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Deep Learning Approaches for Sunflower Disease Classification: A Study of Convolutional Neural Networks with Squeeze and Excitation Attention Blocks

Yavuz ÜNAL[1*], Muhammed Nuri DUDAK[2]

[1]Computer Engineering Department, Amasya University, Amasya, Türkiye
[2]Information systems Department, Amasya University, Amasya, Türkiye
(ORCID: 0000-0002-3007-679X) (ORCID: 0000-0003-2695-8447)

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Diseases in agricultural plants are one of the most important problems of agricultural production. These diseases cause decreases in production, and this poses a serious problem for food safety. One of the agricultural products is sunflower. Helianthus annuus, generally known as sunflower, is an agricultural plant with high economic value grown due to its drought-resistant and oil seeds. This study, it is aimed to classify the diseases seen in sunflower leaves and flowers by applying deep learning models. First of all, it was classified with ResNet101 and ResNext101, which are pre-trained CNN models, and then it was classified by adding squeeze and excitation blocks to these networks and the results were compared. In the study, a data set containing gray mold, downy mildew, and leaf scars diseases affecting the sunflower crop was used. In our study, original Resnet101, SE-Resnet101, ResNext101, and SE-ResNext101 deep-learning models were used to classify sunflower diseases. For the original images, the classification accuracy of 91.48% with Resnet101, 92.55% with SE-Resnet101, 92.55% with ResNext101, and 94.68% with SE-ResNext101 was achieved. The same models were also suitable for augmented images and classification accuracies of Resnet101 99.20%, SE-Resnet101 99.47%, ResNext101 98.94%, and SE-ResNext101 99.84% were achieved. The study revealed a comparative analysis of deep learning models for the classification of some diseases in the Sunflower plant. In the analysis, it was seen that SE blocks increased the classification performance for this dataset. Application of these models to real-world agricultural scenarios holds promise for early disease detection and response and may help reduce potential crop losses.

1. Introduction

Agriculture is a vital field for the nutrition and food security of large populations [1]. One of the important agricultural products is oilseeds. Oil production comes to the fore in oilseed plants used for food purposes. One of the plants grown for its oilseed is Sunflower. In many countries, sunflower is grown primarily for its vegetable oil and animal feed which is an important source of raw materials for the food industry [2]. Sunflower offers a substantial productivity advantage because of its ability to be grown under irrigated and dry farming circumstances, and appropriateness for machine use at all phases from planting to harvest [3].

Diseases seen in sunflowers cause seed yield to decrease. The agricultural economy suffers greatly from productivity losses. Preventing productivity loss is possible by diagnosing diseases in time and taking precautions [4]. Thanks to early detection, we can save plants and prevent losses. Visual detection of diseases in plants is a difficult process and diagnosis can be time-consuming. Visual detection is difficult or impossible in large agricultural areas [5].

Diagnosis of plant diseases using deep learning is becoming increasingly common nowadays [6]. This study aims to identify diseases seen in sunflower leaves and flowers using image processing and deep learning.

*Corresponding author: yavuz.unal@amasya.edu.tr

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Sunflowers are bacteria, fungi, nematodes, parasites, viruses, etc. are exposed to many diseases [4]. The dataset includes three disease classes and one healthy sunflower leaf class. These diseases are gray mold, leaf scars, and downy mildew. Let's briefly look at these diseases.

Gray mold: A fungus known as gray mold affects the flowers, leaves, and stems of a variety of flowering plants. Small, crooked, and hidden beneath perilous areas with dark squares are sunflower leaf and fruit indicators. The botrytis blight, often known as gray mold, causes sunflower buds to decay or prevents them from opening. [7].

Leaf scars: Sunflower leaf scars from the fungus Septoria helianthi are common but do not constitute a serious concern. As a result, it can substantially impair plant growth when combined with other illnesses. The leaves wilt, and the injured tissues succumb to death [7].

Downy mildew: The plasmopara halstedii fungus, which causes downy mildew, is present in almost every nation where sunflowers are grown. The global impact on yield has been estimated to be 3.5 percent of commercial seed output [7].

The remainder of this paper is organized as follows: Section 1.1 describes related works. In section 2, the datasets and methodologies are introduced. Section 3 Results and discussion, section 4 conclusions, and future research.

