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RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

Application of quality control in product supply using deep learning and machine learning

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Abstract

Artificial intelligence is the source technology for the now common in quality control. In this research, two novels deep learning and machine learning-based models have been proposed in order to supply quality control in vegetable and fruit supply. The purpose is to identify tomatoes, apples, oranges, tangerines and potatoes, which are among the most cultivated vegetable, fruit and root vegetable types in Turkey, as fresh or spoiled. The dataset that was used in the study was constructed based on images that were collected online as well as snapped by using a mobile phone, and it was organized to contain both fresh and decayed items. The developed methods are evaluated using accuracy, precision, sensitivity, and F1 score performance criteria. With 97.57% general accuracy, the deep learning model was very effective while the machine learning model obtained an accuracy rate of 90.20%, which is a good substitute method. The deep learning model achieved better performance as it modeled more complex features in the visual data, while the machine learning model was characterized by its rapid processing speed and low hardware requirements. The results suggest that DL techniques achieve better performance in the quality control task, whereas ML-based methods may be also preferred in some specific scenarios. This study addresses fruit and vegetable supply processes, providing quality control and being able to quickly, correctly and economically classify the products, contributing to the artificial intelligence-based quality control automation.

Keywords: Deep Learning, Machine Learning, Quality Control, Supply Chain Management.

JEL Codes: O33, Q13, C45, L15, M11

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1. Introduction

Quality control in vegetable and fruit supply chain is crucial for quality assurance, enhancing customer satisfaction, and reducing waste. Detection of rotten products at an early stage enables the logistics activities to be adjusted and the economic loses to be mitigated. However, conventional QC methods usually rely on visual examination and are associated with labor-intensive procedures that are subject to high misclassification rate.

With the recent advances in machine learning and deep learning, the quality control process can be automated more effectively. In this paper, we evaluate a deep learning model based on CNN and a traditional machine learning approach known as Cascaded Classifier. The models are tested on accuracy, precision, sensitivity, F1 score , and confusion matrix based.

This study focuses on the design and comparison of quality control models for vegetables and fruits supply at the process level to identify their respective pros and cons. In the work an original data set is established for this purpose with tomatoes, apples, oranges, tangerines and potatoes – the most popular produced vegetables, fruits and root vegetables in Turkish agriculture based on the 2024 data of Turkish Ministry of Agriculture and Forestry. This dataset was prepared from both the images that were downloaded from the internet and the images captured from a mobile phone. The results clearly demonstrate the capabilities of deep learning methods in achieving better performance on complex problems, while ML methods provide interesting solutions with a modest computational load.

2. Literature Review

Recently, the application of machine learning and deep learning techniques to vegetable and fruit quality control has increased. The literature reviews general focus on rot / disease detection, ripeness estimation, and fruit and vegetable classification. Furthermore, investigations have been mostly carried out on a maximum of three different items, premade data sets have been predominantly utilized, and thorough quality control scenarios where both ML and DL methods are appraised in unison are rare. In this context, this research has a significant value in literature.

In view of investigations in the literature, Azizah et al. (2017) proposed a four layers CNN model for damaged mango surface detection with an accuracy of 97.5%. Similarly, Liu et al. (2018) applied the SAE approach to detect cucumber spoilage and the result was 91.1% accuracy. On the other hand, Rodriguez et al. (2018) achieved good results with an accuracy performance in the range of 91-97% to identify the early maturity stages of three different plum cultivars based on ECFSAA after using the AlexNet architecture. Mithun et al. (2018) developed an AlexNet-based model to distinguish between artificially and naturally damaged bananas and achieved a 90% accuracy rate. Zhang et al. (2018) performed fruit recognition in a smart refrigerator system with CNN-based ResNet, VGG16, and VGG19 models.

Cömert et al. (2019) developed a model to detect whether apples were rotten or healthy using Faster R-CNN and obtained an 85% accuracy rate. Palokadati et al. (2020) developed a CNN-based quality control model for apples, oranges, and bananas using the Kaggle data set and obtained a 97% accuracy rate. Kayaalp and Metlek (2020) created a VGGNet-based model to detect whether apples were rotten or healthy and achieved over 90% success. Ünay (2020) compared various CNN architectures and determined that SqueezeNet gave promising results.

