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Research Article

Classification of Hazelnuts with CNN based Deep Learning System

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ABSTRACT

The rapid development of technology leads to the emergence of technology-based systems in many different areas. In recent years, agriculture has been one of these areas. We come across technological systems in agricultural applications for many different purposes such as growing healthier products, increasing the yield of products, and predicting product productivity. Today, technology-based systems are used more and more widely in agricultural applications. Classification of products quickly and with high accuracy is a very important process in predicting product yield. In this study, it is suggested to use the CNN-based deep learning model VGG16 in order to classify the hazelnut fruit, which is an important agricultural product. The main purpose is to classify hazelnuts according to their quality with a deep learning approach. For that, a new data set was created. There are 15770 images in the created data set. In the study, the data set was used by dividing it into different parts. The classification of hazelnut images was carried out using the VGG16 deep learning model, which is a powerful model for classifying images. As a result of the experiments on the data set created, the classification process of hazelnuts was realized with 0,9873 F1 score. The detection rate of quality hazelnut is 0.9848, the rate of detection of kernel hazelnut is 0.9891 and the rate of detection of damaged hazelnut is 0.9882. In addition, the classification process was carried out with deep learning using 50%, 25% and 10% of the data set in the study. It was observed that the 98.73 %, 95.46 %, 92.62 %, and 88.42 % accuracy rates were achieved when the whole, 50 %, 25 %, and 10 % data sets were used, respectively.

1. Introduction

Developments in information technologies have also accelerated the emergence of new technologies that affect human life. Artificial intelligence has been included in many areas such as health, communication and agriculture.

Artificial intelligence is a technology for developing systems that are autonomous [1] and close to the ability to think like a human in the areas where it is used. In other words, it is a technology that aims to give computers, automobiles, machines and many different devices or systems the ability to think and make decisions like a human.

In recent years, it has been a very popular approach to integrate information technologies, especially the concept of artificial intelligence, with agricultural activities. This approach allows the development of many studies aimed at increasing productivity in agriculture.

As a result of this rapid integration, systems that make people's work and lives easier are emerging in the area where technology is applied. With the application of technological developments to agricultural activities, many systems that facilitate agriculture and increase productivity. The integration of deep learning, which is today's popular technology, in this field is realized rapidly.

Hazelnut classification is done manually. Manual process has a disadvantage. It is costly and slow due to insufficient human resources and high manual labor costs. It also reduces the accuracy of the classification process. The main purpose of this study is to develop a deep learning-based algorithm to speed up the classification process and increase its accuracy. In this way, it is ensured that producers can access information about the product quickly and accurately.

Machine learning [2] and deep learning [3] approaches have an important role in this development. Accuracy rates

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Dataset link: https://data.mendeley.com/datasets/dvvx6kst3f/1

are increasing in studies with deep learning. With the increase in performance rates, deep learning technology can achieve success above human eye object recognition in areas such as the evaluation of image streams. Achieving higher success with deep learning algorithms created an important motivation for us to use them in this study. There are two important factors underlying this success of the deep learning approach. The first of these factors is that deep learning approach emerges as an advanced model of artificial neural networks (ANN) [4]. As seen in the basic ANN structure in Figure 1, ANN is simply composed of an input layer, a hidden layer and an output layer.

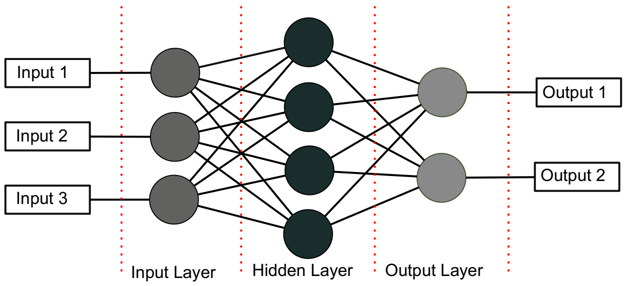


Figure 1. Basic ANN structure

Here, every neuron is interconnected and affects each other. Deep learning has a structure created by increasing the number of hidden layers in ANN. With this new structure, more detailed feature extraction can be performed and much better results are obtained [24]. The second reason for the success of deep learning algorithms is the amount of data used in these structures. These networks usually works better when the amount of data increase. Because neurons in the network capture deep details and learn by using these features.

