ISSN: 2251-9246
EISSN: 2345-6221
pp. 245:251

Quality Classification of Tomato Plant in Field Conditions Using Efficientnet Deep Learning Model

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Abstract

The appropriateness of the agricultural economy is very effective in sustainable food security. The appearance and shape of agricultural products change in different periods. The correct classification of the product in terms of quality after harvest affects the economy of farmers. Today, deep learning classifiers have greatly contributed to the correct classification of product quality. But the database challenges and the same conditions of the database in the training and testing phase affect the classification accuracy. The purpose of this article is to classify the quality of tomatoes in the challenging conditions of the database, including crowded backgrounds, noise in the image, leaves of the same color as the fruit in the image, and the similarity of growth stages. For this purpose, 3 databases with different challenges have been used in the stage of classification training and testing. In this article, the aim is to classify the quality of tomatoes into 3 classes ripe, unripe ,and semi-ripe using Efficientnet deep learning classifier. According to the conditions of the database, the first three processes of noise removal, image contrast improvement ,and image segmentation have been applied to the images. The results of the evaluation of the proposed method show the proper performance of EfficientnetB5.

Keywords: Sustainable Food Security, Deep Learning, Tomato quality classification, Image Processing, Efficientnet Deep Learning Model
Article history: Received 2023/06/11; Revised 2023/07/12; Accepted 2023/07/24, Article Type: Research paper