Aslan (2021) detected peach diseases with the AlexNet model and reached a 99.3% accuracy rate. Li et al. (2021) developed a CNN-based model for quality classification in apples and achieved 95% success. Chakraborty et al. (2021) detected rot in apples, bananas, and oranges with the MobileNetV2 model, achieving 99% accuracy. Buluş (2022) evaluated two distinct deep learning models on a Kaggle dataset. Dhiman et al. 99% accuracy with VGGNet for rot detection in citrus fruits (2022). Baloch (2022) studied the quality of vegetables and fruits with ResNet, VGG16 and CNN based models and obtained an accuracy of 94 percent.

Yağız (2023) classified dried grape quality based on a CNN model with 88.7% accuracy. Thilak et al. (2023) obtained an accuracy of 98.74% using a dataset of 1260 images. Ünal et al. (2023) achieved

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98.33% accuracy with an AlexNet-based model in Granny Smith apples. Dursun (2023) performed rot detection using a CNN model on apple images obtained with a mobile camera.

Yıldırım (2024) used the YOLOv8 model to detect maturity and rot in apples, oranges, bananas, and pomegranates with UAV images and achieved 98.9% accuracy. Ali and Hashim (2024) enabled users to perform deep learning-based quality analysis without coding knowledge with the software called DLFRUIT-GUI. Singh et al. (2024) examined the integration of CNN and RNN combinations into real-world applications of quality control systems. Finally, Karthikeyan et al. (2024) achieved a 99.13% accuracy rate in apple quality detection by strengthening the YOLOv3 model with Darknet53.

These studies show that deep learning and machine learning have achieved significant success in fruit and vegetable quality control. However, most of the current studies have used a limited number of products and premade datasets, and deep learning and machine learning methods have not been handled together. In this context, it is thought that this proposed study will make significant contributions to literature by comparatively evaluating both deep learning and machine learning approaches using a large dataset.

3. Quality Control

Quality refers to the ability of a product or service to meet specific requirements. According to Garvin (1984), quality includes elements such as performance, reliability, durability, and aesthetics.

Quality control is the set of processes that evaluate the conformity of a product or service to the specified standards (Montgomery, 2012). Quality assurance is ensured with sampling, tests, and continuous improvement steps in the process from production to the consumer (Oakland, 2014).

Quality control in vegetables and fruits aims to preserve freshness, safety, and nutritional value. While soil and water analyses and pest control are carried out before harvest, quality is preserved after harvest with visual inspection, chemical analyses, and cold chain applications (Barrett et al., 2010). Product packaging and labeling are also part of quality assurance.

In Turkey, quality control is carried out within the framework of the Turkish Food Codex issued by the Ministry of Agriculture and Forestry (T.R. Agriculture and Forestry Ministry, 2025). In addition, food safety is ensured by adopting international standards such as ISO 9001 and ISO 22000. Similar quality control regulations are applied in the USA, European Union, and Asia-Pacific regions (Hoffman, 2017).

Today, technologies such as artificial intelligence, machine learning, and the internet of things are effectively used in quality control processes. Deep learning models are successfully applied in the quality control of vegetables and fruits, as well as in sectors such as textiles, metal, and automotive (Zhang et al., 2021). These technologies optimize production processes by increasing quality assurance.

4. Method

4.1. Convolutional Neural Networks

Convolutional Neural Networks (CNN) are a prominent structure among deep learning methods, especially in the processing of visual data. Convolutional Neural Networks are networks that automatically learn the features in images and thus can perform classification with high accuracy (Krizhevsky, et al. 2012).

Convolutional Neural Networks generally consist of four main layers. These are; the convolution layer, where important features in the image are extracted and lower-dimensional representations are produced, the activation layer, which enables the non-linear processing of the features from the convolutional layer, the pooling layer, where the spatial dimensions in the image are reduced and the computational load is reduced, and the fully connected layer, where the learned features are used to make final predictions and perform the classification process (Krizhevsky, et al., 2012). The structure of convolutional neural networks is shown in Figure 1.

