

Article

Performance Analysis of Deep Learning CNN Models for Variety Classification in Hazelnut

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Abstract: In evaluating agricultural products, knowing the specific product varieties is important for the producer, the industrialist, and the consumer. Human labor is widely used in the classification of varieties. It is generally performed by visual examination of each sample by experts, which is very laborious and time-consuming with poor sensitivity. There is a need in commercial hazelnut production for a rapid, non-destructive and reliable variety classification in order to obtain quality nuts from the orchard to the consumer. In this study, a convolutional neural network, which is one of the deep learning methods, was preferred due to its success in computer vision. A total of 17 widely grown hazelnut varieties were classified. The proposed model was evaluated by comparing with pre-trained models. Accuracy, precision, recall, and F1-Score evaluation metrics were used to determine the performance of classifiers. It was found that the proposed model showed a better performance than pre-trained models in terms of performance evaluation criteria. The proposed model was found to produce 98.63% accuracy in the test set, including 510 images. This result has shown that the proposed model can be used practically in the classification of hazelnut varieties.

Keywords: hazelnut; image classification; artificial intelligence; machine learning; convolutional neural network



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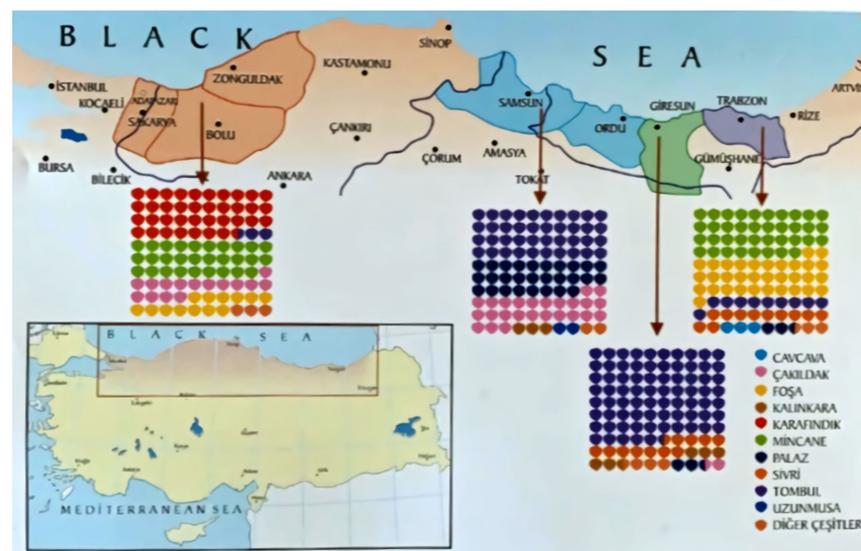
1. Introduction

The world's most important hazelnut producer, Turkey, has 73% of the world's hazelnut production areas with approximately 734.409 ha of hazelnut planting area. Turkey's hazelnut production volume constitutes approximately 70% of world production [1]. Turkey exports 75% of the hazelnut produced. Product quality is an important determinant of hazelnut export, and it affects export revenues directly. The commercial importance of hazelnuts has increased the interest in variety standard and their characterization [2]. Characteristic features (Table 1) and a georeferenced map (Figure 1) of some hazelnut varieties grown in Turkey are presented [3].

It is essential to develop highly accurate, non-destructive, fast, and objective evaluation methods in post-harvest processes for safe production and marketing of agricultural products. Examinations and controls made by the human workforce are still used in large areas. For example, human labor is widely used in the separation and classification of hazelnut in hazelnut processing factories in our country. This method is highly time-consuming, tiring, tedious, low-sensitivity, and costly. For this reason, highly accurate, effective, non-invasive, and safe alternative methods should be developed to determine the varieties and quality of hazelnut.

Table 1. Characteristic of some Turkish hazelnut varieties.

