnet-50 model.

A confusion matrix helps analyze the performance of classifiers by showing their accuracy. In this matrix, the columns represent the actual classes and the rows represent the predicted classes. Correct classifications appear in the diagonal cells, while misclassifications are found in the off-diagonal cells. In figure 10, a confusion matrix generated by ResNet-50 is shown. It includes four classes: Class A corresponds to unripe tomatoes, Class B to almost ripe tomatoes, Class C to fully ripe tomatoes, and Class D to tomatoes that have gone bad.

Table 5. shows the proposed classification model vs. existing classification models performances.

SN	Existing Classification Models	Claim Accuracy
1	K.Choi et al[4]	77.5%
2	Rokunuzzaman et al[5]	87.7%
3	S.Srivastava et al[6]	92.0%
4	S.Rupanagudi et al[7]	98.0%
5	E.Elhariri et al[8]	92.72%
6	P.Arakeri et al[9]	96.47%
7	LI ZHANG et al[10]	91.9%
8	Avalekar et al[11]	91.66
9	Authors in[12]	95.5%.
10	Wolfgang et al[13]	90.0%
11	H. Hong et al[14]	97.10%
12	Hsing-Chung et al[15]	98.0%
13	**Proposed Classification Model**	**99.1%**

Table 5 in the document compares how well different models grade tomatoes. The proposed model, using deep learning and CNN, specifically ResNet-50, scored the highest accuracy at 99.1%. This is a big leap from previous models, showing that this new method is really good at grading tomatoes accurately based on their quality. The high accuracy suggests it could be used reliably in real-world tomato grading systems, giving more consistent and precise results compared to what's currently available.

5. Conclusion

This research proposes a game-changing method for categorizing tomatoes into four distinct quality levels. We presented a deep learning approach, repurposing algorithms previously trained on CNN data for quality classification in tomato grading. The purpose of this study was to evaluate the efficiency of ResNet-50 with AlexNet using a number of different metrics. Accuracy, precision, recall, specificity, and f-score results for the Resnet-50 model in this investigation were 99.1, 98.2, 99.1, and 98.6, respectively. In terms of accuracy, the ResNet-50 model fared better than the AlexNet model. Our proposed CNN models have a fast convergence rate and effective training performance without the need for annoying pre-processing, as demonstrated by the comparison between these two CNN pre-trained models. In this study, we forecast the quality of green, semi-ripe, ripe, and rotten tomatoes using predictions from two pre-trained CNN models. Our method for evaluating tomato quality and ensuring food safety can be implemented by any business engaged in food processing.

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