In this study, deep learning is used for classification of hazelnut. The dataset created from hazelnut images which contains over 15.000 images. The dataset is divided into three classes as quality nut, damaged nut and hazelnut kernel which consists of 10 images of approximately from different angles of hazelnuts. Finally, convolutional neural networks is used for classification. This paper is organized as follows. In Section 2, technology-based studies in the agriculture are included. Section 3 describes the data acquisition, preparation process, algorithm and performance matrix. In Section 4, the results are presented. Finally, the general evaluation of the study and future works examined.

2. Related Works

In this part, technology-based studies in the agriculture are examined, it was observed that there are many different studies. First, it has been seen that different applications are made by using images obtained by remote sensing methods such as satellite or unmanned aerial vehicles. In these applications, many different studies such as determination of agricultural areas [5], paddy fields [6], palm trees and location [7], apple orchards [8] and vine trunks [9] have been presented. In addition to these studies deep learning is used for determination of soy, corn, barley, wheat, sugar beet, alfalfa [10] and freshwater resources [11], calculation of rice yield using leaf area indexes [12], determination of single and total weights of melon fruit [13]. Another use of the deep learning approach in agricultural practices is open farming practices. In such applications, deep learning is used to predict data such as temperature, wind speed and humidity [14]. In another study, it was used for rainfall prediction that directly or indirectly affects crop yield [15]. Predicting frost events that cause significant damage to the product and taking precautions is another area where the deep learning approach is used. [16].

Artificial intelligence-based studies are used to determine the growth rate of tomatoes grown in greenhouses [17]. In another study using deep learning approach, flower and leaf recognition process is performed [18]. The detection and prediction of damages caused by insects in coffee leaves [15] and the detection of diseases occurring in apple leaves, the deep learning approach was used [20]. The identification of the plant from the vascular structure on the leaf appears as another different study [21]. Using the leaf shape, deep learning approach is used in the separation of crop seedlings and weeds [22]. A deep learning approach is used for to separate the crop seedlings from the herbs [23], identification of plant species [24] and detection of diseases [25-28]. It has also been successfully applied in the detection of powdery mildew disease on the leaves of hazelnut fruit. [29]. Also it has been successfully applied to estimate the number of fruit in a tree and in the whole garden [30]. In another study, the amount of product that can be obtained according to the soil structure of the land and the climatic conditions of the region was estimated [31]. Deep learning has been successfully used in the classification of the types of nuts [32-34] and the quality estimation of nuts [35]. The classification of hazelnuts was carried out according to their types as pointed, black and plump [36].

It was seen that the deep learning approach is used in many agricultural applications. However, there isn't remarkable study about to classify hazelnuts, which are very important for producers, as quality hazelnuts, damaged hazelnuts and nuts kernel. In addition, when various datasets were examined, a comprehensive dataset on hazelnut fruit could not be reached. First, a large comprehensive dataset consisting of quality hazelnuts, damaged hazelnuts and nuts kernel was created. Then the classification of hazelnuts was carried out with the VGG16.

3. Methodology

In this section, how the data is obtained, how the data is processed and the structure of the deep learning model are mentioned.

3.1. Data acquisition

The data required for the study were obtained from images of hazelnut fruits taken during daylight hours in a period of five days in December. While obtaining this data, the main camera on the back of the cell phone was used. This camera used has a resolution of 12 megapixels. Images were taken as a square at 3024X3024 pixel resolution and in color. With the help of a platform, pictures are taken manually from a height between 10 cm and 8 cm, with the camera of the phone pointing vertically down. The simple version of this platform is shown in Figure 2.

