DEEP LEARNING METHODS COMPARISON ON IMAGES OF TOMATO AND CUCUMBER LEAF IDENTIFICATION

By Ahmet Kirnap

DEEP LEARNING METHODS COMPARISON ON IMAGES OF TOMATO AND CUCUMBER LEAF IDENTIFICATION

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Abstract: Deep learning and image processing applications have become widespread thanks to hardware developments and increased processing power. The use of technology in agriculture is increasing rapidly with the development of technology. One of the recent applications of technology in agriculture is image processing applications using deep learning. Image processing is aimed at sustainable agriculture. Deep learning is used in applications such as disease detection, agricultural spraying, maturity granding, irrigation, fertilization. In this study, deep learning models AlexNet and SqueezeNet are used to classify tomato and cucumber leaf images. 30 tomato leaves and 30 cucumber leaves are photographed to create the dataset used in the study. Afterwards, the images obtained are increased with data augmentation methods and a data set is created. The dataset consists of 2 classes and a total of 300 images. The data set is used 70% for training and 30% for validation. The results obtained from AlexNet and SqueezeNet deep learning models are given comparatively.

Keywords: AlexNet, SqueezeNet, deep learning, tomato leaf, cucumber leaf.

INTRODUCTION

The world population is growing rapidly. In order to supply the food needs of the growing population, it is necessary to increase the yield in agriculture. Therefore, the use of technology in agriculture has become necessary [1]. Nowadays, technology is frequently used in agriculture for crop disease detection [2, 3], agricultural spraying [4, 5], irrigation [6], maturity granding [7, 8].

In the vast majority of applications in agriculture, it is necessary to collect data with cameras and analyze these data with machine learning methods. Deep learning models are at the forefront of these methods.

Gökalp and Aydın, aimed to recognize emotions with deep learning models [9]. In the study, two different datasets, The Ryerson Audio-Visual Database of Emotional Speech and Song and Toronto Emotional Speech Set are used. SqueezeNet gave the best result with 100% performance, while MobileNet gave the worst result with 15% performance. Şentürk and Uzun, aimed to cervical cancer detection with deep learning models [10]. In order to improve classification, they proposed applying a median filter to the images prior to training the deep learning model. AlexNet, VGG-19, InceptionV3, ResNet-50 and SqueezeNet are used as deep learning models. SqueezeNet are the most validation accurate with 96.90%. Feyzioğlu and Taşpınar, aimed to malicious UAVs classification with machine learning algorithms [11]. Three different deep learning models are used to extract the features of the images. Image features extracted with two VGGs, and SqueezeNet models are classified with SVM, ANN and LR machine learning methods. As a result of the study, the most accurate result is obtained by classifying the features extracted with the SqueezeNet model with ANN with 92%.

Narin and Onur, aimed to classification of lung cancer images with AlexNet and ResNet50 [12]. Also examined the effect of maximum epoch and batch size hyperparameters on accuracy. The highest accuracy obtained 98.58% with the AlexNet. İnik and Turan, aimed to classification of deer, dog, camel, cow, leopard, goat, wolf, pig, horse, elephant, sheep, cat, kangaroo and bear with AlexNet and VggNet [13]. The study is planned to contribute to autonomous driving technology. VggNet gave the best result with 91.2%.

Ajayi et al., aimed to crop classification in precision agriculture [14]. They used AlexNet for this purpose. Training and validation accuracies of AlexNet are 99.25% and 71.81%. Soujanya and Jabez, aimed to classification plant diseases by leaf image using improved AlexNet [15]. AlexNet achieved 96.5% accuracy in the study. Matin et al., aimed to detection disease of rice leaf [16]. Rice leaf disease detection dataset and AlexNet model are used in the study. As a result of the studies, 99% accuracy rate is obtained. Atik aimed to classification disease of tomato leaves [17]. The used dataset consists of 10 classes and includes 18160 tomato leaf images. 5 different machine learning models are used. GoogleNet gave the best result with 95.18%.

In this study, two different deep learning models, AlexNet and SqueezeNet, are used to classify tomato and cucumber leaf images. For this purpose firstly, images are obtained. Then, the images are augmentation and a data set is created. Finally, simulation studies carried out in MATLAB have shown the effectiveness of the used AlexNet and SqueezeNet models.