1.1. Literature Review

Deep learning approaches have been proposed by researchers in recent years, and some of these have been investigated and reviewed, as stated below:

Banerjee et al. [2] used a new convolutional neural network (CNN) and support vector machine (SVM) based model to predict sunflower diseases in their study. They used three convolutional layers, three maximum pooling layers, and two fully connected layers to train the proposed model. The proposed model is trained with a dataset of different diseases affecting sunflowers. The results of the proposed research study achieved an F1 score of 83.45 and an overall classification accuracy of 83.59%.Gosh et al. [4] developed a hybrid model with transfer learning and a simple CNN to detect sunflower diseases. Of the eight models tested on a dataset consisting of four different classes, the VGG19 + CNN hybrid model achieved the best results in terms of sensitivity, recall, f1 score, and accuracy. They reached 93% classification accuracy. Dawod and Dobre [8] used ResNet interpretation methods to classify leaf diseases in sunflowers and visualization techniques were applied to explain misclassifications. Their study discovered that a classification using segmented lesions provides higher accuracy because many factors that lead to misclassification are eliminated in this way. Rajbongshi et al. [9] used 650 sunflower image datasets that they created themselves. First of all, they segmented the diseased areas in these images using the k-means clustering method. They extracted features from the segmented regions and classified them with various classifiers. They achieved the best result with Random Forest and achieved 90.68% classification success. Malik et al. [10] created a hybrid model using deep learning techniques to detect sunflower leaf diseases. They applied VGG16 and MobileNet transfer learning models on a dataset consisting of 329 sunflower images. Then, they compared these two models by applying them as a hybrid and reached 89.2% classification accuracy. In his study [11], Singh segmented sunflower leaves with the particle swarm optimization algorithm. The accuracy of the proposed system is around 98%.

Table 1 shows studies classifying sunflower diseases.

Table 1. A list of studies that were found in the literature

No	Class	Number of Data	Method	Accuracy(%)	References
1	12	3830	CNN+SVM	85.37%	[2]
2	4	838	ResNet152	98.02%	[8]
3	5	329	VGG16+MobileNet	89.2%	[10]
4	5	650	Random Forest	90.68%	[9]
5	6	149	Particle swarm	98%	[11]
6	4	467	VGG19+CNN	93%	[4]
7	4	467 1668	Our Approach	94.68% 99.84%	Our Approach

2. Material and Method

In this chapter, primarily the dataset, the deep learning methods, and the performance metrics used in the study will be explained.

2.1. Dataset

A publicly available dataset from mendeley data including occurrences of sunflower fruits and leaves dataset was used in this study [12]. This dataset consists of four hundred sixty-seven (467) original photographs and one thousand six hundred sixty-eight (1668) augmented images of healthy and disease-affected sunflower leaves and flowers. Sample images in the data set are given in Figure 1.

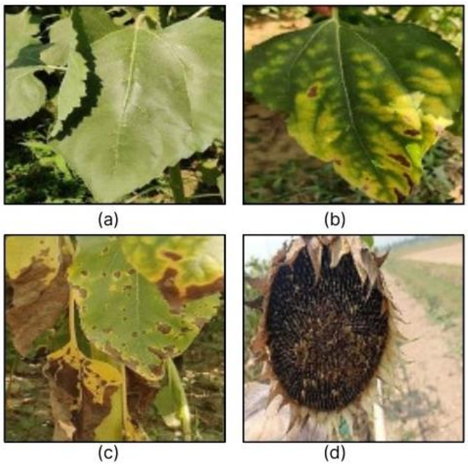


Figure 1. Sunflower plant leaf diseases dataset sample images (a) Fresh Leaf (b) downy mildew (c) Leaf scars (d) gray mold.

The dataset consists of four groups: gray mold, downy mold, leaf scars and fresh leaves. The number of classes in the data set and the number of images in each class are given in Table 2.

Table 2. Distribution of dataset by class

Class Name	Number of Original Images	Number of augmented Images
Gray Mold	72	398
Downy Mildew	120	470
Leaf Scary	141	509
Fresh Leaves	134	491
Total	467	1668

The original image is 467 in total. The number of augmented images is 1668 in total. The creators of the data set did the augmentation process. Augmentation operations include general enlargement operations in two ways, such as location and color change. All of the photos have a constant width and height of 512x512 pixels.