Figure 2. Platform structure where the images are taken

There is only 1 hazelnut in each image. Nuts were selected by an expert in 3 different classes as quality nuts, damaged nuts and nuts kernel. 535 nuts from quality nuts, 519 nuts from damaged nuts and 523 nuts from nuts kernel were used to create the data set. Ten different images were taken from a hazelnut at different angles. A data set consisting of a total of 15.770 hazelnut images was created. The information about the number of nuts is shown in Table 1. Figure 3 shows the images of a hazelnut selected from each class taken from different angles.

Table 1. Number of images taken from nuts

	Number of nuts	The number of images of each nut	Total number of images
Quality nuts	535	10	5350
Damaged nuts	519	10	5190
Nuts kernel	523	10	5230

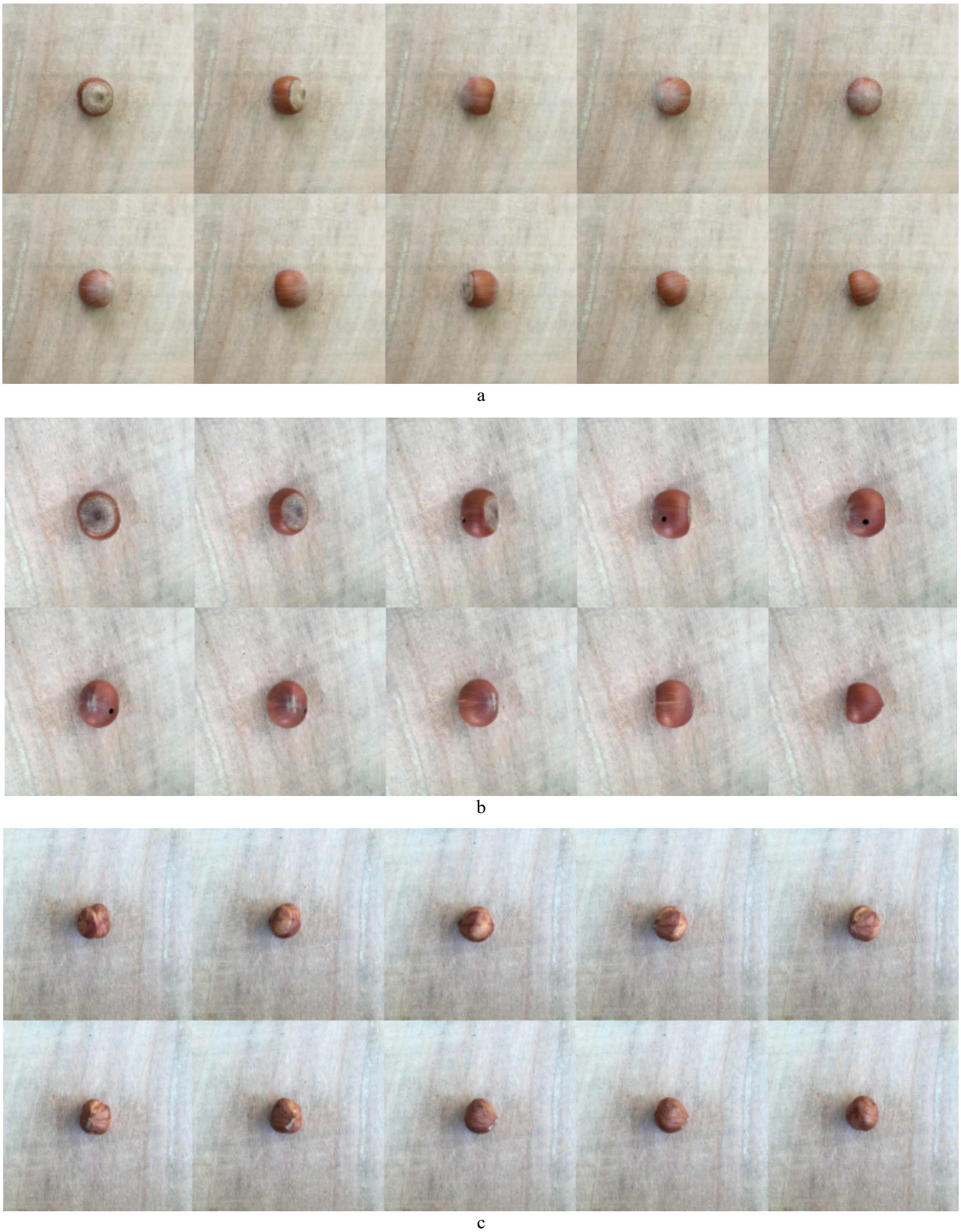


Figure 3. Images of hazelnut of different classes from different angles: (a) quality nuts, (b) damaged nuts, (c) nuts kernel

3.2. Data preparation

The total size of the data set created after the images are acquired is more than 70 GB. Processing such a large amount of data is not at a usable level both in terms of time and the system to be used in the study. For this reason, 1000X1000 pixel cropping was performed first to remove excess areas from the images. The new images formed after cropping were resized at 224X224 pixel values, which is the input image size of the ready-made model to be used in the study. No action has been taken regarding the color of the image. In Figure 4, a=3024X3024, b=1000X1000 and c=224X224 pixel resolution images of a hazelnut randomly selected from the data set are shown.

