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Classification of Hazelnut Species with Pre-Trained Deep Learning Models

Selçuk Harmancı [a, *], *Yavuz Ünal* [a], *Barış Ateş* [a]

[a] *Amasya University, Amasya, Türkiye*

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ABSTRACT

A form of shelled nut in the Betulaceae family is the hazelnut. The majority of it is grown in Türkiye internationally. It grows in the provinces of Türkiye's Black Sea region, which is a significant global production hub. Hazelnuts can be eaten in a variety of ways and are a great source of protein, fat, fiber, vitamins, and minerals. There are numerous applications for hazelnuts in the food business. This study uses pre-trained networks to categorize eight of the most popular hazelnut kinds farmed in Türkiye. In this study, locally named hazelnut varieties grown in Türkiye were examined. An automated computer vision system was used to capture the images of the different hazelnut kinds. Our dataset includes a total of 2722 images, consisting of 155 palaz, 340 yagli, 399 deve disi, 236 tombul, 399 damat, 354 cakildak, 437 kara findik, and 402 sivri hazelnuts. Using transfer learning, the DenseNet121 and InceptionV3 models of convolutional neural networks were employed to categorize these images. The dataset was split into training and testing portions, respectively. With InceptionV3 and DenseNet121, respectively, the research revealed classification accuracy of 96.99% and 96.18%.

1. INTRODUCTION

The hazelnut product is mainly found in a wide area of the temperate climate zone located between 42-45 latitude degrees in the northern hemisphere of our world. It generally yields better results in coastal regions and in temperate climates. The best example of this can be given as the Black Sea coastal region of Türkiye [1]. Hazelnut production is also widespread in coastal areas of Spain and Italy [2]. In the United States, hazelnut production is carried out in the Willamette region, which is affected by the Pacific. The Caucasus and the Balkans are also important production areas. Hazelnut varieties are also grown in different ecologies such as China and India. On the other hand, in the last 20 years, cultivation has also increased in the southern hemisphere, such as in Chile [3].

Hazelnuts are a rich source of protein, healthy fats, fiber, vitamins, and minerals. Additionally, due to the antioxidants it contains, it can be beneficial for health and support heart health. However, it is important to control portions while consuming hazelnuts due to its high calorie and fat content [4]. Furthermore, the use of hazelnut shells as activated carbon has become an increasingly popular application in recent years. Hazelnut shells can be used in the production of activated carbon as they contain high levels of carbon.

Hazelnut products provide an important source of income for our country in terms of agricultural value. It is among the traditional export products of our country. An important part of the world hazelnut production is made in Turkey [5].

Artificial intelligence applications are now becoming more prevalent in agriculture on a daily basis, solving issues there and offering a different approach to the practices now in use. Plant identification systems have been successfully applied in recent years to address issues including yield, disease, and species estimate. Deep learning is successfully applied in this area as well [6, 7].

Deep learning is a subfield of artificial intelligence and machine learning. Deep learning can analyze large and complex datasets using artificial neural networks and can undergo a learning process from these data to achieve better results. Deep learning is successfully used in many fields such as speech recognition, image processing, natural language processing, game, and robot control. Especially when working on large datasets and discovering more complex features than humans can extract manually, deep learning methods play an important role [8, 9].

In this study, it is aimed to classify the hazelnut product, which is agriculturally important and industrially significant in our country, with deep learning models. The rest of the study is organized as follows. In Section 1.1, the literature review is presented, in Section 2, material and methods are described, in Section 3, experimental results

* **Corresponding Author:** harmanci_selcuk@hotmail.com

are presented, and in the final section, conclusions and recommendations are discussed.

1.1. Literature review

The studies conducted on hazelnut products and the studies conducted on machine learning and deep learning have been reviewed and presented in this section.

Ünal and Aktaş developed a system that breaks the shells of hazelnuts and images the inner kernels in their study. Based on these images, the products from the hazelnut cracking machine were classified into undersized, damaged kernel, whole kernel, and shell. In the classification stage, they achieved classification accuracies of 97.85% and 99.28% using pre-trained transfer learning models, InceptionV3 and EfficientNet, respectively [10].