In the data set, there were four different classes of photos, and 80% of those images were used in the training set and 20% in the test set.

2.2. Convolutional Neural Networks

CNN is a popular deep learning technique that was created by drawing inspiration from the visual cortex of live beings. CNN architectures, which were initially employed in object recognition studies, are now employed in a wide range of applications. As with conventional artificial neural networks, CNN architectures are made up of neurons that learn to optimize themselves. The ability of CNN architectures to spot patterns in images sets them apart from traditional artificial neural networks in a big way. Even though CNN architectures can be developed in a variety of ways depending on the application, they typically start with convolution and pooling layers that are then divided up. In conventional backpropagation neural networks, they subsequently incorporate one or more fully linked layers [13].

There are many studies about CNN architecture. Layers consisting of data inputs enable CNN architectures to learn and classify features. CNN typically consists of five layers: convolution, pooling, activation, fully connected and softmax layer [14].

2.3 ResNet Neural Network

This architecture has distinguished itself in the field of computer vision, taking home first place honors in the 2015 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) contests [15].

Residual blocks are used in the layers of ResNet models. These blocks help deep networks operate more effectively. The overall layout of residual blocks creates a link between the layer's input and the output of the following layers [16]. A residual block in a deep residual network is shown in Figure 2.

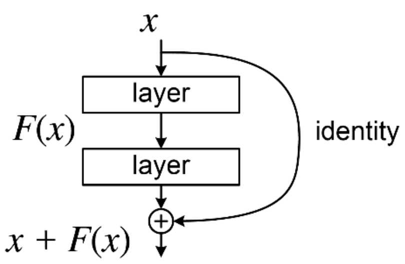


Figure 2. Residual learning: a building block [15]

The ResNet family has several versions that have been created, including ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152. The amount in the network name indicated how many levels were included in the network. In the proposed study, the classification stage is carried out using the pre-trained residual network ResNet-101 [17].

ResNet101 belongs to the ResNet (Residual Network) family and is recognized for its capability to address the vanishing gradient issue, making it suitable for training extremely deep networks. The designation "101" indicates the model's layer count. ResNet incorporates skip connections or shortcuts to streamline information flow within the network, resulting in more seamless and effective training [21].

2.4 Squeeze and Excitation (SE) Block

Squeeze-Excitation (SE) block is a channel-based attention mechanism where the network can selectively learn informative features and remove useless ones. SE performs feature recalibration to improve important features and disable less useful features. This block is independent of the network module of the specific network structure and can be embedded into the existing CNN network model with only a small increase in computational cost, thus improving the network training performance of the network model and increasing the efficiency of the network [18].

2.5 ResNext Neural Network

ResNext is a combination of ResNet and Inception. Unlike Inception v4, ResNext uses the same topology for each branch and does not require complex Inception structural details to be designed by hand. Group convolution is referred to as ResNext, and the number of groups is governed by variable cardinality. The group convolution machine strikes a balance between depth-separable convolution and regular convolution. [19] [20].

The three-layer convolutional block of the ResNet is swapped out in ResNext for a parallel stacking block with a comparable layout. ResNext employs group convolution with 3x3 filters to extract the features. The ResNext improves feature extraction capabilities while minimizing the number of network constraints by using group convolution and residual-like connections at both levels [21].

2.6 Proposed Model

In the study, classification of sunflower images was carried out with deep learning models. This process takes place in six main steps: entering images into the system, data augmentation, split data, applied classifier, performance evaluation and output. The proposed model is visualized in Figure 3.

