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Detection of Mealybugs Disease Using Artificial Intelligence Methods

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Abstract

Today, the need for agricultural lands has increased even more due to the increasing population density. For this reason, increasing the yield of crops in agricultural areas becomes a very important need. It is very important to minimize the pests that negatively affect plant productivity in agricultural areas. In the study, it was aimed to detect the mealybug disease, which negatively affects plant productivity in agricultural areas, by using artificial intelligence methods. 539 disease-bearing and disease-free plant images collected from open access websites were used. These images are classified by VGG-16, Resnet-34 and Squeezenet deep learning algorithms. The most successful among the three architectures was determined as the VGG-16 and ResNet-34 model with an accuracy rate of 97%.

Keywords: *Deep learning; classification; mealy lice disease.*

1. Introduction

In order to meet the most basic food and clothing needs of humanity, agricultural production must increase with the increasing world population today. For this reason, pest control methods have an important place in organic agriculture in terms of productivity increase, environment and human health [1]. Today, agriculture is one of the most important strategic sectors in the world [2] and it brings 15-20% return to the country's economy [3]. However, problems caused by plant diseases and pests in the agricultural sector are one of the important causes of productivity loss. For this reason, it is aimed to reduce the loss of productivity by collecting data on the factors affecting the loss of productivity in the agricultural sector and analyzing the data using artificial intelligence methods [4]. Artificial intelligence systems perform many functions such as obtaining information, perception, learning, thinking and decision-making by analyzing the mental functions related to intelligence in humans with computer models and applying them to different agricultural systems by making meaningful results [5].

One of the important pests in the agricultural sector is known as mealybugs

disease. Mealy louse is a polyphagous pest that is seen in all ecozones, especially in the nearctic and palearctic, which are frequently encountered in agriculture due to sudden temperature changes and sudden environmental changes [6]. The main hosts are citrus species and varieties, and they cause significant damage to figs, vines, pomegranates, pears, greenhouses and ornamental plants [7]. There are 92 pests, 34 diseases, 16 nematodes and 155 weed species in the citrus orchards of Turkey, which may adversely affect the cultivation. Citrus mealybug, with its Latin name Planoccus citri Risso (Hemiptera: Pseudoccidae), is one of the important pests that we have encountered in this group in recent years [8]. Citrus mealybug damages plants directly by sucking (by sucking the plant sap) and indirectly by causing fumagine by secreting a honey-like substance [9]. In the vine plant, it spreads all over the plant and causes significant damage to the leaves, shoots, clusters and stems. For this reason, the mealy louse sucks the sap of the plant, causing the vine to weaken, lose yield and eventually dry out [10].

Biological, chemical and traditional methods used in the fight against mealybugs have important deficiencies due to the fact that the area to be combated is not well defined, and the method to be used is randomly applied to the area to be applied. The lack of selectivity in the methods used causes different problems. One of the important problems is the destruction of useful creatures due to pesticides applied to unwanted points. On the other hand, the inability to predict the amount of chemical, biological or conventional application to be used causes unnecessary product consumption and time losses.

Late detection of diseases especially seen in short lived plants reduces the quality and quantity of the product. Detection of diseases or pests in plants with artificial neural networks and image processing techniques has begun to increase. Detection of diseases on plants has become easier by using CNN models. Thus, it has made important contributions to the rapid decision-making on the spraying methods to be applied to diseases and pests in plants [11]. The plants are introduced to the computer using image processing techniques and the classification process takes place. Plants and pests are detected quickly with preprocessing [12].

When the literature is examined, many studies have been carried out on the separation of pests in plants with artificial intelligence and image processing.

Togacar et al. In their study, they classified the flower images by applying the feature selection method to