In their study, Koç et al., developed a system that classifies the hazelnut fruit in its shell through photographs. They classified the plump sivri and kara findik varieties using machine learning and deep learning methods. In their study, considering the shell compression strength, the boosting method obtained 72%, the Bagging method (Random forest) 83% and the DL4J (Deep learning algorithm) 71% classification accuracy [11].

Giraudo et al., used a sample set consisting of 2000 half-cut hazelnut kernels in their study. With the help of a digital camera, intact and defective (rotten or infested) hazelnut kernels were imaged. Defective classification model using both defective hazelnut kernels (PLS-DA) and PLS-DA range (iPLS-DA) algorithms based on multivariate analysis of RGB images using Red-Green-Blue (RGB) image analysis, approximately 97% accurately. they have classified. More than 92% of the rotted and pest-affected test set samples achieved correct classification accuracy [12].

Bayrakdar et al., they classified 3 different hazelnut species through images in their study. They reached an accuracy rate of 84% by utilizing shape and size features such as diameter, radius, and area from the images of plump, sivri and almond-type hazelnut cultivars [13]

Solak S. and Altunışık U. used the images of 25 hazelnut products in their study and classified these hazelnuts as small, medium and large. In this study, images were obtained using Logitech C110 USB camera with 1.3 Megapixel CMOS, 640 x 480 resolution. The images in question are processed on a computer running Ubuntu 12.04. OpenCV Library and Weka software were used in the processing and classification of images. Using mean-based and K-means clustering methods, hazelnut fruits are classified as small, medium and large. In this study, it is determined that the two algorithms and the classification show similarity between 90% and 100% [14].

Guvenc et al., they divided the hazelnut kernels into three classes as with skin, without skin and rotten. They used 900 hazelnut kernels in total. They were classified with SVM, Bayes, Artificial neural networks using color features. They obtained 93.57% classification accuracy with artificial neural networks [15].

Keles et al. used artificial neural networks and discriminant analysis to categorize the cultivars of the hazelnut (Corylus avellana L.) in their study. Three primary axes of the physical, mechanical, and visual characteristics of 11 hazelnut cultivars were identified. Hazelnut cultivars were included as dependent variables and physical, mechanical, and optical characteristics parameters as independent variables. To categorize the many hazelnut cultivars, models were made for each of the three axes. Artificial Neural Networks (ANN) and Discriminant Analysis (DA) have classification success rates of 89.1% and 92.7% for the X-axis, 92.7% and 92.7% for the Y-axis, and 86.8% for the Z-axis, respectively. They discovered it to be 88.7% [16].

İkramullah K. and Eros P. classified hazelnut varieties by feature extraction classification in x-ray images for hazelnuts they made. It contains 748 healthy images obtained with x-ray images. Hazelnut products, 20 damaged hazelnuts and 20 infected hazelnut images were used. 95% of the samples belonged to the “good” category only. A sample of 5% was found in the “bad” category. Anomaly detection algorithm was used for the detection of selected spoiled hazelnuts for these data [17].

Here are many studies conducted in this area. The data of these studies are given in Table 1.

2. Materials and Methods

In this study, a total of eight hazelnut cultivars grown in Turkey were used. These; It is classified as palaz, yagli, deve disi, tombul, damat, cakildak, kara findik, sivri. In this study, a total of 2722 images were studied, including 354 from cakildak hazelnuts, 399 from damat hazelnuts, 399 from devedisi hazelnuts, 437 from kara findik, 155 images from palaz hazelnuts, 402 from sivri hazelnuts, 236 from tombul and 340 from yagli hazelnuts. The types of hazelnuts used in the study and how many are used are given in Table 2.