Cultivars	Length (mm)	Width (mm)	Thickness (mm)	Shape Index	Nut Weight (g)	Shell Weight (g)	Shell Thickness (mm)	Kernel Ratio (%)
Acı	17.6 ± 0.3	14.6 ± 0.1	12.5 ± 0.2	1.3	1.3	0.8	1	43.8
Allahverdi	20.7 ± 0.1	18.1 ± 0.1	18.0 ± 0.1	1.15	1.8	0.79	0.89	48.8
Cavcava	18.8 ± 0.1	17.5 ± 0.1	16.1 ± 0.1	1.1	1.6	0.7	1	54.5
Çakıldak	19.1 ± 0.1	18.7 ± 0.1	17.0 ± 0.1	1.1	1.9	0.9	1.2	47.9
Foşa	17.2 ± 0.1	15.9 ± 0.1	13.9 ± 0.1	1.2	1.1	0.6	1	38.3
İncekara	22.0 ± 0.1	17.8 ± 0.1	16.2 ± 0.1	1.3	2	1	1.2	43.3
Kalınkara	19.8 ± 0.1	18.2 ± 0.2	15.7 ± 0.1	1.2	2.3	0.9	1.4	32.2
Kan	17.9 ± 0.2	15.8 ± 0.1	14.4 ± 0.1	1.2	1.6	0.9	1	51.2
Karafındık	18.8 ± 0.1	16.9 ± 0.1	13.7 ± 0.1	1.2	1.7	0.8	1.2	33.9
Kargalak	20.4 ± 0.1	25.9 ± 0.1	23.4 ± 0.1	0.8	3.8	2.1	1.4	45.5
Kuş	19.3 ± 0.1	16.6 ± 0.1	15.1 ± 0.1	1.2	1.8	1	1.3	49.7
Palaz	16.9 ± 0.1	19.5 ± 0.1	17.1 ± 0.1	0.9	1.9	1	1.3	47.3
Sivri	20.7 ± 0.1	16.1 ± 0.1	14.4 ± 0.1	1.4	1.8	0.9	1.2	47.6
Tombul	18.2 ± 0.1	17.6 ± 0.1	15.8 ± 0.1	1.1	1.9	0.9	1.2	49.9
Uzunmusa	18.1 ± 0.1	18.1 ± 0.1	16.4 ± 0.1	1.1	1.8	0.8	0.9	55.7
Yassı Badem	25.6 ± 0.1	17.5 ± 0.1	12.8 ± 0.1	1.7	2.5	1.4	1.5	45.5
YuvarlakBadem	24.3 ± 0.1	15.2 ± 0.1	13.4 ± 0.1	1.7	1.7	0.8	0.9	48.6

**Figure 1.** The georeferenced map of the different Turkish hazelnut varieties [3].

Different methods have been put forward to classify the varieties of hazelnuts. Gi-raudo et al. automatically identified defective hazelnuts with multivariate analysis methods in RGB images and then used them to create classification models [4]. Solak and Altınışık succeeded in classifying hazelnut varieties using image processing and the mean-based, k-mean clustering technique [5]. Menesatti et al. demonstrated the potential use and effectiveness of shaped techniques to distinguish hazelnut varieties [6]. Güvenç et al. classified the partial shell-removed hazelnut kernel, shell removed, and rotten hazelnut kernels using a computer vision approach [7]. Koc et al. performed the classification of hazelnut types DL4J and ensemble learning algorithms [8]. DNA-based studies have also been carried out to classify hazelnuts, but this is laborious and expensive work [9,10]. No study on deep learning could be found in the classification of hazelnut varieties.

In this context, we come across many different practices in which artificial intelligence is used to process and evaluate data. The main difficulty in using artificial intelligence is solving tasks that people solve intuitively but are challenging to perform

numerically [11–14]. Machine learning, which is a sub-branch of artificial intelligence, enables researchers to handle real problems numerically. Machine learning creates algorithms to recognize the patterns in data and make predictions accordingly [15–17]. Machine learning-based methods are applied in many areas, such as ecology, mining, urban planning, defense, space research, and especially agriculture [18–20]. Of these methods, deep learning is one of the most commonly used, and its most important feature is that it has the ability to learn relevant features from images automatically. Features can be learned in depth by different deep learning architectures, and they can be extracted as the input of classification models.