Figure 4. (a) 3024X3024 pixel uncut image, (b) 1000X1000 pixel cropped image, (c) 224X224 pixel image

As a result of these processes, a data set consisting of color images with a total size of approximately 1.2 GB was created in accordance with the model we will use. These operations are done with the help of FSResizer program. The intended use of this program is its ability to process images collectively. Tagging the images was done manually by an expert person. Since there is only one hazelnut in each picture, using the R program, which hazelnut which type is marked in csv format. As a result of the experience gained in deep learning studies, the data set was divided into 60% train, 28% validation and 12% test. Since the images in the data set are sufficient for the study, no duplication was performed. In order to contribute to future studies, the data set created in the study has been shared [43].

3.3. Algorithm

In the deep learning approach, convolutional neural networks are a class of deep neural networks commonly used to analyze visual images [37]. Convolutional neural networks achieve high successful results, especially in audio [38] and video based applications [39]. The most important difference that separates convolutional neural networks from other networks is that they have a structure consisting of hidden layers. Different models used in these network structures can have different number of layers. Although there are many different and complex models of convolutional neural networks, it basically consists of a total of 7 layers: the input layer, 2 convolution layers, 2 pooling layers, smoothing layer and output layer [40]. The basic layered structure of convolutional neural networks is shown in Figure 5.