Table 1. Studies in This Field in The Literature

No	Crop	Data Pieces	Class	Method	Accuracy (%)	References
1	Hazelnut	2094	4	InceptionV3 EfficentNet	97.85 99.28	[10]
2	Hazelnut	50	3	Boosting, Bagging, DL4J	72 83 71	[11]
3	Hazelnut Kernel	2000	2	PLS-DA	92	[12]
4	Hazelnut	300	3	SigmaScan Pro5.0	84	[13]
5	Hazelnut	25	3	Mean based classification	90-100	[14]
6	Hazelnut	900	3	ANN	93.57	[15]
7	Hazelnut	40	11	ANN, DA	89,1 92,7 86,8 88,7	[16]

Table 2. The Hazelnut Varieties Used in The Study

Hazelnut Variety	Number of Samples
cakildak	354
damat	399
deve disi	399
kara findik	437
palaz	155
sivri	402
tombul	236
yagli	340
Total	2722

These images were taken with the help of the setup given in Figure 1. Images are 3088x3088 in color and in jpg format. images were taken without flash with an aperture of F1.9 and sensitivity of ISO40.

The images were captured from a distance of 10 cm using Samsung Galaxy A02 digital camera with a resolution of 13 megapixels.

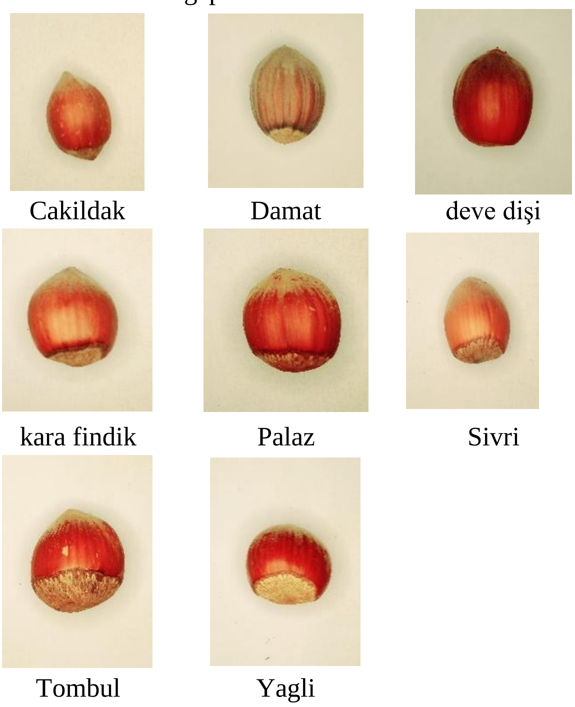

Figure 1. Some Hazelnut Varieties Grown in Türkiye

2.1. Image Acquisition

The images of the hazelnut products used in our study were obtained using the closed box mechanism. In this mechanism, there is a box with four sides and a lighting system on it. Images are obtained thanks to the camera located in the middle of the lighting system. The reason why the box is closed on all four sides is to protect the hazelnut look inside the box from the light coming from the surroundings and to prevent shadowing. The images were obtained by transferring them to a fixed storage medium via the camera. A white background was used to obtain clear images during imaging.

The mechanism used to transfer deep learning hazelnut product materials to the system is shown in Figure 2.

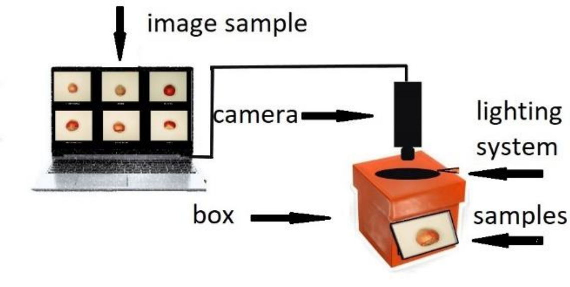

Figure 2. Computer Vision System Used To Obtain Grapevine Leaves Images

2.2. Deep Learning

Deep learning refers to the ability of computers to learn from large data sets using complex mathematical models such as artificial neural networks. Deep learning is used to identify and learn features by layering on large and complex datasets, such as many images or text documents. These layers consist of a sequential set of mathematical operations that handle different aspects of the data. Through these processes, neural networks can discover patterns and relationships in datasets, extract their features, and make detection [18].