RESEARCH METHOD
Dataset

Tomato and cucumber leaf images are used in this study. While creating the dataset, 30 tomato leaves and 30 cucumber leaves are photographed. The images are resize to 227x227 pixel to be suitable for the input of AlexNet and SqueezeNet deep learning models. Then, data augmentation is performed by rotation. During data augmentation, each image is rotated left and right by 10, 20 degrees and 4 images are obtained from 1 image. Thus, the data set consists of 150 tomato leaf images and 150 cucumber leaf images, totaling 300 images.
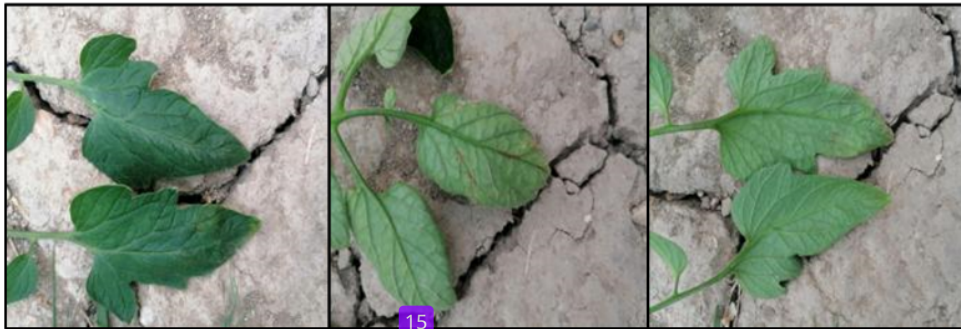

Figure 1. Sample images of tomato leaf

Figure 2. Sample images of cucumber leaf

Samples of tomato leaf images in the dataset are shown in Figure 1 and cucumber leaf images are shown in Figure 2. As can be seen from the figures, the tomato leaves are lighter in color and have more veined than the cucumber leaves.

AlexNet

AlexNet is an architecture of deep learning model. AlexNet is introduced by Krizhevsky, Sutskever, and Hinton in 2012 [18]. AlexNet is recognized as having the highest accuracy in the Large Scale Visual

Recognition Challenge (ILSVRC) organized by ImageNet in 2012 [19]. The error rate of computerized object identification is reduced from 26.2% to 15.4%, a leap forward in this field by AlexNet. After ILSVRC success of the AlexNet model, deep learning models have become popular.

AlexNet consists of total 8 layers. These layers consists 5 convolutional layers and 3 fully connected layers [20]. AlexNet has a neural network with 650,000 neurons and 60 million parameters. The input of the AlexNet is 227×227×3 with RGB depth.
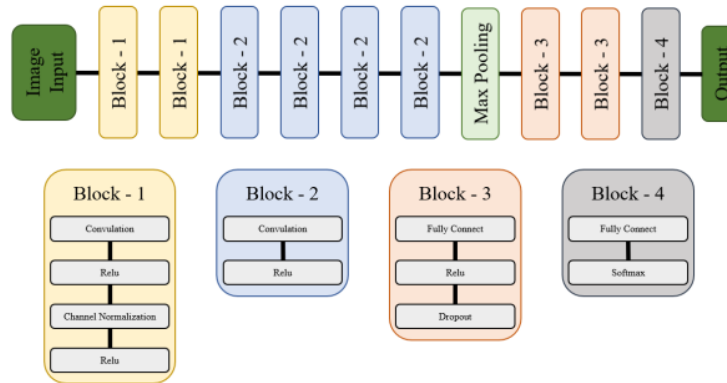

Figure 3. General structure of AlexNet

In Figure 3, where the general structure of AlexNet is given [21], the detailed contents of block 1,2,3 and 4 are also presented below the image. The network, where the photograph is given as input, gives the prediction result as output.