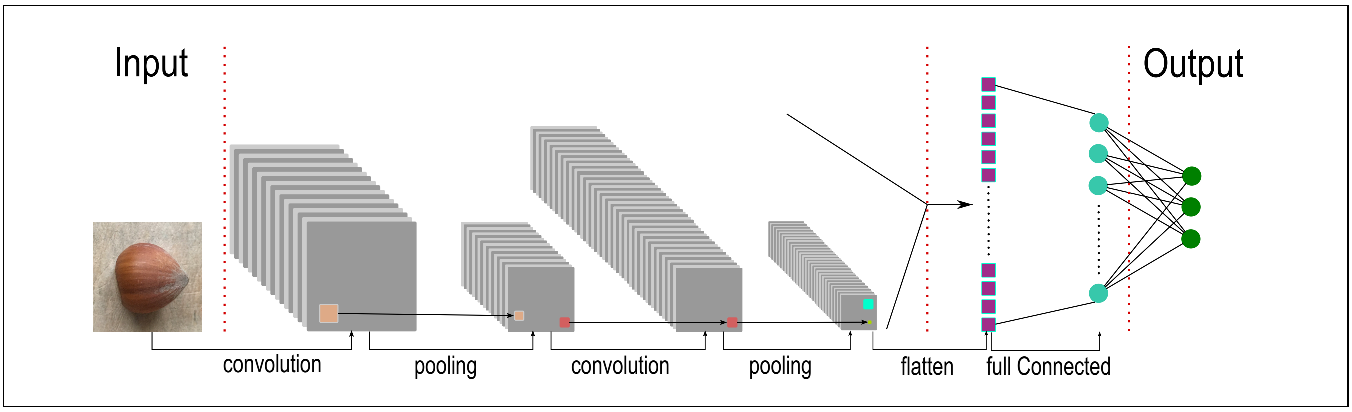


Figure 5. The basic layered structure of convolutional neural networks

Models used in convolutional neural network structure execute operations sequentially. In other words, the model works so that the output of one layer is used as the input of the next layer [41]. Digitized image is given as input to the input layer of the model. Different features are extracted by applying different filters to the image that comes to the convolution layer after the input layer. Then the image coming to the pooling layer is shrunk in pixel size according to the filter applied here and sent to the other layer. The data coming to the convolution layer is repeat features extracted and sent to the pooling layer. The data formed after the pooling layer is flattened and transformed into a one-dimensional array. After this process, the feature selection process is carried out automatically as much as the desired size in fully connected layers. Finally, with the help of these features, it performs the classification process and gives it to the output layer.

In this study, the VGG16 [42] model, which is widely used in image classification in convolutional neural networks, is used. In this model, there are a total of 21 layers: two convolution, one pooling, two convolution, one pooling, three convolution, one pooling, three convolution, one pooling, three convolution, one pooling and three fully connected layers. The layer structure of the VGG16 model is shown detailed in figure 6. The images formed as a result of some filters applied to the data in VGG16 are shown in figure 7.