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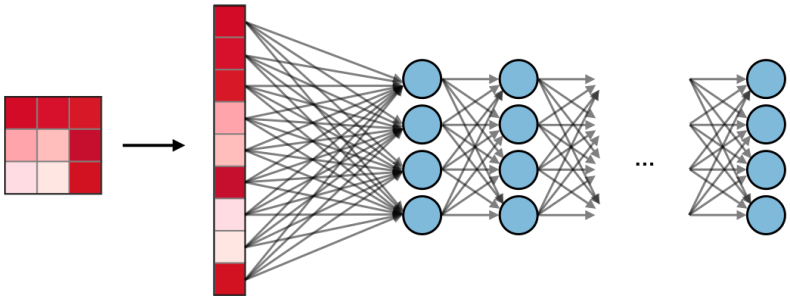
Figure 1. Architecture of Convolutional Neural Networks



Convolutional Neural Networks yield successful results especially in visual recognition tasks such as image classification and object detection. These networks enable the hierarchical learning of features in the learning process, allowing the transition from low-level details to high-level meaningful information (Zeiler & Fergus, 2014).

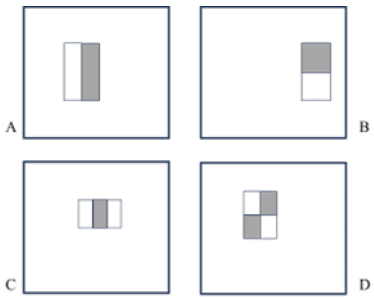
The success of Convolutional Neural Networks has further increased with the advantages provided by large datasets and powerful computing infrastructures. In particular, multi-layered structures enable networks to learn complex and abstract relationships. This method is successfully applied in many fields other than visual recognition, such as speech recognition, natural language processing, and bioengineering.

4.2. Haar Cascade Classifiers

Haar Cascade Classifier is a machine learning algorithm commonly used especially in tasks such as face recognition and object detection. This method was first developed by Paul Viola and Michael Jones in 2001 (Viola & Jones, 2001). Haar Cascade is an algorithm trained to detect objects in images using a series of simple features and classifiers. The basic principle of this algorithm is to obtain correct results by combining strong and weak classifiers.

Haar Features: Haar Cascade uses simple, vertical, horizontal, and corner-shaped structures called Haar features, shown in Figure 2, to recognize the features in different regions of the image. These features represent the differences in the contrast of the image and are used to understand the positions of certain objects in the image.

Figure 2. Haar Features



Source: Viola & Jones, 2001

In the image processing process, the sum of the pixel values in the white areas is subtracted from the sum of the pixel values in the gray areas. In this process, 'A' and 'B' represent two-rectangle features, 'C' represents three-rectangle features, and 'D' represents four-rectangle features. Assuming that each rectangle is 24x24 pixels in size, it is possible to obtain more than 180,000 such Haar-like features from any image. These rectangular features are scanned by sliding over the image (Viola and Jones, 2001).

AdaBoost Algorithm: Haar Cascade uses the AdaBoost algorithm to make weak classifiers stronger. AdaBoost was developed to increase the classification accuracy of basic (weak) learning algorithms. In

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their studies, Freund and Schapire revealed that the training error of a strong classifier approaches zero exponentially. The biggest advantage of AdaBoost is that it can train large-scale models extremely quickly (Viola & Jones, 2001).