Deep learning algorithms train themselves by processing large amounts of data and automatically adjust the parameters necessary to ultimately deliver accurate results on that data. In this way, systems can be created that can perform operations that humans do in many different areas, such as image recognition and natural language processing [19].

Deep learning is used in many different fields today. For example, it is used in many fields such as image processing, voice recognition, automatic translation, advertising recommendation, driverless vehicle technology, data mining [20].

Deep learning algorithms use multi-layer artificial neural networks where data is fed to the input layer and the results are obtained from the output layer. Data is fed to neurons in the input layer of the network and then processed through the layers of the network. In each layer, new features are obtained by processing the input data and proceed to the output layer. In the output layer, a result is produced based on the information that the network has taked in [21].

2.3. Transfer Learning

The transfer learning method is a machine learning method that involves reworking a task with a previously trained model. Rather than retraining any type of model, transfer learning uses large datasets with an already trained model and treats it for a specific task [22].

Transfer learning is a machine learning technique that involves reusing a previously trained model in a related task. Rather than training a model from scratch, transfer learning starts with an existing model trained on a large dataset and fine-tunes it for a specific task or problem [23].

The use of transfer learning is widespread, including applications in speech recognition, natural language processing, and computer vision. It has gained popularity in machine learning, particularly in situations when the amount of labeled data is constrained or the computational cost of building a new model from start is high [24].

2.4. Data Augmentation

The process of creating new and synthetic data by changing the data we have with various techniques is called data augmentation. By altering the samples in the current dataset or creating new samples, data augmentation aids the learning model in generalizing more effectively and performing amend [23].

Data augmentation techniques can be used in models that process images, audio, text, and other types of data. For example, data augmentation techniques for image data can expand the existing dataset by operations such as flipping, cropping, rotating, mirroring, color correcting, or adding noise to images. For text data, techniques such as changing words, changing word order, translating or adding sentences and changing relationships between words can be usage [25].

These techniques can increase the size of the datasets, helping the model meet more diversity and perform better. However, in some cases, data augmentation can also cause an overfitting problem due to duplication of samples in the dataset or creation of similar instances [26].

These classical data augmentation methods are not effective in the hazelnut images that stand out in the analyzes made with more color and texture than the shape information it contains. For this reason, instead of the classical methods of data augmentation, adaptive new images were created from high-resolution and high-dimensional hazelnut images, suitable for the input dimensions of each accessive neural network (ESA) architecture.

With the applied data augmentation method, a hazelnut image is divided into equal parts according to the input resolution of the architecture to be used. Uneven images resulting from the image size are resized according to the input resolution. Data augmentation has been applied for DenseNet121 with an input resolution of 224x224 pixels and InceptionV3 architecture with an input resolution of 299x299 pixels.

The parameters we use in data augmentation are given in Table 3.

Table 3. The Augmentation Techniques

Augmentation Technique	Range
Rotation	40
Width Shift	0.2
Height Shift	0.2
Shearing	0.2
Zooming	0.2
Horizontal Flip	True
Fill Mode	Nearest

Augmentation parameters in this study; Rotation range value was 40, Width Shift value was 0.2, Height Shift range value was 0.2, Shearing angle value was 0.2, Zooming Range value was 0.2, Horizontal Flip Range value was True and Fill Mode Nearest was found.

2.5. DenseNet121

DenseNet, short for Dense Convolutional Network, is a convolutional neural network architecture introduced in 2017 by Gao Huang, Zhuang Liu, and Kilian Q. Weinberger. To restrict the amount of parameters and lower the dimensionality of feature maps, transition layers are introduced in between dense blocks. The four layers are transition, bulk normalization, 1x1 convolution, and 2x2 average pooling. A fully connected layer with softmax activation and an overall average pooling layer are added at the network's conclusion before the image is classified. DenseNet has several advantages over traditional convolutional neural networks. Densely connected layers allow for more efficient feature reuse, leading to better parameter efficiency and less overfitting. DenseNet also achieves state-of-the-art performance across a range of image recognition tasks, using fewer parameters and requiring fewer computational resources. Overall, DenseNet is a powerful deep neural network architecture that makes significant contributions to the field of computer vision and advances the latest in image recognition assignments [27, 28] .