Moreover, deep learning is very effective for big data analysis [21–27]. In particular, the convolutional neural network (CNN), one of the deep learning models, has come to the forefront due to its success in computer vision in application areas. CNNs are a type of artificial neural network that use convolution processes in at least one of the layers [28].

One of the deep learning models, CNNs, includes several layers called convolutional, pooling and fully connected (Figure 2). The function of convolutional layers is feature extractions, while pooling layers function as compressors, and fully connected layers make the classification. Image features are extracted, and a convolutional layer learns representations of image features. Several filters are a given stride used to perform a 3-D convolution and produce feature maps from the input image. At the output of the layer, each feature map represents features extracted from locations of the input image with the help of one set of shared weights. A pooling layer is used to modify the output results of the convolutional layer. The low-level feature representation could be transformed into high-level feature representation, which is approximately invariant to small translations of the input by using pooling function, reducing the dimensionality of each feature map but retaining the essential information. The fully connected layer consists of the weights, biases, and neurons and connects the neurons between two different layers. These layers are usually placed before the output layer [29].

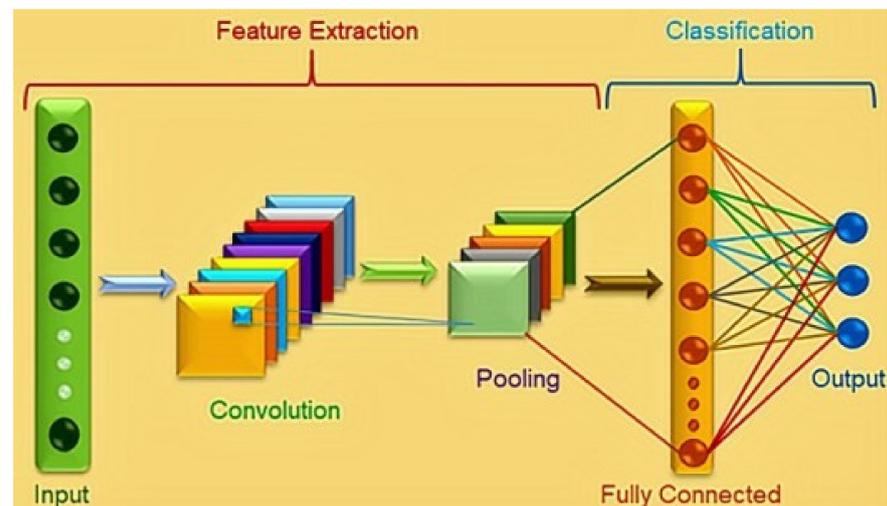


Figure 2. Convolutional neural network structure.

The deep learning neural networks have shown a powerful and excellent performance on several agricultural applications, such as fruit classification [30], plant identification [31], crop classification [32], weed classification [33], quality evaluation [34], and field pest classification [35].

CNNs gained great popularity as an effective method for classifying images in many areas. Especially in agriculture, CNN-based approaches have been used for fruit classification. Torres et al. developed a CNN model which classified three apple and three peach varieties with 95.45% success [36]. Sakib et al. obtained two CNN models [37] for fruit classification using Fruits-360 data set [38]. Mureşan and Oltean presented the evaluation

of a basic CNN model, AlexNet, and GoogLeNet models for fruit recognition [39]. Wang and Chen created a CNN model with eight layers, and they classified the 3600 images of 18 species of fruit with 95.67% success [40]. Zhu et al. used an AlexNet network model to classify vegetable images. The authors trained CNN models on different data sets by changing the number of vegetable images. The results of the classification showed that accuracy decreased as the number of images decreased. In addition, they compared the accuracy rates of the CNN-based method with the backpropagation neural network and support vector machine (SVM) classifier [41]. A six-layer CNN was designed by Lu et al. to classify fruit. The fruit dataset included 1800 images from 9 types of fruits taken by a digital camera. The proposed CNN model was compared with voting-based-SVM (VB-SVM), wavelet entropy (WE), and genetic algorithm (GA) [42]. A modified visual geometry group (VGG) model was used by Zeng [43] to classify vegetables and fruit. A bottom-up graph-based visual saliency model was used for fruit region segmentation, followed by a CNN model learning image for the classification task.