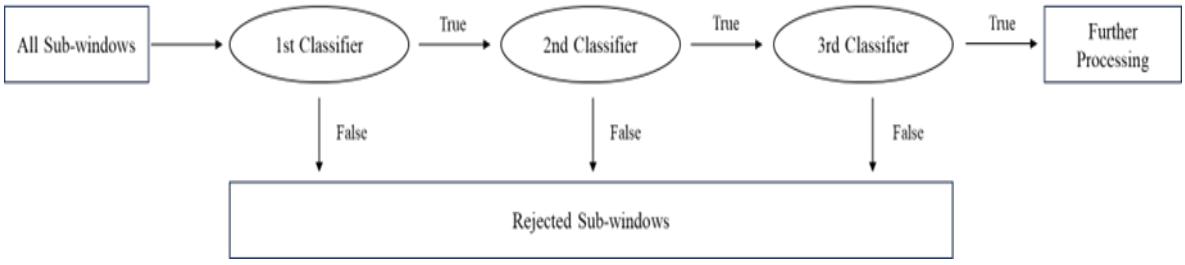
The operating principle of the AdaBoost algorithm, introduced by Viola and Jones (2001), can be summarized as follows: A set of sample images (x_1, y_1), ..., (x_n, y_n) is taken as input. Here, y_i, takes the value of 0 for negative images and 1 for positive images. Initially, each sample is assigned an equal weight $\boldsymbol{w_{1,i}} = \frac{\mathbf{1}}{\mathbf{2m}}, \frac{\mathbf{1}}{\mathbf{2l}}$; where m represents the number of negative samples and l represents the number of positive samples. These initial weights are then normalized. The equation $\boldsymbol{w_{t,i}} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$ is used for normalization. In this equation, $\boldsymbol{i}$ defines each image and $\boldsymbol{n}$ defines the total number of features. In each iteration of the algorithm (t = 1,...,T), a single feature classifier (h_j) that performs the best according to the current weights is selected. The error rate (ϵ_j) of this classifier on the samples is calculated with the equation $\boldsymbol{\epsilon_j} = \sum_{j=1}^{n} \boldsymbol{w_i} \left| \boldsymbol{h_i(x_i - y_i)} \right|$. The h_t classifier with the lowest error rate is selected and the weights of the samples are updated. If a sample is classified correctly ($h_t(x_i) = y_i$, $e_i = 0$), its weight is reduced by the factor βt. $\boldsymbol{\beta_t} = \frac{\epsilon_t}{1-\epsilon_t}$ The weights of incorrectly classified samples ($e_i = 1$) do not change. The new weights are calculated as $\boldsymbol{w_{t+1,i}} = \boldsymbol{w_{t,i}} \boldsymbol{\beta_t^{1-e_i}}$. Finally, to create a strong classifier (H_x), the weak classifiers (h_t) selected in each iteration are combined in a weighted manner. The weights (α_t) of the weak classifiers are determined by the equation 1 given below:

$$h_x = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & in\ other\ cases \end{cases} \quad (1)$$

In the equation above $\boldsymbol{\alpha_t} = \mathbf{log} \frac{\mathbf{1}}{\boldsymbol{\beta_t}}$ dir. Thanks to this iterative approach, a strong classification performance is obtained by selecting the most distinctive ones among a large number of initial potential features (for example, more than 180,000) (Taşpınar and Selek, 2020).

Cascade Structure: The cascade algorithm is a classification method that significantly reduces the computation time while increasing the detection performance. The basic principle of this method is to create reinforced classifiers that are smaller and therefore more efficient, quickly eliminate negative sub-windows, and detect almost all positive samples (Viola & Jones, 2001). The detection process has a degenerative decision tree structure. This decision tree structure is shown schematically in Figure 3 (Viola & Jones, 2001).

Figure 3. Architecture of Cascade Method



Source: Viola & Jones, 2001

5. Application

The dataset used in this study was created from the images of tomatoes, apples, oranges, tangerines, and potatoes, which are the most produced vegetables, fruits, and root vegetables in Turkey according to the 2024 data of the Ministry of Agriculture and Forestry.

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The dataset was created from images provided over the internet and photos taken with a mobile phone camera. As an internet source, images of healthy and spoiled vegetable-fruit samples and open-access databases were used. In addition, in order to make the dataset more original and diverse, photos of healthy and spoiled vegetable-fruit samples were taken using a mobile phone camera.

All images obtained were divided into two main classes as healthy and spoiled, according to the quality status of the products. Healthy products consist of vegetables and fruits that maintain their freshness and do not have any physical damage or quality problems; spoiled products, on the other hand, include rotten, physically deformed, or damaged samples. Examples of images from the healthy data set are presented in Figure 4, and examples from the spoiled data set are presented in Figure 5.

Figure 4. Examples from the Dataset (Healthy)

Figure 5. Examples from the Dataset (Spoiled)

Resizing and data augmentation operations were performed on the collected images. Explanations regarding how these operations are performed are given below.

Resizing: In order to process images with different resolutions consistently in training and testing processes, the resizing process was applied. Images were brought to 224×224-pixel resolution with OpenCV and TensorFlow libraries on the Google Colab platform using the Python programming language.

Data Augmentation: In order to increase the diversity of the dataset and to train the model with a wider dataset, operations such as rotation, zooming, horizontal and vertical flipping were performed on the images. In this way, a total of 2400 images were obtained for each vegetable and fruit, and 1200 of these images are in the healthy category and 1200 are in the spoiled category.

As a result of this process, a dataset containing a total of 12,000 images was created. The quality control of fruits and vegetables could be evaluated through this dataset by applying it for training and testing phases of the proposed deep learning model. The same dataset was employed for the ML model, however due to the structure of the model a smaller number of images were used.