2.6. InceptionV3

For object detection and image categorization, Google built the deep learning algorithm InceptionV3. The third installment of the Inception series, InceptionV3, was created to offer greater accuracy than its predecessors. With the help of the imageNet dataset, which it was trained on, InceptionV3 is able to identify 1000 distinct object classes. Many applications of InceptionV3 have produced positive results, particularly in the area of visual method [29].

InceptionV3 is particularly useful for difficult visual processing problems such as object detection. Object detection is the process of determining the position and size of objects in an image. InceptionV3 includes many techniques, features, and algorithms used in this process, which can provide high accuracy for object detection. InceptionV3 is used in many application areas today. For example, object detection and autofocus used in smartphone cameras are performed with deep learning models such as InceptionV3. In addition, the InceptionV3 model is used for transfer learning in other fields such as translation, speech recognition and natural language processing [30].

2.7. Performance Evaluation

When developing a new model for classification tasks or utilizing pre-existing models, the evaluation of its performance is based on the accuracy of its predictions. This aspect focuses more on determining the correctness of classification rather than assessing the overall quality of the model. Hence, the confusion matrix is employed to represent the evaluation of predictions made by the classification model. The confusion matrix is a matrix that encompasses details about the predicted classes and the actual classes derived from the application of a classification model on test data [31, 32]. Table 4 shows the confusion matrix used in the classification of hazelnuts.

Table 4. Confusion Matrix

		TRUE CLASS	
		Positive	Negative
PREDICTED CLASS	Positive	TP	FP
	Negative	FN	TN

Confusion matrices contain four key metrics: true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). True positives refer to instances correctly classified as belonging to the positive class, while true negatives represent instances correctly classified as belonging to the negative class. False negatives occur when instances of the positive class are incorrectly classified as negative, whereas false positives refer to instances of the negative class that are falsely classified as positive [33].

2.8. Performance Measures

Performance metrics are measurement and evaluation tools used to assess the level of success of a system, process, or operation. These metrics are employed to gauge the extent to which specific objectives are achieved and to evaluate the effectiveness of performance [34, 35].

Accuracy; "Accuracy" is a benchmark term and refers to the rate at which a model or prediction is correct. It is mainly used in machine learning and statistical analysis. Its formula is as follows Eq. 1.

$$\frac{\mathrm{TP}+\mathrm{TN}}{TP+TN+FP+FN} \tag{1}$$

Sensitivity; "Sensitivity" is a term used in fields such as medicine and statistics and refers to the ability of a test or model to detect disease accurately. Its formula is as follows Eq. 2.

$$\frac{2\mathrm{TP}}{2TP+FP+FN} \tag{2}$$

Specificity; "Specificity" is a term used in fields such as medicine and statistics and refers to the ability of a test or model to accurately detect healthy status. Its formula is as follows Eq. 3.

$$\frac{\mathrm{TP}}{TP+FN} \tag{3}$$

Precision; "Precision" is a metric that measures how many of the samples that a classification model predicts as positive are actually positive. Its formula is as follows Eq. 4.

$$\frac{\mathrm{TP}}{TP+FP} \tag{4}$$

f1-score; "f1-score" is a criterion used to evaluate the performance of a classification model. Represents the harmonic mean of precision and recall measurements. The formula is as follows Eq. 5.

$$\frac{\mathrm{TN}}{TN+FP} \tag{5}$$

3. Experimental Results

In this study, hazelnut species were classified by two pre-trained CNN methods. These are the InceptionV3 and Densenet121 methods. The analysis of the study was carried out with the python language on the COLAB (Google Collaboratory) platform. Intel(R) Xeon(R) @ 2.20GHz CPU, NVIDIA Tesla T4 16 GB display card and 16 GB of RAM is employed in the deep learning experiments in this study.

The parameters set for training both methods are given in Table 5.