CNNs are very effective for classification and recognition, and they decrease errors in classification significantly [44]. Although CNNs have received much more attention than other machine learning algorithms, they have not been used in hazelnut researches, and not a single article using CNN has been reported on this topic.

The study area of our review is defined as the identification of fruit classification tasks to determine class according to the specific type.

Based on the attention CNNs have received in recent years and the fact that CNN has not been studied on hazelnuts before, we are presenting a review of the use of CNNs applied to the fruit imaging process, especially in the fields of classification and determination. In addition, our study is an example of practical application to be used in different samples by providing an approach to researchers about CNNs.

2. Materials and Methods

2.1. Dataset

Seventeen hazelnut varieties commonly grown in Turkey were used in our study (Figure 3). The hazelnuts were obtained from the Republic of Turkey Ministry of Agriculture and Forestry Hazelnut Research Institute. A camera with a resolution of 14.1 megapixels was used in taking the images. All images were taken from the same distance (20 cm) with a special setup. Light difference was taken into consideration while taking the images. Two hundred fifty images were taken for each variety. The images were obtained in two seasons as 2019 and 2020 to ensure variation.

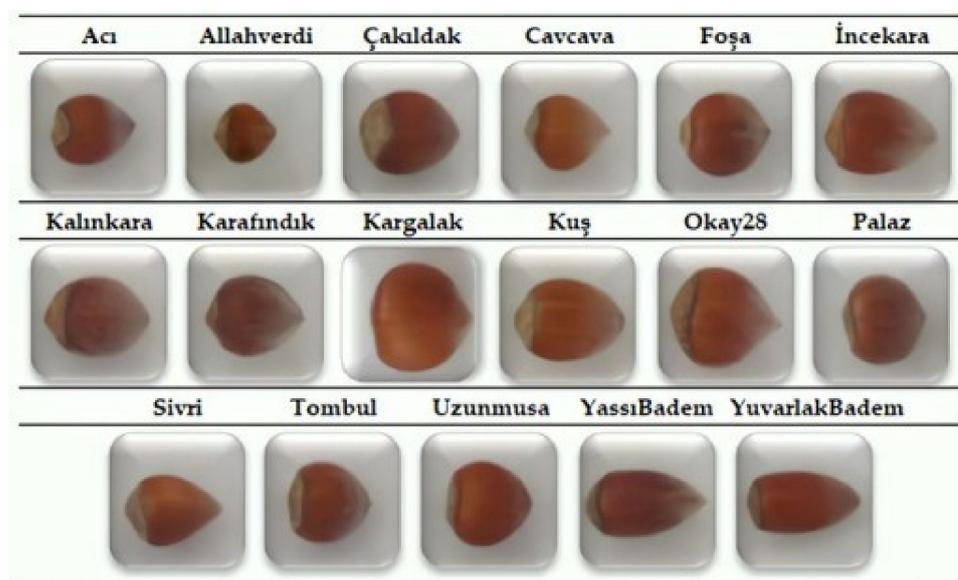


Figure 3. Hazelnut varieties used in the study.

The data set includes a total of 4250 images. This data set was grouped into training, validation, and test sets. There were 3485 data in the training set, 255 data in the validation set, and 510 data in the test set (Table 2).

Table 2. Hazelnut data set.

Varieties	Training	Validation	Test
Acı	205	15	30
Allahverdi	205	15	30
Çakıldak	205	15	30
Cavcava	205	15	30
Foşa	205	15	30
İncekara	205	15	30
Kalınkara	205	15	30
Karafındık	205	15	30
Kargalak	205	15	30
Kuş	205	15	30
Okay28	205	15	30
Palaz	205	15	30
Sivri	205	15	30
Tombul	205	15	30
Uzunmusa	205	15	30
YassıBadem	205	15	30
YuvarlakBadem	205	15	30
Total	3485	255	510

2.2. Convolutional Neural Networks

The five CNN models were used in the study to classify 17 hazelnut varieties. These models are Lprtnr1 and pre-trained (VGG16, VGG19, ResNet50, and InceptionV3) models. Lprtnr1 model and pre-trained models were compared.