To properly assess machine learning and deep learning model performances, it is common practice that data sets are split into three subsets: train, validation, and test. The deep learning approach in this study adopted a analogous strategy, with 80% for training/validation and 20% for testing. Training data and validation data The training and validation data are used for training the model and monitoring the training. In this regard, 80% of the training data set was used to train the parameters of the model, and

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20% was used for validation. Therefore, the proportions of the dataset for training, validation, and testing was %64, %16, and %20 respectively.

This process is particularly critical for the concerns of generalizing the model, avoiding overfitting, and estimating the true performance of a model when applying it to the real world. Utilizing the validation dataset in the training process helps to prevent the model to overfit and to achieve the best performance (Goodfellow et al., 2016). Similarly, the evaluation on an independent test dataset is used to measure the success of the model on data it has not encountered before (LeCun et al., 2015).

Different metrics are employed to measure the performance of machine learning and deep learning models. The main evaluation criteria for dLMs presented in this paper for the dLM/ML models are:

5.1. Accuracy

Accuracy the Number of correctly classified samples/Total number of samples. It is calculated by dividing the sum of true positive and true negative results by the total number of samples as shown in the equation 2 below. It is a general indicator of the success of the model.

$$Accuracy = \frac{\text{True Positive } (TP) + \text{True Negative } (TN)}{Total\ Number\ of\ Samples} \tag{2}$$

5.2. Precision

Precision measures the proportion of samples labeled as positive that are actually positive. High precision means the model minimizes false positives.

$$\text{Precision} = \frac{\text{True Positive } (TP)}{\text{True Positive } (TP) + \text{False Positive } (FP)} \tag{3}$$

5.3. Recall

Sensitivity measures how many of the actual positive samples of a class are correctly predicted as positive (Bishop, 2006).

Especially in situations when having prediction errors is expensive, high sensitivity is a must.

$$Sensitivity = \frac{\text{True Positive } (TP)}{\text{True Positive } (TP) + \text{False Negative } (FN)} \tag{4}$$

5.4. F1 Score

The F1 score is a measure of test's accuracy which considers both precision and recall. It is the harmonic mean of these two quantities as can be seen from the following Equation 5 and in particular is a better success metric, in particular for datasets with class imbalance (Goodfellow et al., 2016).

$$F1 = 2 \times \frac{Precision \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

5.5. Confusion Matrix

Especially in situations when having prediction errors is expensive, high sensitivity is a must. The confusion matrix contains the following four elements:

TP = True Positive,

TN = True Negative: an true negative is an outcome where the model correctly predicts the negative class.

FP false positive an false positive = an event when the model incorrectly predicted it as positive.

FN false negativethat= an false negative = an event when the model mistakenly predicted it as negative.

These indicators are also conducive to better analyze the performance of the model in its entirety and provide useful information for improving the reliability of the developed systems.

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5.6. Development of the Deep Learning Model

In this paper, a Convolutional Neural Networks (CNN) based model among the deep learning techniques was proposed to provide quality assurance in the supply chain of vegetables and fruits. The design of model architecture is based on sequential stack of Conv2D (convolutional layer) and MaxPooling2D (max pooling layer) layers.

RGB images with 224 × 224 pixels are input at the input layer to the model. In the first convolutional layer, 32 filters of size 3×3 are applied, and this layer detects edges, texture and other low-level features of the image. In the second and third conv layers, two and three conv layers, the number of filters are doubled from 64 to 128. Due to this architecture, the model can capture more sophisticated and abstract visual information.

Pooling layers (MaxPooling2D) are utilized to decrease the model computational cost and improve the model generalization. The output of the convolutional layers is flattened into a one-dimensional vector using the Flatten layer and passed to the fully connected layers. The first fully connected layer comprises 128 neurons and utilizes the ReLU activation function. This layer allows learned visual features to be merged and interpreted. The output layer of the model is a single neuron with sigmoid activation, and this architecture is intended to be adapted to a binary classification (spoiled/healthy) problem.

In order to avoid overfitting, 10 epochs were specified during model training. This is the number of epochs necessary for the model to learn adequately and is the number of epochs that lead to a minimum of overfitting. The value of the batch size was set to 32 to achieve an adequate trade off between computation time and memory requirements. It is a value which is often preferred in deep learning models and produces good results.