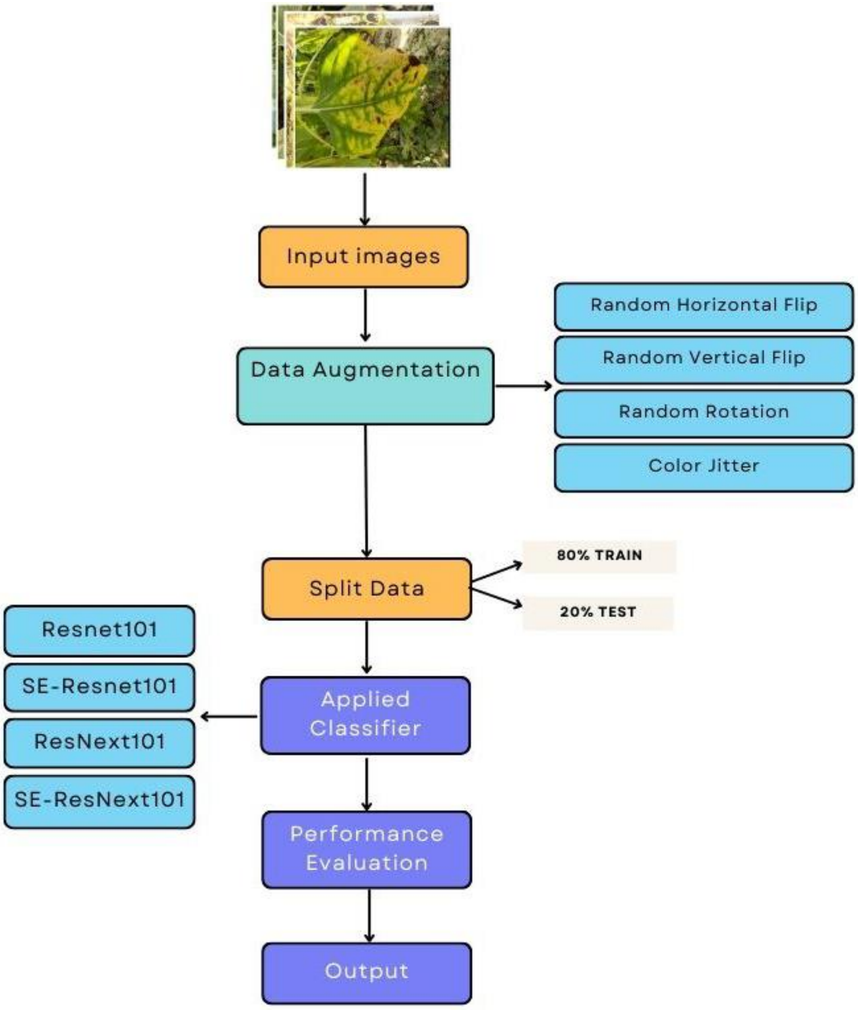


Figure 3. Flowchart of the proposed method

The number of images should be increased as we know that a large amount of data is required to train the deep learning model. Thus, model performance increases according to the increasing amount of data. During the data augmentation process of the study, a general augmentation process was performed in two ways, such as location and color change. In increasing by position, random rotation, random horizontal flip, random vertical flip methods were used. In the color enhancement process, only brightness was performed. By incorporating these augmentation techniques, the dataset used for training is effectively expanded, providing a larger and more diverse set of examples for the model to learn from. This increased variety of images helps the deep learning model to generalize better and improve its performance. The parameters used in the augmentation process for this sunflower data set is given in Table 3.

Table 3. Augmentation parameters of deep learning models

Augmentation Type	Parameters
Random Rotation	True
Random Horizontal Flip	True
Random Vertical Flip	True
ColorJitter (brightness)	0.1

ColorJitter(brightness) value was selected as 0.1.

3. Results and Discussion

This section includes evaluation metrics and obtained results.

3.1. Evaluation Metrics

The accuracy, precision, recall, and F1-score were used to evaluate the performance of the models in the experimental data. When utilizing machine learning or deep learning techniques to solve classification problems, accuracy is a performance parameter that is used to gauge how well a model performs. This metric counts the proportion of samples that the model properly classifies. One of the basic performance criteria in classification problems is accuracy [14]. The formula is as follows.

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

Machine learning techniques are used to evaluate a model's performance in classification tasks using a performance parameter called precision. This metric represents the proportion of samples that the model actually classifies as positive [22]. The formula is as follows.

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

Recall is a performance indicator used to assess a model's effectiveness in classifying issues when employing machine learning techniques. It gauges how well the model can predict how many genuine positive examples will be found among all positive examples [22]. The formula is as follows.

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

This metric combines precision and recall measurements to produce a single performance measure. While recall evaluates how well the model can accurately predict the proportion of real positive examples out of all the actual positive cases, precision measures how well the model can accurately predict the proportion of true positive examples out of all the positive examples. The formula is as follows [22].

$$F1 - Score = \frac{(2TP)}{(2TP + FP + FN)} \quad (4)$$

Where, P = Positive class, N = Negative Class, TP = True positive, TN = True Negative, FP = False Positive, FN = False Negative.