A CNN model named Lprtnr1 was designed by the authors (Figure 4). The Lprtnr1 model consists of an input layer, four convolutional layers, a flattening layer, a fully connected layer, and an output layer. Codes of the Lprtnr1 model are given in Supplementary Materials.

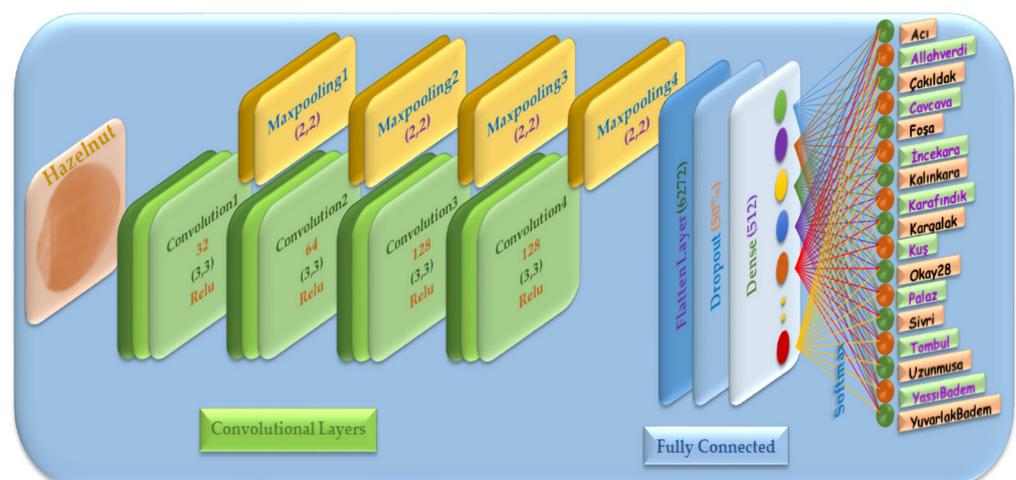


Figure 4. The specific configurations of designed CNN (Lprtnr1) architecture.

A kernel was applied to the input image matrix with the convolution process in the first convolutional layer. Then ReLu activation function was used. After passing through the activation layer, the pooling layer was applied to reduce the image size and processing power in the network on the feature map. The max-pooling method was used

here. Similarly, the Lprtnr1 model had four convolutional layers and a pooling layer. The number of kernels used in convolutional layers was 32, 64, 128, and 128, respectively. Flattening was applied after passing from convolution layers, and a fully connected layer was formed in the next process step. To prevent the overfitting of the network and to increase model performance, dropout was performed. In the proposed model, a dropout of 0.5 was applied to the ANN with one hidden layer. For the network to make an accurate estimation, the cost function should automatically be reduced to the lowest value. The “Adam” optimization algorithm was used to determine and update the weight values that provide this. “Categorical Cross Entropy” cost function was preferred because multiple classifications were made in our study. Softmax activation function was used because 17 different classifications would be made from the images of hazelnut varieties [45–48]. Some Mathematical Expressions about CNN are given in Supplementary Materials.

Pre-trained models were preferred because of their performance and ability to bring out specific architectural innovations. The four different pre-trained models were included in this study. These are VGG16, VGG19, ResNet50, and InceptionV3 models.

The VGG model was developed in 2014 by the Visual Graphics Group (VGG) at Oxford. Many variations of the VGG were implemented, such as VGG16 and VGG19, and these variations were different only in terms of the number of convolution layers used [49].

ResNet50, which was developed at Microsoft and described in 2015, uses a residual model which involves shortcut connections. In this model, color images are expected to have the square shape 224×224 [50].

The third version of the Inception networks family is InceptionV3, which was initially developed for the GoogLeNet model. Unlike traditional CNNs, the main idea of Inception architectures is to make multiple kernel filter sizes operate on the same level rather than stacking them sequentially, which is known as making the networks wider instead of deeper [51].

These models were used for feature extraction. To adapt the chosen models to the data set in our study, the convolution layers in all of these models were frozen and kept in their original form, while the last classification layer was removed. The number of varieties, which is 17, was added in the last layer to classify the hazelnut varieties.