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the Convolutional Neural Networks (CNN) architecture and achieved 91.10% success [13]. Aksoy et al., by using deep learning methods named AlexNet, DenseNet-121, ResNet-34, VGG16-BN and Squeezenet1_0, classified the diseases of apple plants with an accuracy rate of 99.52% [14]. Soydan detected rice burn disease by using image processing and artificial neural networks in his study. In the study, the images obtained from the ground and from the air with the drone were compared with the real diseased field data, and 100% accuracy was obtained [15]. Altas et al. determined the scabies disease in the vine leaves by using the image processing toolbox module of MATLAB. When the expert observation data and image processing technique data were compared, they observed that the results were very close to each other [16]. Sardogan detected diseases in apple and tomato plant leaves using the MATLAB program. To train the model, an CNN based model was created and the results were classified by the Learning Vector Quantization algorithm. He obtained an accuracy rate of 86% using a single filter on tomato leaves and 98.5% using four different filters on apple leaves [17]. Yaman et al. In their study, they detected leaf diseases in plants using deep learning model and feature selection method. They combined the data obtained from DarkNet-53 and ResNet-101 models and obtained 99.58% accuracy with a hybrid method [18]. In his study, Ghoury detected diseases in grape fruit and grape leaves by using the previously trained SSD_MobileNet v1 and Faster-R-CNN Inception v2 deep CNN models with a transfer teaching approach. Tested all test data with Faster-R-CNN Inception v2, it achieved an accuracy of 95.57%, and an accuracy of 59.29% with SSD_MobileNet v1 [19]. Ozerdem et al. In their study, the Gray Level Co-occurrence Matrix (GLCM) feature extraction method, which classifies the rust disease in lily plants in black and white form, and Multi-Layer Perceptron (MLP), K-Nearest Neighbors (k-NN), Least Squares Support Vector Machine (LS-SVM) achieved an accuracy rate of 88.9% using machine learning algorithms [20]. In the Kızılboğa study, seven different diseases seen in apple and quince plants were classified using the evolved deep network model, transfer learning methods (VGG16, Inception and ResNet deep network architectures) and SVM methods. It performed 88% success with CNN, feature extraction with 89.75% success with different CNN based InceptionV3 architecture, and classification with 89.5% accuracy [21]. Turkoglu et al. In their study, they classified the freckle disease seen in apricot plants with AlexNet, VGG-16 and VGG-19 deep learning models and classified the feature extraction obtained by k-NN method. They obtained 94.8% accuracy with the VGG-16 model, which is one of the deep learning architectures [22]. In Hayıt study, classified the yellow rust disease in wheat plants using artificial neural networks and nine methods together with traditional methods. He used CNN based Yellow, Rust and Xception models in his classification by completely applying a deep learning model. With the Xception model, one of the CNN models, an accuracy rate of 91% was obtained [23]. Kilic et al. In their study, they detected the diseases that occur on the leves of citrus plants using CNN, AlexNet and VGG16 artificial neural networks and achieved a92% accuracy rate [11]. In Aslan's study, he classified the diseases in the peach plant using an ESA-based AlexNet deep learning model and achieved an accuracy rate of 99.3% [24].

In the first stage of the study, the fight against pests encountered in agriculture and the negative effects of these, and the effects of mealybugs disease on the plant were discussed. In the second stage, academic studies carried out for the detection of plant pests using artificial intelligence methods were examined. In the third stage, the data set to be used in artificial intelligence was created with the images of the mealybug pests obtained from the open access internet pages. The created image dataset is trained with SqueezeNet, VGG-16 and Resnet34 CNN based deep learning architectures. CNN based deep learning architectures trained in the fourth stage were evaluated with F-Score, sensitivity, originality and accuracy performance evaluation criteria.

2. Material and Methods

The study material section consists of the data set used in the study, CNN-based deep learning architectures and performance evaluation criteria. In the method part of the study, the information about the work flow diagram of the study is discussed in detail below

2.1. Material

2.1.1. Data Set

The data set used in the study was collected from different open access websites. The collected data set consists of two classes, images with and without mealybugs disease. The dataset includes 209 images of diseased plants infected by mealybugs and 330 images of healthy citrus, vine, pomegranate, pear and cactus plants. An example image of the data set used in the study is given in **Figure 1** and the numerical contents of the images used in the study are given in **Table 1**.

(a) *(b)*

Figure 1. *(a) View of mealybug spread on the plant [25]. (b) Healthy plant images in the dataset.*

Table 1. *Plant varieties and numbers in the data set*

Plants	Unhealty Plant Data Set	Healty Plant Data Set
GreenhousePlant	50	30
Citrus	67	111
Grape	33	99
Pomegranate	29	58
Pear	25	32

2.1.2 Esa-Based Models Used in The Study

Three different deep learning models were used in the training phase. These are VGG-16, ResNet-34 and SqueezNet.