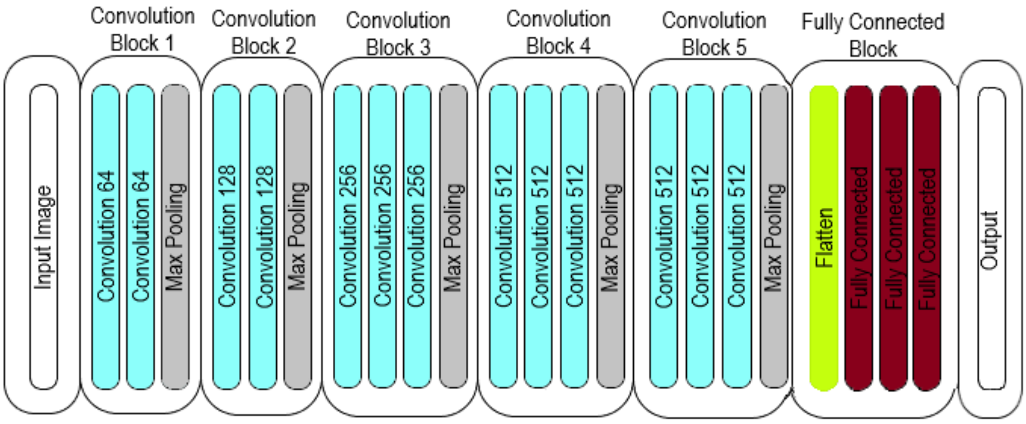


Figure 6. VGG16 Model

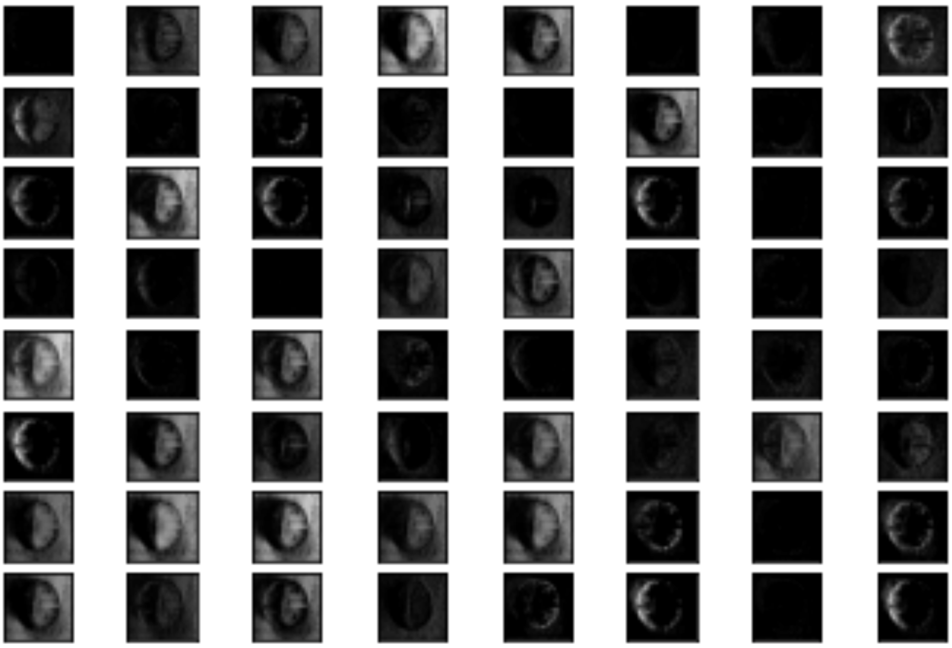


Figure 7. Some results of filters applied to the image

3.4. Performance Metrics

The complexity matrix [44] is used to measure the performance of the model in detail. Accuracy, precision, recall and F1 score values are obtained from the complexity matrix are used. This complexity matrix is shown in Table 2.

Table 2. Confusion Matrix

		Predicted Values	
		Positive	Negative
Actual Values	Positive	True Positive (TP)	False Positive (FN)
	Negative	False Positive (FP)	True Negative (TN)

True positive (TP) and true negative (TN) values indicate that the estimated values and true values are the same, while false positive (FP) and false negative (FN) values indicate that the estimated values and actual values are different from each other. Accuracy is the result of dividing all correct predictions by all predictions. Equation 1 shows the accuracy formula.

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

Precision is obtained by dividing the positively predicted value by all positive values. Equation 2 shows the precision formula.

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

Recall is obtained by dividing the true positive predicted values by the total true positive value. Equation 3 determines the recall value.

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

The F1 score is used by combining these metrics of precision and recall. It is a metric that is twice the product of precision and recall divided by the sum of precision and recall. Equation 4 shows the F1 score.

$$F1\ score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (4)$$

4. Experiments and Results

In this section, the environment in which the application is developed and the results obtained as a result of the application are mentioned.

4.1. Experiment Environment

The computer used in the study has WINDOWS 10 operating system, INTEL CORE i7-7700k 4.2 GHz processor, GTX 1080ti 11GB graphics processor, 32 GB RAM, 512 GB SSD and 1 TB HDD. Experimental environment was prepared by using Python 3.8 programming language and libraries for deep learning model.

As a result of the study, it was seen that the algorithm used (VGG16) made the hazelnut classification with high performance accuracy. The existence of a large dataset is very important in studies developed using convolutional neural networks. The large-sized dataset (consisting of more than 15 thousand images) used in this study played an important role in achieving high performance as a result of the study. As shown in Table 3, it is seen that the F1 score is above 0.98

Table 3. Results of the study

		Quality nuts	Nuts kernel	Damaged nuts
True positive		649	635	585
False positive	Quality nuts	-	6	4
	Nuts kernel	6	-	1
	Damaged nuts	4	3	-
Precision (%)		98.48	99.22	98.48
Recall (%)		98.48	98.60	99.15
F1 score (%)		98.48	98.91	98.82