This study was conducted on the hazelnut data set consisting of 17 varieties. Because the number of images in the data set was small, and to prevent overfitting, extensive data augmentation was applied, including the techniques mentioned earlier. The data set was grouped as 82% training, 6% validation, and 12% test. First, training and validation sets were used to perform the training process and parameter selection.

It is important to make sure that we have the best possible training model in the study. In this context, a technique called model checkpoint was applied. This model checkpoint observes the changes during training. If there is a positive change in the validation loss, the model checkpoint replaces the existing retained model with a new one in which validation loss is better than the existing one. Thus, the best possible model was obtained at the end of the training process. The results on the unknown data were evaluated by using the test set with the best model obtained. These procedures were applied for each of the 5 models used in the study. All parameters were used in the same way for each model.

2.3. Evaluation Metrics

Various evaluation metrics are used to find out the performance of the classifier. The evaluation metrics used in the study are explained below [52].

A confusion matrix was used to express classification accuracy numerically. The confusion matrix is one of the most commonly used techniques in machine learning, and it includes information about the actual and predicted classes obtained by a classification system. The confusion matrix has two dimensions: actual and predicted classes. While each row represents an actual class example, each column represents the state of a predicted class. In the confusion matrix, TP is the number of true positive, TN is the number of true negative, FP is the number of false positive, and FN is the number of false negative.

2.3.1. Accuracy

The accuracy of the classifier is quantified with this metric. The number of correctly classified data is divided by the total number of the data to calculate accuracy.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

2.3.2. Precision

Precision shows how much of the data predicted as positive are predicted correctly. In other words, high precision means fewer false positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

2.3.3. Recall

The recall is the metric of determining the completeness of the classifier. Higher recall indicates lower false negatives, while lower recall indicates higher false negatives. Precision often decreases with an improvement in recall.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

2.3.4. F1-Score

To obtain the F1-score, the product of recall and precision is divided by the sum of recall and precision.

$$\text{F1-Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (4)$$

3. Results

CNN is used widely for image classification. In this study, the performance of different CNN architectures was evaluated for the classification of hazelnut varieties, the classification accuracy of the proposed CNN model (Lprtnr1) pre-trained models (VGG16, VGG19, ResNet50, and InceptionV3) was compared. While the proposed model was trained from scratch, pre-trained models were previously trained, and they were used as feature extractors. The same optimization algorithm was applied to each model, and the performances of these models were observed.

Table 3 shows the evaluation metrics of both validation sets and test sets of 5 CNN models. Here, the results are summarized for each model. The training process was carried out using the same settings in each model to obtain results that can be compared. For this purpose, the same input shape and batch size, the same training-validation-test split, the same learning rate, and the same optimizer were used. As the complexity or depth of the model increases, overfitting also increases even if data augmentation and dropout are applied. This situation results from the fact that the data set used is not large enough.