2.1.2.1. VGG-16 Deep Learning Architecture

The VGG-16 architecture was presented by Simonyan and Zisserman in 2015 [26]. The VGG-16 architecture consists of 16 layers (13 convolutional, 3 fully connected layers) and is often used in object classification applications [27]. VGG-16 has a deeper (network depth = 16) architecture with more trainable parameters (about 138M) compared to AlexNet [28]. In **Figure 2**, the visual of the VGG-16 architecture is given. [29].

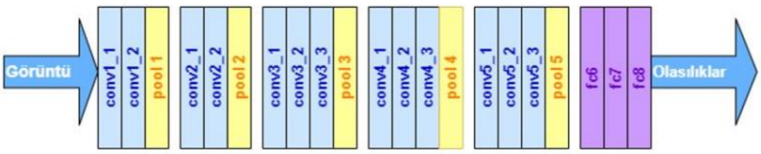


Figure 2. *Architecture of VGG16*

2.1.2.2. ResNet-34 Deep Learning Architecture

ResNet-34 is the type of CNN used in 2015 by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their "Deep Residual Learning for Image Recognition" study to facilitate training of networks that are significantly deeper. The biggest difference from other architectures is that the blocks feeding the next layers are also added to the model. The ResNet-34 architecture is shown in **Figure 3** [30].

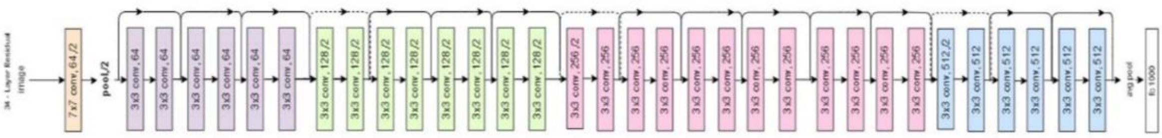


Figure 3. *Network architecture of the first 34 layers of Microsoft ResNet*

2.1.2.3. SqueezeNet Deep Learning Architecture

The SqueezeNet architecture was developed by Landola et al. It was presented by in 2016 [31]. SqueezeNet is an CNN network with 1.24M trainable parameters despite a mesh depth of 18 [31]. With this architecture, it is possible to create a neural network with fewer parameters and achieve AlexNet level accuracy with 50 times less parameters [32].

2.1.3 Performance Evaluation Criteria

There are many different performance evaluation criteria to evaluate the models that determine which class the observations obtained in classification problems belong to. The accuracy of the model is determined by comparing the accuracy value obtained in the classification method with the actual accuracy values [33-34]. The complexity matrix was used to evaluate the model in the study. The complexity matrix is a two-dimensional evaluation criterion, kxk as positivity and negativity, which shows the true accuracy value and the estimated accuracy value when classifying. The complexity matrix evaluation criterion is given in **Table 2**. [14, 34].

Table 2. *Complexity Matrix*

REAL VALUE	ESTIMATED VALUE	
	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

Sensitivity, originality, accuracy and F-score performance evaluation criteria were used to evaluate the performances of the deep learning models used in the study. Mathematical equations of performance evaluation criteria are given in equations 1-4 [12].

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{1}$$

$$Or\imath g\imath nal\imath ty = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FN}} \tag{2}$$

$$Accuracy \ = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{3}$$

$$F - Skor \ = \frac{2 * \mathrm{TP}}{2 * \mathrm{TP} + \mathrm{FP} + \mathrm{FN}} \tag{4}$$

2.2. Method

The work flow diagram is shown in **Figure 4**. First, a total of 539 images collected from open access websites were reduced to 224x224 size. The images brought to the size of 224x224 were randomly divided into 80% training and 20% testing. In the next step, the training dataset was trained with VGG-16, Resnet-34 and SqueezeNet deep learning architectures with 20 repetitive training. During the training, the learning rate was optimized for each model and the most appropriate learning rate was selected. By using the feature extraction obtained as a result of the training, the classification process was completed with the classical neural network.