Table 5. Training Parameters

Parameter Name	Value
Execution Environment	GPU
Max Epochs	50
Learn Rate Drop Factor	0.1
Initial Learn Rate	0.001
Mini batch Size	32
Optimization Algorithm	Adam (Adaptive Moment Estimation)

The resulting values are obtained after training and testing for all methods proposed in the study. DenseNet121 trained in the first method achieves 96.18% accuracy.

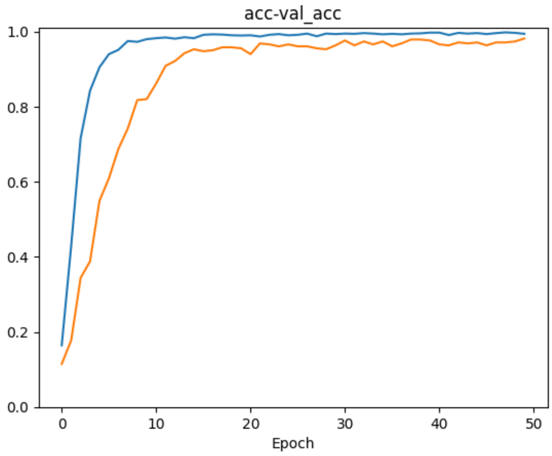

Figure 3. Validation Accuracy Curves With 50 Epochs for Densenet121

Training and validation plot of the DenseNet121 model during model training for the classification of hazelnut cultivars in Figure 3.

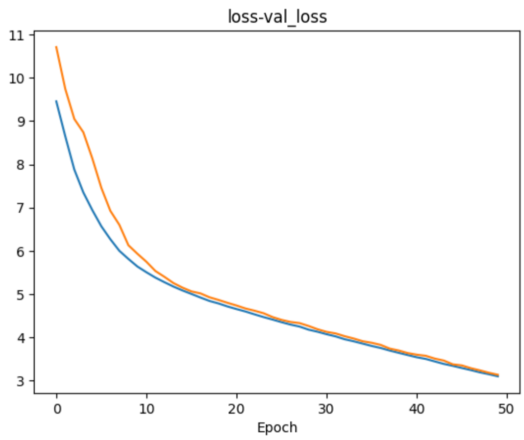

Figure 4. Validation Loss Curves With 50 Epochs for Densenet121

Figure 4 shows the training and validation loss of the DenseNet121 model during model training for hazelnut variety classification.

In confusion matrices, the columns represent the actual class and the rows the predicted class Figure 5. It shows the confusion matrix for the validation set of the DenseNet121 model. In the confusion matrix, the numbers on the diagonal axis indicate the number of correct classifications, while the other numbers indicate the number of incorrect classifications. “0” stands for cakildak class, “1” for damat class, “2” for deve disi class, “3” for kara findik class, “4” for palaz class, “5” for sivri class, “6” for tombul class and “7” for yagli findik class.

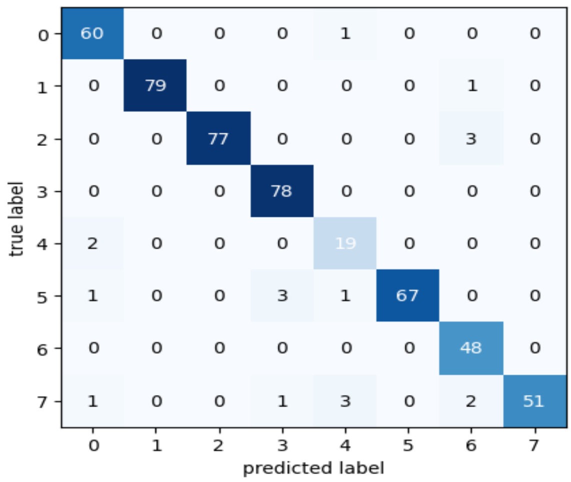

Figure 5. Confusion Matrix Using DenseNet121 method

The results of the analysis made with the DenseNet121 model for eight hazelnut species are given in Table 6.