https://doi.org/10.30495/ ijsee.2023.1988506.1269

1. Introduction

One of the most important agricultural products in the world, which affects the economy of farmers and human health, is the tomato. Classification of tomato fruit quality after harvest is very important for its price and farmers' economy. Diagnosing the health and disease of the product can be done by human power. But it takes a lot of time and has errors. Today, image processing along with artificial intelligence and machine learning has increased the accuracy of product quality classification. Due to the diversity of the disease, the change in the appearance of the fruit in different periods of growth and disease ,and the lack of a database with different classes, grading the quality of the product is still a challenging issue Considering the challenges in the image, image processing methods such as background removal, noise removal, image contrast improvement, image segmentation are of great help to machine learning classification algorithms. Machine learning consists of different types of algorithms, each of which works in the same way. But there are three common steps in all methods. In the first step, information from the subject is entered into the algorithm in the form of data. These data can have different forms such as images. In the second step, the algorithm learns or is trained to achieve the desired goal. For example, recognizing an object in an image. In the learning phase, feature extraction and classification or regression are performed. In the feature extraction section, useful features should be extracted from the data. For example, in an image, to identify the square in the image, the features of the edges and lines must be extracted. These features are given to the input of the algorithm and the algorithm is trained using these features. Algorithms are usually classification or regression algorithms and their task is to assign each input data to the corresponding class. The feature extraction stage is done manually or automatically. In the feature extraction method, a series of formulas are manually applied to the data and the features are obtained. For example, an edge detection filter is applied to the image and the edges are revealed. In this method, the features and their extraction method are specified by the user and applied to the data. But in the automatic method, the algorithm learns which features are good and how to extract them. The last step is classification. According to the feature extraction stage, the classification is done with different classifiers. Some researchers examined the grading of product quality according to the considered classes from the healthy stage to the disease stage in the form of disease severity. They conducted this research with several hyperspectral imaging methods, statistical methods and artificial intelligence. In researche [1][2], using hyperspectral images, they estimated the disease severity of different plants. But in hyperspectral imaging, complex and expensive devices are needed, which do not have high efficiency [3]. Several researchers calculated the severity of the disease with statistical methods. First, they took images of the controlled area and made adjustments to the background of the image. Then they segmented the diseased part of the leaf with different thresholding methods and calculated the severity of the disease based on the different forms of the lesion [4]. In another research, they first separated the diseased area of the leaf with the k-means algorithm. Then they performed feature extraction on this image. Finally, by calculating the area of the diseased and healthy areas of the leaf, they calculated the severity of the leaf disease with statistical methods [5]. A large number of researchers classified disease severity with machine learning algorithms. [6] divided the severity of Late Blight disease in tomato plants into 4 stages. They classified disease severity with SE-Res-CapsNet, SE-Alex-CapsNet ,and CapsNet classifiers. At first, some processing was done on the images. Then the features were extracted with (SE) Squeeze and Excitation Networks and Capsule networks (CapsNet) were used for classification. They compared their method with AlexNet, SqueezeNet, ResNet50, VGG16, VGG19 ,and Inception V3 architectures. They also added various noises to the image to evaluate the accuracy of the proposed method, which slightly reduced the accuracy of disease stage classification. However, adding artificial noise cannot replace field data. [٧] divided the severity of early blight into 3 levels: mild, moderate, severe ,and healthy leaves. They used ResNet101 to detect disease severity and compared their results with VGG16, VGG19, GoogLeNet, AlexNet, and ResNet50. The highest accuracy was related to ResNet101. [8] made a comparison between several classifications VGG-16, VGG-19, ResNet50, InceptionV3, MobileNetV2, and EfficientNetB0 to detect the severity of pear leaf disease. They divided the severity of the disease on DiaMOS Plant dataset images into 5 levels: no risk, very low, low, medium ,and high. The highest accuracy was related to EfficientNetB0. But in other research, the quality of the product is classified based on the appearance of the fruit, i.e. the color, size ,and shape of the product. In [9], the stages of tomato ripening are explained in 6 stages. The most obvious sign of tomato maturity is its color change from green to yellow. The study [10] estimated the appearance of the fruit by extracting the features of color, size, and shape of the tomato fruit in creating a fuzzy logic system. Researchers [11] investigated the quality of tomatoes according to the features of shape, size, and degree of ripeness with an edge detection algorithm and color detection algorithm. In another research [12], image processing algorithms were used to identify the six stages of tomato ripening. The study[13] used KNN, MLP, and K-means clustering techniques with features in RGB, HSI, and L*a*b* color spaces to classify tomato maturity based on color. In [14], Otsu's threshold and K-Means clustering algorithms are used to extract fruit features. Also, a support vector machine algorithm has been developed for quality grading. In [15], tomato maturity was determined based on tomato leaf color and fungal infection diagnosis. In[16], five types of tomato diseases were identified using color, shape, and texture features and a classification tree algorithm. In another study [17], they estimated the stages of tomato fruit ripening with fuzzy logic rules. They classified tomato ripening stages into 6 classes with a decision tree. Their methods were compared with random forest (RF), multilayer perceptron (MLP) ,and support vector machine (SVM). In[18], using the Radial-Basis Function (RBF) algorithm, tomato quality was evaluated based on color. In [19], using a deep convolutional neural network (AlexNet) identified 3 different diseases in tomato leaves. Other efforts with deep learning classifiers by [20] a model based on the SqueezeNet architecture, [21] Two deep learning network architectures SqueezeNet and AlexNet, and [22] a convolutional neural network model named LeNet for tomato plant disease classification focused on leaves including healthy leaves. [23] Three pre-trained deep architectures, namely VGG16, Inceptionv3, and ResNet50, were used to classify tomato fruit as defective or non-defective. VGG16 has the highest accuracy in disease classification. In [24], a comparison has been made between different deep learning and machine learning methods for disease classification, product quality classification, disease diagnosis ,and tomato plant pest diagnosis. In some methods, different processing has been done and feature extraction has been done with different methods. Transfer learning has been used for the initial weighting of deep learning methods. The results show the superior performance of deep learning classifiers. In most of the studies, the classification of product quality has been done in the same conditions as the database. One of the important challenges in the accuracy of deep learning classifications is the sameness of the database conditions in the training and testing phase[25]. The purpose of the proposed method is to classify tomato quality in different database conditions with EfficientNet classification. Also, according to the different conditions of the database, different processes have been performed on the images. The continuation of the article is as follows: In section two, the proposed method and database conditions are explained. The third part shows the performance results of the proposed classifier and the performance of other deep learning classifiers.

2. Proposed method

The purpose of this article is to classify tomato quality in farm conditions at three different levels. Three levels of unripe, ripe, and semi-ripe are considered for tomatoes. According to the studies, deep learning classifiers with a convolutional layers strategy can extract useful features from the image and perform the classification process. In this article, 3 databases with images of unripe, ripe, and semi-ripe tomatoes are used. Two databases, including the Fgrade database and images taken from the Internet, are used in the training phase. A third database, Kaggle, is used in the testing phase. The Kaggle database and images taken from the Internet contain farm challenges. The Fgrade database shows the shape and color of the fruit in laboratory conditions. In this article, the EfficientNet classifier is used to detect the stage of tomato disease in 3 levels according to the different challenges of the database. Because the conditions of the training and testing phase are not the same, in the beginning, some processing has been done to increase the classification accuracy of the images. Therefore, the structure of the proposed method is as follows:

- Create a database
- Preprocessing
- Classification with EfficientNet

A) Create a database

The purpose of this article is to classify tomato quality in different and challenging database conditions. One of the most important features in determining the stages of tomato growth is its color. In this research, to classify the quality of tomatoes, the features of color, shape, and leaves of tomatoes have been used. For this purpose, three databases with different images of tomatoes in different database conditions have been used. According to the tomato images in these databases, three stages of ripe, unripe, and semi-ripe are considered for classification. Two databases,Fgrade and the database containing images taken from the Internet has been used in the training phase (Figures 1 and 2). As you can see in Figure 1, the images taken from the Internet have different challenges. But the images of the Fgrade database have different classes of tomato categories, in this article, only the images of tomatoes with ripe, and semi-ripe categories have been selected (Figure 2). The purpose of this article is to classify tomato quality in the Kaggle database that has field conditions. Therefore, the images of this database have been used in the test phase. The Kaggle database contains 895 images with examples of ripe, unripe, and semi-ripe tomato images. The images of this database have the challenges of crowded backgrounds, low quality of the image, different angles and distances of the tomato to the image, leaves of the same color as the tomato in the image, etc(Figure 3). The number of classes and related images is shown in Table 1. The size of all images is set to 224x224.

B) Preprocessing

In the proposed method, pre-processing has been done on the images of the database to improve the quality of the image. Improving image appearance includes several techniques such as image filtering to remove noise and increase image contrast, background removal, etc. According to the challenges in the Kaggle and images taken from the Internet database, three techniques of noise removal, image contrast improvement ,and image segmentation have been performed on the database images.

Noise removal: The median filter [26] denoises by sorting the pixel values in a neighborhood, finding the median value, and replacing it with the original pixel value in that neighborhood. The median filter makes the photo blurry and captures the impact noise.

Enhance Image Contrast: In this article, image contrast enhancement is done using the histogram equalization method[26]. For this purpose, first, the histogram of the input image is calculated. The brightness intensity function (T) is calculated from the histogram of the input image. This function is applied to each pixel of the image. As a result, histogram equalization is done.

Image segmentation: The segment of the color image in the classification of plant diseases to focus only on the leaf, fruit and the diseased part of the fruit is a necessary and important need to start processing on the desired area. Segmentation separates the image into regions that have a similar nature. There are different image segmentation

Fig. 1. Tomato database images are taken from the Internet,unripe, ripe, semi-ripe

Fig. 2. Images of FGrade database in 2 levels ripe and semi-ripe

Fig. 3. Some examples of Keggel database images

Table.1.
The number of images in the training and test phase

Class	Training image	Test image
ripe	1044	277
unripe	1342	311
semi-ripe	1022	250

techniques, and K-means clustering [27] is used in the proposed method. According to the images with different conditions of the farm, the values of k equal to 2, 4, and 8 were considered.

C) EfficientNet classification

EfficientNet classifier is among advanced CNN models by achieving 84.4% accuracy with 66 M parameters. The efficient classification consists of 8 models between B0 and B7. As the number of models grows, the number of calculated parameters does not increase much, while the accuracy increases significantly.

EfficientNet uses the Swish activation function. The main factor behind the construction of EfficientNet is the inverted bottleneck MBConv. In MBConv, blocks consist of a layer that is expanded first. Then they compress the channels. The schematic representation of the EfficientNetB0 model is shown in Figure 4. EfficientNet achieves more efficient results by uniformly scaling depth, width, and resolution. EfficientNet uses a technique called compound factoring to scale models in a simple but effective way. Instead of randomly increasing width, depth, or resolution, compound scaling uniformly scales each dimension with a fixed set of scaling factors. The combined scaling method [28] is shown in Figure 5. First, a suitable scaling factor is applied to the baseline network to scale the width, depth, and resolution. Equation 1 shows the network calculations.

$$d = \alpha^{\emptyset} \quad Depth,\ w = B^{\emptyset} \quad Width\ ,r = \gamma^{\emptyset} \quad Resolution \tag{1}$$

$$\alpha \geq 1, B \geq 1, \gamma \geq 1, \alpha \cdot B^2 \cdot \gamma^2 \approx 2$$

The values of α ‹β ‹γ are fixed and can be determined by the grid search algorithm and determine how additional resources are allocated to the width, depth, and resolution of the network. φ is a user-defined coefficient that controls the number of resources available for scaling the model [29]. The coefficients are set as follows:

Step 1: φ = 1 and The best value for α, β, and γ is: a=1.2, b=1.1, and y=1.15. This is for the EfficNet-B0 model.Step 2: For EfficNet-B1 to B7, the values of α, β, γ are considered constant and the baseline network is scaled with different φ values. The transfer learning method has been used for the initial weighting of the model. Hyperparameters of all deep learning methods are considered as follows:

{"Loss function": BCE (binary cross-entropy), "Learning Rate": 0.001, "Mini Batch Size": 32, "Number of Epochs":30, "Optimization Function": Adam }

D) Performance evaluation metrics

To evaluate the performance of the proposed classifier, two criteria, accuracy, and precision, have been used. In these criteria, 4 parameters true positive (Tp), false positive (FP), true negative (TN), and false negative (FN) are used. Accuracy and precision are calculated according to relations 2 and 3.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$precision = \frac{Tp}{TP + FP} \tag{3}$$