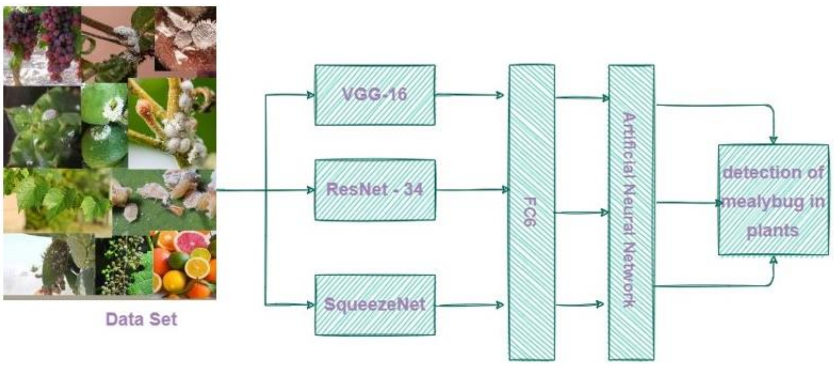
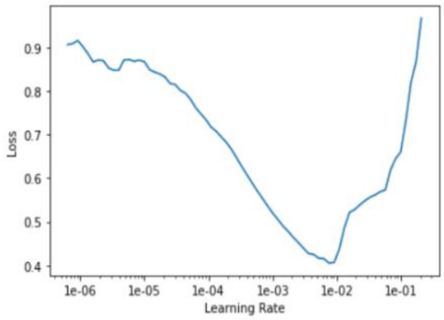


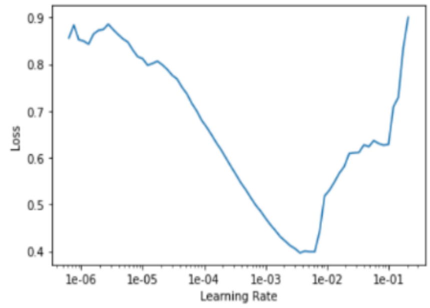
Figure 4. *Workflow Diagram*

3. Research findings

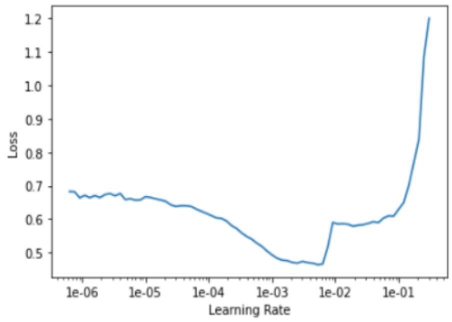
In the study, pests were detected by using ResNet-34, SqueezeNet and VGG-16 deep learning model. It has been trained in two classes as diseased plants and healthy plants infected by mealy lice. After the training process, the learning rate is optimized to increase the accuracy of the model. In the optimization process, the learning rate-loss graph was drawn and the most appropriate learning rate was selected in the decline region, and the model was retrained **Figure 5** shows the learning rate-loss graphs.



(a)VGG-16



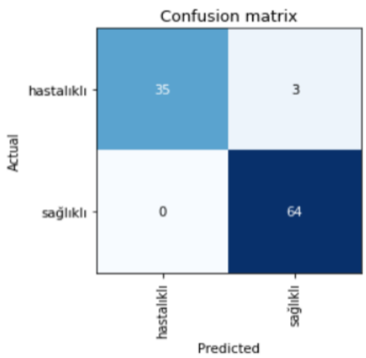
(b) ResNet-34



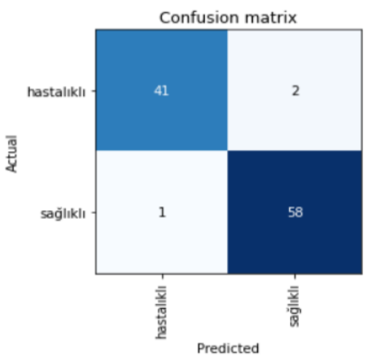
(c) SqueezeNet

Figure 5. *Learning rate-loss graphs (a-b-c).*

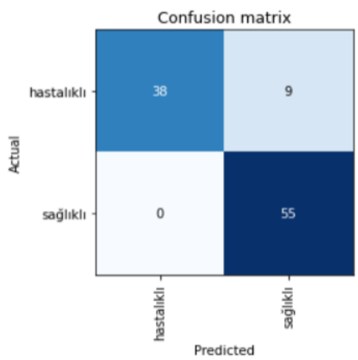
The models were retrained according to the learning rate selected in the learning rate-loss graph. The complexity matrix results obtained by evaluating the trained models with the test data are shown in **Figure 6**.