The model architecture is not too deep and complex, and the model is optimized to balance its prediction accuracy and computation complexity to achieve fast and reliable prediction with fewer computing resources. Deep learning architectures, such as AlexNet (Krizhevsky et al., 2012) and GoogleNet (Szegedy et al., 2015), are typically pre-trained on large-scale dataset (e.g., ImageNet) and are more computationally intensive due to the large number of layers and parameters. However, it is well known that such a huge model may be prone to overfitting with small to medium size datasets. Therefore, a more straightforward and simpler yet faster and more efficient CNN model was the best choice with respect to the objective of the paper.

5.6.1. Findings of the Deep Learning Model

This research utilized a deep learning model for advancing quality control applications in the supply chain of vegetables and fruits. The model was evaluated on five common products, namely tomatoes, apples, oranges, tangerines and potatoes that are widely cultivated in Turkey and attained high accuracy rates. The accuracy rates of the model were calculated as 98.33% for tomatoes, 98.50% for apples, 96.25% for oranges, 97.25% for tangerines, and 97.50% for potatoes, and the general average accuracy rate was determined as 97.57%. These results show that the model offers high accuracy in classifying vegetables and fruits as spoiled or healthy. Performance metrics and general averages for all products are presented in Table 1.

Table 1. Performance of the Deep Learning Model

Convolutional Neural Network	Precision	Recall	F1 Score	Accuracy
Tomato	0.9824	0.9843	0.9833	0.9833
Apple	0.9849	0.9851	0.9849	0.9850
Orange	0.9626	0.9644	0.9635	0.9625
Tangerine	0.9725	0.9724	0.9725	0.9725
Potato	0.9750	0.9761	0.9755	0.9750
General Average	0.9755	0.9765	0.9759	0.9757

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Within the scope of the real-life application of the developed model, an application was also developed using the Python programming language in the Google Colaboratory environment. With this application, the output images produced by the model were examined, and the results belonging to the healthy class are shown in Figure 6, and the results belonging to the spoiled class are shown in Figure 7. Although the visual inspection time of the model varies depending on the number of products to be checked, considering the process of photographing and uploading the products to the model, the analysis of 100 samples is completed in approximately 4 minutes and 30 seconds.

Figure 6. Healthy Output Images

Figure 7. Spoiled Output Images

5.8. Development of the Machine Learning Model

In this study, in addition to the deep learning method, the Cascade Classifier method, which is one of the machine learning methods, was also used to support quality control processes in the vegetable and fruit supply chain. This method was preferred in the detection of healthy and spoiled products because it is a fast and practical machine learning technique.

5.8.1. Preparation of the Dataset and Training of the Model

To implement the Cascade Classifier method, positive and negative datasets need to be created. These were developed from 12,000 previously processed images. The positive healthy product detection dataset was drawn from the healthy image of the particular vegetable or fruit. The positive set for bad product detection was created from the spoiled image of the specific vegetable or fruit. The negative set for the detection of the healthy product is composed of the spoiled image of a specific vegetable or fruit plus other vegetables and fruits. The negative set for bad product detection comprises the healthy images of the particular fruit or vegetable, as well as other fruits and vegetables.

Both positive and negative datasets were constructed with 150 images. The literature reports that the ratio of positive and negatives samples in the algorithms like Cascade Classifier can increase the performance of the classifier (Viola & Jones, 2001). This accounts for the 150-image dataset on the basis of prior work that demonstrated that useful models can be trained from miniature datasets (Liu et al., 2013).

The training of the Cascade Classifier was done through the Cascade Trainer GUI. 15 stages were favored in the training procedure. This stage number was chosen in order to optimize the accuracy of the model with the the least false positives. The output of false positive can be decreased by increasing the number of stages that is stated by literature; however it results more computational cost and longer training time (Viola & Jones, 2001). The 15-stage architecture was selected to attain a well-balanced performance of the detector in terms of training time and detection accuracy.

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5.8.2. Testing of Training Results

After the training was completed, an application was prepared using the OpenCV library in the Python programming language in the Google Colaboratory environment using the obtained XML file. The output images belonging to the healthy class are shown in Figure 8, and the output images belonging to the spoiled class are shown in Figure 9.