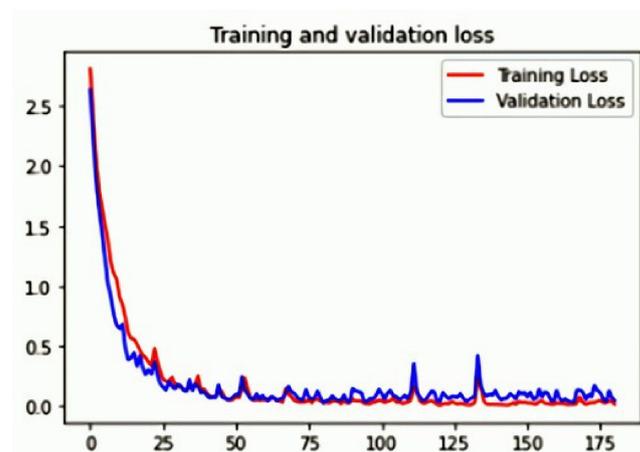
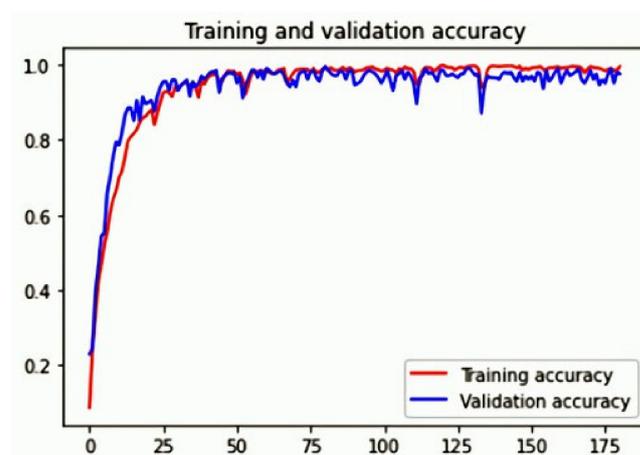
For this reason, the results change depending on the depth of the CNN model, the complexity of the classification, and the amount of data. The Lprtnr1 model (the proposed CNN model) gave much better results because it is a much simpler model than the pre-trained models. Because pre-trained models provided lower test accuracy/F1-score and higher test loss, they were unsuitable models for classification. In the hazelnut classification data set, the Lprtnr1 model was found to reach 98.63% accuracy.

To consider a model as the best model, it must have performed well in the training data set and the validation data set [53]. In this sense, the Lprtnr1 model was found to be the best model. Sensitivity analysis also indicated that the proposed model is the most influential model to classify hazelnut varieties [54].

Table 3. Average evaluation metrics of the five CNN models.

Data Set	Evaluation Metrics	CNN Models				
		Lprtnr1	VGG16	VGG19	InceptionV3	ResNet50
Validation	Loss	0.03491	9.1336	7.5501	5.4935	7.8169
	Accuracy	0.9882	0.6941	0.6745	0.5843	0.7725
	Recall	0.9894	0.7178	0.7247	0.6350	0.8019
	Precision	0.9882	0.6941	0.6941	0.5843	0.7725
	F1-Score	0.9888	0.7058	0.7091	0.6086	0.7870
Test	Loss	0.0443	7.1046	6.6648	5.4052	6.9467
	Accuracy	0.9863	0.7314	0.7214	0.6118	0.8000
	Recall	0.9867	0.7580	0.7580	0.6669	0.8240
	Precision	0.9863	0.7255	0.7471	0.6118	0.8000
	F1-Score	0.9865	0.7414	0.7525	0.6381	0.8118
Depth		6	16	19	159	168

In the Lprtnr1 model, the variation trend of training loss almost overlaps validation loss (Figure 5). At the same time, the variation trend of training accuracy is also consistent with that of validation accuracy (Figure 6). This situation shows that the model does not have an overfitting problem with the parameters chosen during the training process. These results show that the proposed network can distinguish the matched images in the input well.

**Figure 5.** Training and validation loss of Lprtnr1 model during the model training for hazelnut variety classification.**Figure 6.** Training and validation accuracy of Lprtnr1 model during the model training for hazelnut variety classification.

5. Conclusions

This article proposed an effective model to classify hazelnut varieties. The proposed model was trained on a data set that included the images of 17 hazelnut varieties. This model was compared with four pre-trained models, only the last layer of which were changed. The model was fine tuned to improve the classification performance of each model. The models were optimized and validated to increase the rate of accuracy and decrease the rate of error. The accuracy of the proposed model was found as 98.63%.

The results showed that pre-trained models could not meet the requirement for the classification of hazelnuts. Therefore, a new CNN architecture was proposed and used in this study.

The classification performance of data sets regarding other nuts can be improved by adapting the CNN model proposed in this study. Because it is not easy to obtain appropriate advice from agriculturists for manual determination and classification of varieties, this practice will help individuals with limited information about hazelnut varieties. At the same time, it will provide an opportunity for highly accurate, fast, and reliable classification. In the future, we aim to increase the amount of data and the number of varieties and to further develop this research study by using different deep learning methods.

Supplementary Materials: The following are available online at <https://www.mdpi.com/article/10.3390/su13126527/s1>, Codes and Mathematical Expressions.

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