(a) VGG-16



(b) ResNet-34



(c) SqueezeNet

Figure 6. *Complexity matrix (a-b-c)*

When the confusion matrix was examined, it was determined that the VGG-16 model detected 35 correct and 3 incorrect images out of 38 diseased plant test images, and correctly predicted all 64 healthy plant test images. It is seen that the ResNet-34 model detected 41 correct and 2 incorrect images out of 43 diseased plant test images, and predicted 58 correct and 1 incorrectly predicted out of 59 healthy plant test images. It was determined that the SqueezeNet model detected 38 correct and 9 incorrect images out of 47 diseased plant test images, and predicted all 55 healthy plant test images correctly. The results of the three deep learning architectures used in the study according to sensitivity, originality, accuracy and F-score performance evaluation criteria are given in **Table 3**.

Table 3. *Performance Evaluation Criteria of Models*

Model	Sensitivity	Originality	Accuracy	F-score
VG G-16	0.921	1	0.970	0.958
ResNet-34	0.953	0.983	0.970	0.964
SqueezeNet	0.808	1	0.911	0.894

When **Table 3** is examined, it is seen that more than 90% accuracy was obtained from all three models. Among these three models, VGG-16 and ResNet-34 models were found to be the most successful models.

4. Discussions

The increasing world population has also triggered an increase in the needs in the field of agriculture. In order to meet the agricultural demands, it is necessary to make the right agricultural movements. Preventing productivity losses in agriculture is possible with the development of new and useful systems in parallel with today's technology, and it is important in terms of meeting agricultural needs. Productivity losses caused by mealybugs disease are also a danger in agriculture.

Preventing productivity losses by using artificial intelligence and image processing methods to mealybugs supports sustainability in agriculture. In this respect, Onur Ağin et al. they discussed the sustainability of agriculture in their study titled "The Role and Importance of Image Processing Techniques in Sustainable Agriculture" and pointed out that the use of image processing techniques in various fields of agriculture (spraying, irrigation, fertilization, etc.) is beneficial [35].

With the image processing techniques and deep learning methods used in the study, different plant species in agriculture were handled and classification and separation studies were carried out. Kadir Sabancı et al. In their study titled "Determination of Potato Classification Parameters with the Help of Image Processing and Artificial Neural Networks", they made an example study of the use of image processing in the agricultural field. The study was carried out with the help of image processing and artificial neural networks for the dimensional classification of potatoes and the differentiation of good quality potatoes [36]. Kaymak et al. On the other hand, in their study named “The Example of Use of Image Processing Technologies for Apple Orchards”, they aimed to detect and count the red apples on the trees in an apple orchard with image processing techniques. In order to realize this aim, a software has been developed in the computer environment. The software successfully finds the apples on the tree by using digitally transferred apple tree images and image processing techniques [37].

The successes obtained from the image processing studies have led to the design of machines in which image processing techniques are integrated in the future. For example, Melih Kuncan et al. In their project named “Image Processing Based Olive Sorting Machine”, they aimed to determine the olives according to their color and to perform the separation process. An electromechanical system has been developed for this process, and the image processing algorithms developed within the scope of the study have been tested on this system in real time and the results have been observed [38]. Kadir SABANCI et al. With the precision spraying robot developed in their project named “Image Processing-Based Precision Spraying Robot”, weeds in between rows in sugar beet agriculture were detected using image processing techniques and they performed a variable-level herbicide application model on the weed [39]. Bahadır ŞİN et al. In their project titled “Weed Detection Using Unmanned Aerial Vehicle (UAV) and Image Processing Techniques”, they used image processing methods to detect weeds [40].

Thus, artificial intelligence and image processing methods have been used in agriculture many times in different studies and have been integrated into projects. It is envisaged that the detection of mealybugs disease by image processing will be used in machinery and systems to be developed to prevent productivity losses in agriculture in the future.

5. Conclusion

Artificial intelligence applications have become a frequently used method due to the contributions it provides in applications in the agricultural sector today. It is very important to minimize the yield losses by detecting diseases and pests in plants by using artificial intelligence applications.

In the study, diseased and healthy plant images in the data set created from open access websites were trained with VGG-16, ResNet-34 and SqueezeNet deep learning models. The results were evaluated by plotting the success of the models, the learning rate-loss graph and the confusion matrix. Obtaining more than 90% accuracy in all three models shows that the data set is compatible with the deep learning models used in the study.

With the study carried out, artificial intelligence-based models were presented to prevent plant productivity losses caused by mealybugs disease. With the models presented, it is aimed to contribute to the academic literature for the diagnosis of similar diseases in plants. In future studies, it is aimed to increase the accuracy rates by expanding the data set and using different artificial intelligence models.

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