Table 6. Performance Metrics of DenseNet121 Based Methods

Number of Hazelnut Species	Hazelnut Species	Accuracy	Precision	Recall	f1-score
0	cakildak	0.9618	0.9375	0.9836	0.9600
1	damat		1.0000	0.9875	0.9937
2	deve disi		1.0000	0.9625	0.9809
3	kara findik		0.9512	1.0000	0.9750
4	palaz		0.7917	0.9048	0.8444
5	sivri		1.0000	0.9306	0.9640
6	tombul		0.8889	1.0000	0.9412
7	yagli findik		1.0000	0.8793	0.9358

According to the results given in Table 6;

Precision value for "Cakildak" class is 0.9375, recall value is 0.9836, f1-score is 0.96. Precision value for “Damat" class is 1.00, recall value is 0.9875, f1-score is 0.9937. Precision value for “Devedisi” class is 1.00, recall value is 0.9625, f1-score is 0.9809. Precision value for “Karafindik” class is 0.9512, recall value is 1.00, f1-score is 0.9750. Precision value for “Palaz” class is 0.7917, recall value is 0.9048, f1-score is 0.8444. Precision value is 1.00, recall value is 0.9306, f1-score is 0.9640 for “Sivri” class, precision value is 0.8889, recall value is 1.00, f1-score is 0.9412 for “Tombul” class. Precision value for “Yaglifindik” class is 1.00, recall value is 0.8793, f1-score is 0.9358.

The overall classification accuracy of all cultivars for the test data set was 96.18% compared to the DenseNet121 model.

The resulting values are obtained after training and testing for all methods proposed in the study. InceptionV3 trained in the first method achieves 96.99% accuracy.

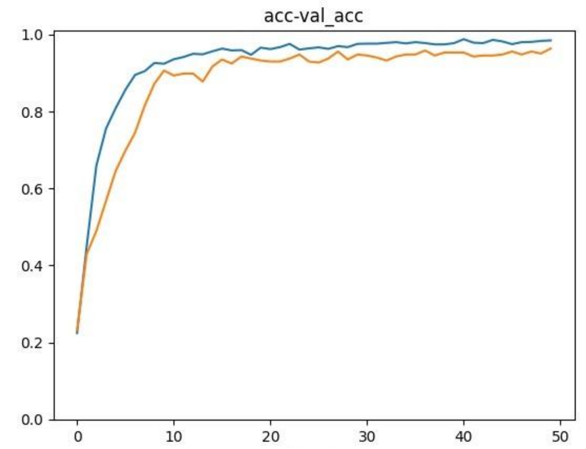

Figure 6. Validation Accuracy Curves With 50 Epochs For Inceptionv3

The training and validation plot of the InceptionV3 model during model training for the classification of hazelnut cultivars in Figure 6.

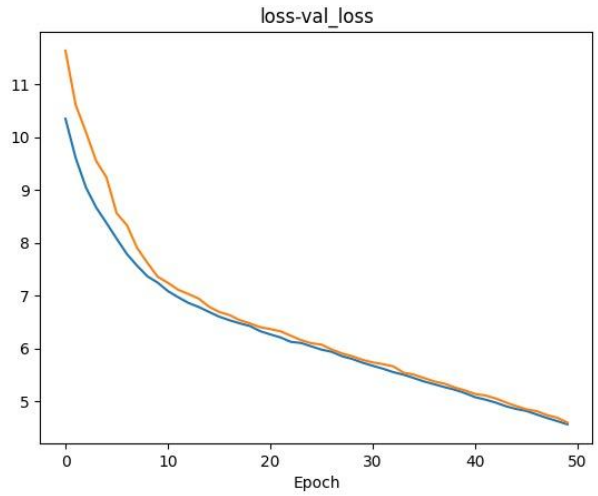

Figure 7. Validation Loss Curves With 50 Epochs For Inceptionv3

Figure 7 shows the training and validation loss of the InceptionV3 model during model training for hazelnut cultivar classification.

Figure 8 shows the confusion matrix for the validation set of the InceptionV3 model. In the confusion matrix, the numbers on the diagonal axis indicate the number of correct classifications, while the other numbers indicate the number of incorrect classifications. “0” stands for cakildak class, “1” for damat class, “2” for deve disi class, “3” for kara findik class, “4” for palaz class, “5” for sivri class, “6” for tombul class and “7” for yagli findik class.