In the application carried out, the hazelnut dataset created for the study was classified using the VGG16 deep learning model. In the hazelnut data set used, there are a total of 15.770 hazelnut images from three different classes. VGG16 model trained with learning rate = 0.0000001 and 250 epoch. As a result of the training of the VGG16 model, the accuracy, the verification accuracy and test accuracy are 99.38%, 98.87% and 98.73% respectively. The loss is 2.81%, and the verification loss is 3.93%. The accuracy and loss values are presented in the graph in Figure 9.

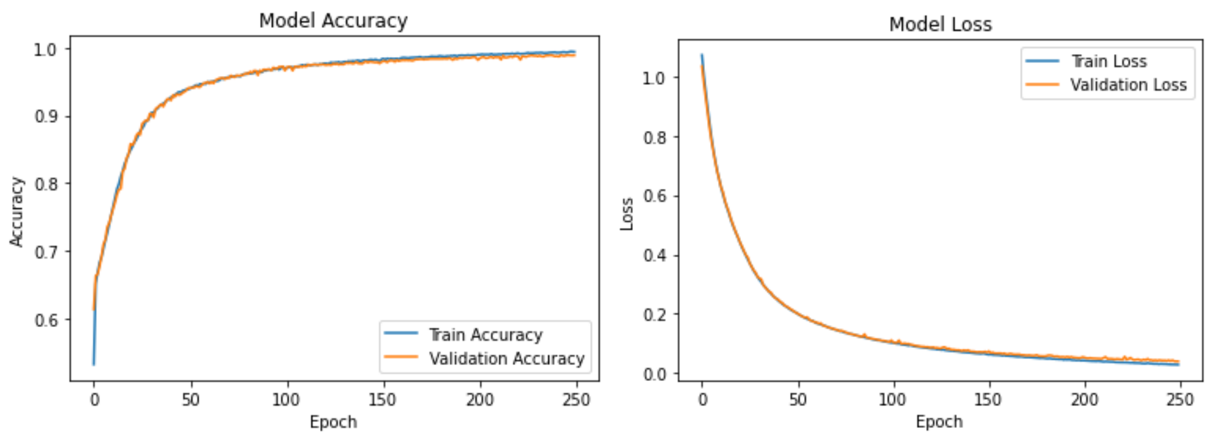


Figure 9. Accuracy and loss of model

Secondly, in order to show the effect of the size of the dataset used on the results obtained, the dataset is divided into different dimensions as shown in Table 4. As a result of the study, the importance of the size of the data set used in the deep learning approach was tried to be emphasized. In addition to the results obtained when the whole data set consisting of 15.770 images was used, the algorithm was run using 10%, 25% and 50% of the data set. Thus, when different numbers of images are used, the results obtained by the algorithm are presented comparatively. The results obtained when the dataset is used in different sizes are shown in Table 5.

Table 4. Numbers of split data

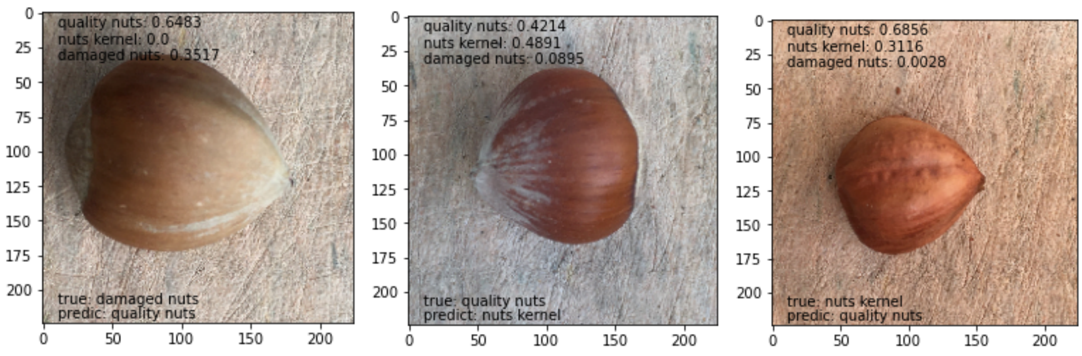
	Train	Validation	Test	Total
10% of the data set	946	441	190	**1577**
25% of the data set	2365	1103	474	**3942**
50% of the data set	4731	2207	947	**7885**
The entire data set	9462	4415	1893	**15.770**