SqueezeNet

SqueezeNet is introduced by Iandola et al. in 2016 [22]. SqueezeNet's architecture aims to develop a neural network with 50 times fewer parameters than AlexNet while maintaining AlexNet-level accuracy [23]. SqueezeNet, like AlexNet, has input size of 227×227×3 with RGB depth [24]. The most important feature of SqueezeNet is its smaller size thanks to the 8 fire modules in the model architecture [25].
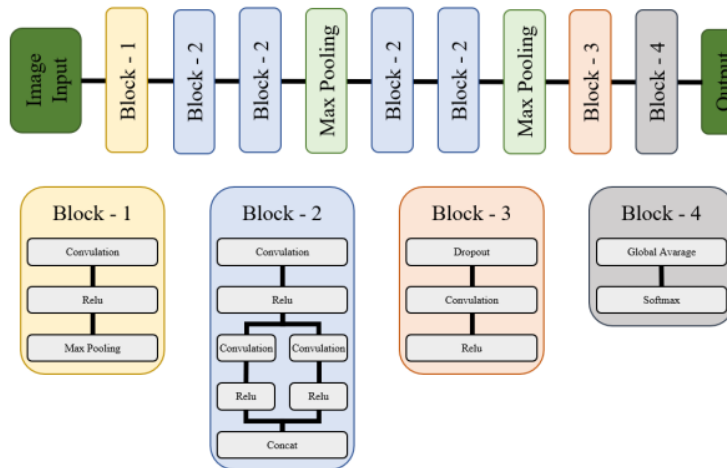

Figure 4. General structure of SqueezeNet

In Figure 4, where the general structure of SqueezeNet is given [21], the detailed contents of block 1,2,3 and 4 are also presented below the image. The network, where the photograph is given as input, gives the prediction result as output.

RESULT AND DISCUSSION

Deep learning models based analysis have been performed for the AlexNet and SqueezeNet which are one of the most effective and novel deep learning models. For this purpose, a data set is created by taking photographs. The images obtained are subjected to data augmentation methods. The dataset consists of 150 tomato leaves and 150 cucumber leaves, totaling 300 images. Before training the deep learning models, the dimensions of the images are normalized to 227x227. The 300 images in the dataset are divided into 70% train (210 samples) and 30% validation (90 samples). The flow diagram of the method followed in the study is given in Figure 5.
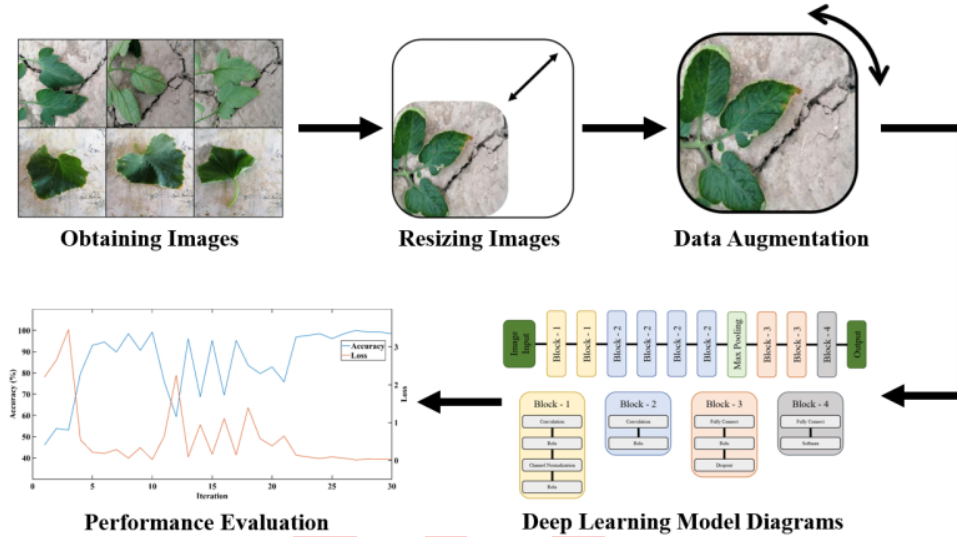

Obtaining Images   **Resizing Images**   **Data Augmentation**

Performance Evaluation   **Deep Learning Model Diagrams**

Figure 5. The flow diagram of the method

In the diagram given in Figure 5, the obtaining of images, resizing of the obtained images, data augmentation, deep learning model and performance evaluations are given as a flowchart respectively.