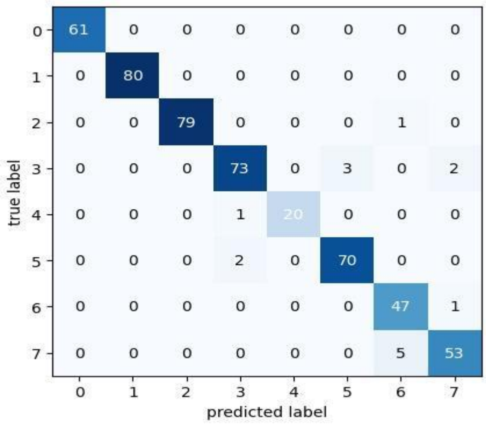

Figure 8. Confusion Matrix Using Inceptionv3

The results of the analysis made with the InceptionV3 model for eight hazelnut species are given in Table 7.

Table 7. Performance Metrics of Inceptionv3 Based Methods

Number of Hazelnut Species	Hazelnut Species	Accuracy	Precision	Recall	f1-score
0	cakildak	0.9699	1.0000	1.0000	1.0000
1	damat		1.0000	1.0000	1.0000
2	deve disi		1.0000	0.9875	0.9937
3	kara findik		0.9605	0.9359	0.9481
4	palaz		1.0000	0.9524	0.9756
5	sivri		0.9589	0.9722	0.9655
6	tombul		0.8868	0.9792	0.9307
7	yagli findik		0.9464	0.9138	0.9298

According to the results given in Table 7;

For the "cakildak" class, the precision value is 1.00, the recall value is 1.00, and the f1-score is 1.00. The precision value for the “damat” class is 1.00, the recall value is 1.00, and the f1-score is 1.00. For the “deve disi” class, the precision value is 1.00, the recall value is 0.9875, and the f1-score is 0.9937. Precision value for “kara findik” class is 0.9605, recall value is 0.9359, f1-score is 0.9481. Precision value for “palaz” class is 1.00, recall value is 0.9524, f1-score is 0.9756. The precision value for the “sivri” class is 0.9589, the recall value is 0.9722, and the f1-score is 0.9655. For the “tombul” class, the precision value is 0.8868, the recall value is 0.9792, and the f1-score is 0.9307. Precision value for "yagli findik" class is 0.9464, recall value is 0.9138, f1-score is 0.9298.

The overall classification accuracy of all cultivars for the test dataset was 96.99% compared to the InceptionV3 model.

4. Discussion and Conclusions

This study aimed to classify eight different types of hazelnut images with two different pre-trained models. There are 2722 visuals of hazelnut models in the data set of the study. 155 pieces of palaz hazelnuts, 340 pieces of yagli hazelnuts, 399 pieces of damat hazelnuts, 236 pieces of tombul hazelnuts, 399 pieces of damat hazelnuts, 354 pieces of cakildak hazelnuts, 437 pieces of kara findik and 402 pieces of sivri hazelnuts were studied. Hazelnut images were classified with pre-trained models, DenseNet121 and InceptionV3. The dataset is divided into sections, 80% training and 20% testing. As a result of the classifications; Classification success of 96.18% and 96.99%, respectively, was achieved. As can be seen, the highest classification success was obtained with the InceptionV3 model. Various confusion matrices and performance measures were used to further analyze the performances of the models. Again, the highest values were obtained with these measurements models. In CNN architectures, layers are not always directly proportional to classification success. Success can be achieved with models containing the optimum number of layers according to high classification. Future research in this area will follow the example established by the study's methodology.

On the other hand, many classification achievements are feasible. many artificial intelligence techniques. Hazelnut types may be recognized quickly and accurately depending on the amount of images in the collection, and different classification successes can be produced from different models. It is possible to do another classification research. It is possible to gather images of various nuts. The application, which may be made mobile, is used in agriculture to identify the type of hazelnut.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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