The performance of the VGG16 model used in the study was tested using datasets consisting of different numbers of hazelnut images. When there are 15.770 images in the data set, the accuracy rate of the algorithm has reached approximately 99%. However, when 7885 images were used by reducing the dataset by 50%, the accuracy rate decreased to 95%. When 3942 images were used, taking 25% of the dataset, the success rate was 93%. Finally, when 10% of the dataset was used with 1577 images, it was seen that the correct estimation rate fell to 88%. These results show that deep learning depends on the dataset size. It is seen that the model success increases as the dataset size increases, while the model success decreases as the dataset size decreases. In Table 5, these results are presented comparatively. The results show that between using the whole dataset and using 10% of the dataset, the correct estimation rate varies by more than 10%. These results clearly show the effect of the size of the dataset used in the deep learning approach on the results obtained.

Table 5. Comparisons according to dataset size.

	Quality nuts	Nuts kernel	Damaged nuts	Total	Quality nuts F1 score	Nuts kernel F1 score	Damaged nuts F1 score	Total F1 score
10% of the data set	64	73	53	190	0.9062	0.9028	0.8333	0.8842
25% of the data set	156	164	154	474	0.9061	0.9509	0.9201	0.9262
50% of the data set	316	334	297	947	0.9518	0.9637	0.9474	0.9546
The entire data set	659	644	590	1893	0.9848	0.9891	0.9882	0.9873

No matter how high the accuracy rate of deep learning is, it cannot reach 100%. For example, objects in different classes may look very similar to each other. Due to this similarity, deep learning algorithms can make erroneous definitions. Figure 10 shows some of the images that the algorithm has detected incorrectly. In Figure 10.a, the image labeled as a damaged nut was detected as a quality nut by the algorithm. In Figure 10.b, an image labeled as a quality nut is classified as a nuts kernel, in 10.c, an image labeled as a nut kernel is incorrectly classified as a quality hazelnut by the algorithm.



a b c

Figure 10. Incorrectly predicted samples from dataset

5. Conclusion

In this study, a dataset consisting of more than 15 thousand images taken from different angles in three different categories was created and this dataset was made available for use in other studies. This dataset was classified using the deep learning model suggested in the study. Hazelnut images were classified in 3 different classes with high success with the VGG16 deep learning model. Thus, this study showed that the classification process that hazelnut producers carried out manually in a long time can be performed with a deep learning approach in a much shorter time with a high rate of accurate prediction.

In future studies, it is aimed to make various classifications from images obtained with drones and to realize algorithms that will enable early detection of negativities such as powdery mildew.

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Author contributions

Conceptualization: [Engin Gunes, Eyup Emre Ulku, Kazim Yildiz]; Methodology: [Engin Gunes, Eyup Emre Ulku, Kazim Yildiz]; Formal analysis and investigation: [Engin Gunes, Eyup Emre Ulku, Kazim Yildiz]; Writing - original draft preparation: [Engin Gunes]; Writing - review and editing: [Eyup Emre Ulku, Kazim Yildiz]; Resources: [Engin Gunes]; Supervision: [Eyup Emre Ulku, Kazim Yildiz]

Conflicts of interest/Competing interests

Authors are requested to disclose interests that are directly or indirectly related to the work submitted for publication.

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