For the training process, similar parameters are used for both the AlexNet and SqueezeNet models. For both deep learning models, max epoch is chosen as 30, learning rate 0.0023, solver stochastic gradient descent with momentum (sgdm), minibatchsize 32. The simulation study was carried out in MATLAB. Single CPU is used for the training process. The accuracy and loss graphs for the training process for AlexNet model are shown in Figure 6 and for SqueezeNet model in Figure 7. The results obtained are given in Table 1.
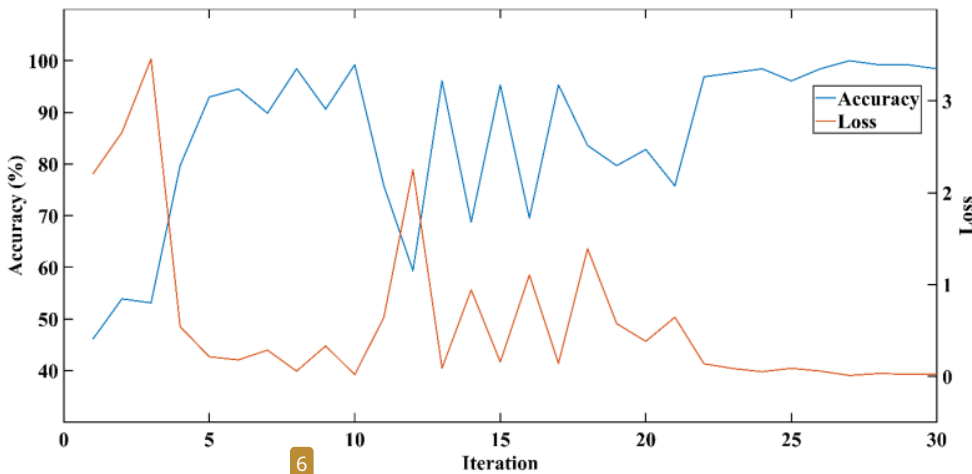

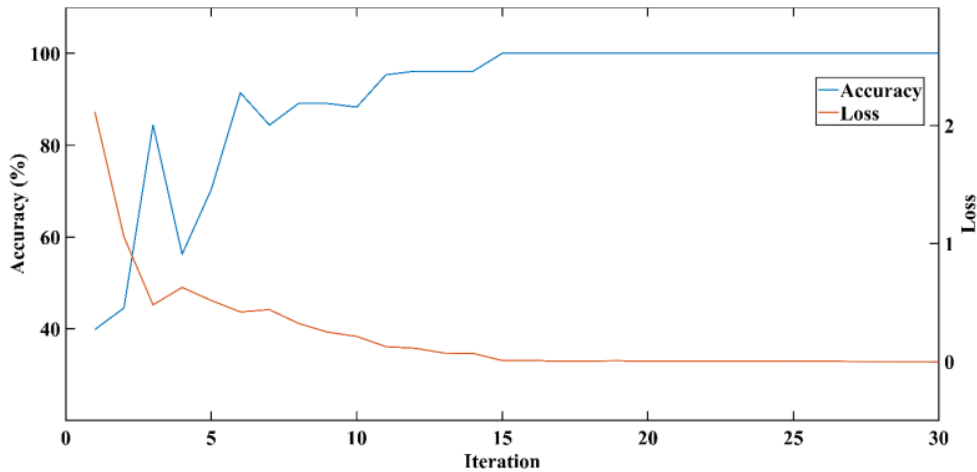**Figure 6.** Training performance of AlexNet

Figure 7. Training performance of SqueezeNet

Figure 6 and Figure 7 are analyzed, at the beginning of the training, the accuracy rate is low but the loss value is high. As the iterations progressed, the accuracy rate increased and the loss value decreased as desired. SqueezeNet gave a more stable training graph than AlexNet.

Table 1. Simulation results.

Deep Learning Model	Train Accuracy (%)	Train Loss	Validation Accuracy (%)	Validation Loss	Time
AlexNet	98.4375	0.0228	100	0.0216	2 min 49 sec
SqueezeNet	100	4.0512e-05	100	4.0463e-04	4 min 3 sec

When Table 1 and the training graphs are analyzed, it is seen that AlexNet has a train accuracy of 98.4375% and a validation accuracy of 100%, while SqueezeNet has both a train accuracy and a validation accuracy of 100%. AlexNet model training time is 2 minutes and 49 seconds, while SqueezeNet model training time is 4 minutes and 3 seconds.

CONCLUSION

In this study, high accuracy deep learning models that can identify tomato and cucumber leaves for use in agriculture are compared. For this purpose, a unique data set is created. AlexNet and SqueezeNet are used as deep learning models. The results showed that the accuracy of SqueezeNet is higher than AlexNet. However, the training time of AlexNet is shorter than SqueezeNet. Single CPU is used in the study. So, the use of GPU will shorten the training time for future studies. The fact that the results obtained have high accuracy rates and low loss values shows that both deep learning models can be used for purposes such as identify plant leaves in the agricultural sector.

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