3. Results

In this article, the aim is to classify the different stages of tomato quality with the EfficientNet classifier in the challenging conditions of the database. In this article, the Fgrade database and images taken from the Internet are used in the training phase. Kaggle database images are used in the test phase. The size of the images is 256 x 256. After pre-processing, the size of the images is set to 224x224. data augmentation is used for the Fgrade database. In addition, to avoid overfitting, the K-fold cross-validation method with k = 5 was used. All experiments have been run in MATLAB 2018 with 16 Gb RAM and Intel Core i7 CPU @ 2.8 GHz hardware. To evaluate the performance of the EfficientNet classifier, two criteria, accuracy, and precision, have been used. Noise removal, image contrast enhancement, and image segmentation processing have been performed on different images. Table 2 and Figure 6 show a comparison between the accuracy performance of EfficientNet classifiers. The results show that the highest accuracy is related to the EfficientnetB5 classification. In this article, EfficientNet classifiers are compared with DenseNet169 ‹Xception, and InceptionResNetV2 deep learning models [25] in Figure 7. The processing was done only on the EfficientNet classifications. From the results of Figure 7, it can be concluded that EfficientNet classifiers have higher accuracy. Also, different processing increases classification accuracy.

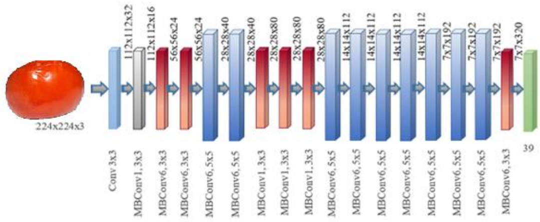

Fig. 4. EfficientNet classification

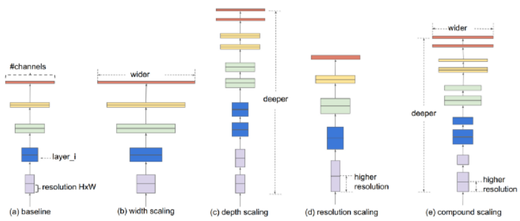

Fig. 5. Different scaling methods versus compound scaling[28]

Table.2.
Comparison of accuracy between Efficientnet classifiers

Class	B0	B1	B2	B3	B4	B5	B6	B7
Accuracy	87.54	86.98	87.22	87.76	87.73	87.83	86.58	86.85
Precision	86.35	85.75	86.15	86.58	86.47	86.61	85.39	85.67

4. Conclusion

The purpose of this article is to classify tomato plant quality in challenging farm conditions. For this purpose, 3 databases with different challenges, which have 3 classes of ripe, unripe, and semi-ripe, have been used in two stages of training and testing. According to various challenges in the image, the first 3 processes of noise removal, image contrast enhancement, and image segmentation have been performed on the images. Then the classification is done with the EfficientNet structure. EfficientnetB5 has higher accuracy than other models. Also, the proposed method is compared with 3 other deep learning classifiers Xception, InceptionResNetV2, and DenseNet169. In this section, no processing has been done on the images of these 3 classifiers. The results show the superior performance of the proposed strategy. Future goals are to use databases with more classes of tomato plant disease stages. The use of stronger processing on images and expert deep learning classifications in the ensemble strategy increases the classification accuracy.

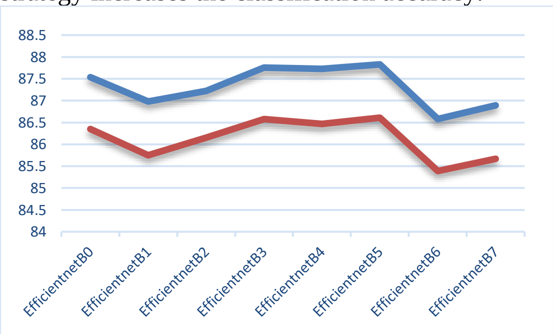

Fig. 6. Comparison of Accuracy and Precision of the EfficientNetB0 to B7 classification

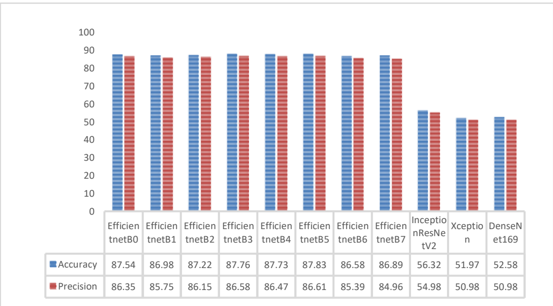

Fig. 7. Comparing the accuracy performance of different deep learning classifiers

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