Figure 8. Healthy Output Images

Figure 9. Spoiled Output Images

The model was tested with the prepared application, and an independent test dataset of 1500 images in total, consisting of 150 healthy and 150 spoiled images for each vegetable and fruit, was used. Test results were evaluated with metrics such as accuracy, precision, recall, F1 score, and confusion matrix, as in the deep learning model. The performance metrics for all the vegetables and fruits are reported in Table 2.

Table 2. Performance of the Machine Learning Model

Cascade Classifier	Precision	Recall	F1 Score	Accuracy
Tomato	0.9333	0.9334	0.9334	0.9333
Apple	0.9233	0.9234	0.9233	0.9233
Orange	0.9133	0.9140	0.9137	0.9133
Tangerine	0.8767	0.8771	0.8769	0.8767
Potato	0.8633	0.8635	0.8634	0.8633
General Average	0.9020	0.9023	0.9021	0.9020

For the selected vegetables and fruits, the model's accuracy is 93.33% for Tomato, 92.33% for Apple, 91.33% for Orange, 87.67% for Tangerine, 86.33% for Potato and the overall average is 90.20%.

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These results indicate Our model is successful in discriminating vegetables and fruits between fresh and rotten and also achieving comparable performances to related works in the literature (Cömert et al., 2019; Kayaalp & Metlek, 2020; Mithun et al., 2018; Yağız, 2023).

The Cascade Classifier approach is a less resource consuming approach when compared to deep learning models, meaning can provide results with smaller amount of data and faster results. Therefore, it is an important advantage for low computing power device and no GPU (Graphics Processing Unit). What's more is that this method can also show positive results with small amounts of data, which is in contrary with deep learning techniques that need large amounts of data.

Nevertheless, when considering overall performance metrics the average accuracy of the deep learning-based model is 97.6%, and when compared with other works reported in the literature (Çetinkaya, 2024), the DL model achieves a far better performance than that of ML model. Thus, in cases where there are enough images and GPU can be utilized, it would be then more reasonable to choose the DL model for the quality control application.

6. Conclusion and Recommendations

In this paper, two models deep learning based, and machine learning based were employed and compared for vegetable and fruit supply quality control improvement. Both the deep learning based Convolutional Neural Network (CNN) and the machine learning based Cascade Classifier approach were tested on the dataset of 12,000 images generated for five basic high production products in turkey (tomato, apple, orange, tangerine, and potato).

Results indicate that the deep learning-based CNN model (97.57%) outperforms the machine learning based Cascade Classifier method (90.20%) on the performance metrics of accuracy, precision, recall and F1-score. The C NN was successful in visually analyzing and identifying good and bad products with great accuracy. However, the Cascade Classifier technique is beneficial on low hardware capability system since it needs less computational power and has faster processing time.

This work shows that quality control-enabled by AI provides more accurate and efficient results than the conventional subjective evaluation. Suppliers can benefit from artificial intelligence-supported quality control systems by creating their own datasets for different vegetables and fruits, similar to the dataset used in the study.

In future studies, research can be conducted to expand the datasets for different vegetables and fruits, testing the CNN model with different deep learning architectures such as AlexNet, GoogleNet or ResNet, and detecting deterioration types such as rot, crushing, and staining in addition to healthy-spoiled separation. In addition, it will be beneficial to develop video-based analysis systems to make quality control processes real-time.

As a result, this study demonstrated the effectiveness of artificial intelligence-supported quality control processes in vegetable and fruit supply and makes significant contributions to literature in this field.

Statements

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No funding was received for conducting this study.

Conflict of Interest

The authors declare no conflict of interest.

Ethics Approval / Ethical Statement

This research follows all ethical guidelines for academic studies. Since the study was conducted using digital images of botanical specimens (tomatoes, apples, oranges, tangerines, and potatoes) collected from online sources and direct photography, it did not require approval from an ethics committee.

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Data Availability

The data that support the findings of this study consist of images collected from public online domains and original photographs taken by the authors. The compiled dataset is available from the corresponding author upon request.

Author Contributions

All authors contributed to all sections of the research, including the methodology, data analysis, and manuscript preparation. Each author has reviewed and approved the final document and is accountable for the integrity of the study.

Artificial Intelligence Use Statement

The authors declare that AI tools were employed for grammar checks during the preparation of this article. The article was then reviewed and carefully edited by authors as required.

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