3.2. Experimental Setup

In the first stage of the experimental study, sunflower leaf and flower images were classified with ResNet101 and ResNext101, both original images and augmented images. The selection of a ResNet variant depends on several factors, including the complexity of the task, available computational resources, and the amount of training data. Deeper networks, such as ResNet-150, are capable of capturing more complex features but require more computational power and a larger amount of data. On the other hand, shallower networks like ResNet-50 are preferred when there are limitations in computational resources. ResNet-101 architecture strikes a balance between complexity and resource requirements. It allows for the modeling of moderately complex patterns in the data without being excessively demanding to train. Through our experiments, we have determined that ResNet-101 offers a good fit for our specific problem and available resources. In order to make the results more effective, in the second stage, both the original images and the augmented images were reclassified with the Resnet101 and ResNext101 models to which Squeeze-and-Excitation Block was added. Testing of experimental studies was done through the COLAB platform. Nvidia Tesla T4 16GB graphics processor card was used in the Colab environment. The experiments were coded in Python 3 programming language.

The hyper parameters used in the study were determined by taking into account the amount of data in the dataset. The hyperparameters used in training the models are given in Table 4.

Table.4 Training parameters of deep learning models

Parameter	Value
Optimizer	Adam
Loss function	Cross-entropy
Batch Size	32
Epoch	30
Learning Rate	0.0001

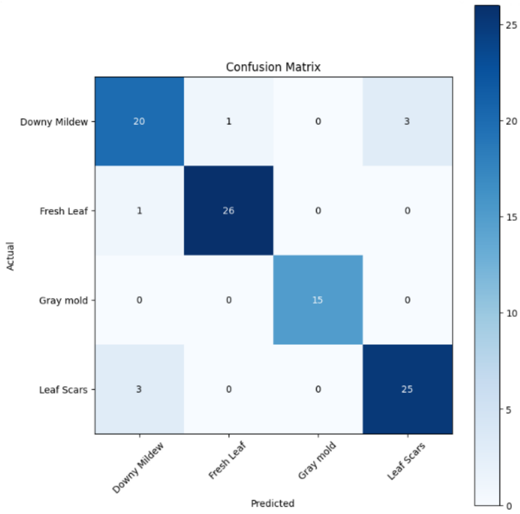
The data, consisting of four classes: fresh leaf, downy mildew, leaf scars and gray mold, were classified with four different deep learning models: Resnet101, SE-Resnet101, ResNext101 and SE-ResNext101, with the parameters mentioned above, and the classification results are given in Table 5. Separate results are presented for original images and augmented images.

Table.5 Classification Results

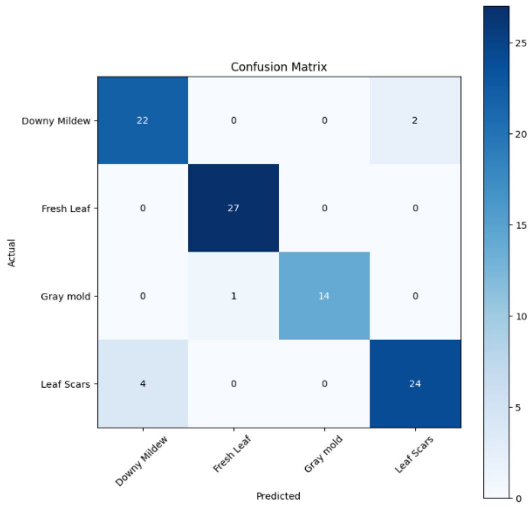
Model	Accuracy (%)	Precision	Recall	F1-score
Resnet101 (Original images)	91.48%	0.92	0.92	0.92
SE-Resnet101 (Original images)	92.55%	0.93	0.93	0.93
ResNext101 (Original images)	92.55%	0.93	0.93	0.93
SE-ResNext101 (Original images)	94.68%	0.95	0.95	0.95
Resnet101 (Augmented images)	99.20%	1.00	0.99	0.99
SE-Resnet101 (Augmented images)	99.47%	1.00	0.99	0.99
ResNext101(Agumented images)	98.94%	0.99	0.99	0.99
SE-ResNext101 (Augmented images)	99.84%	0.99	0.99	0.99

The best classification accuracy for original images and augmented images was achieved with SE-ResNext101.

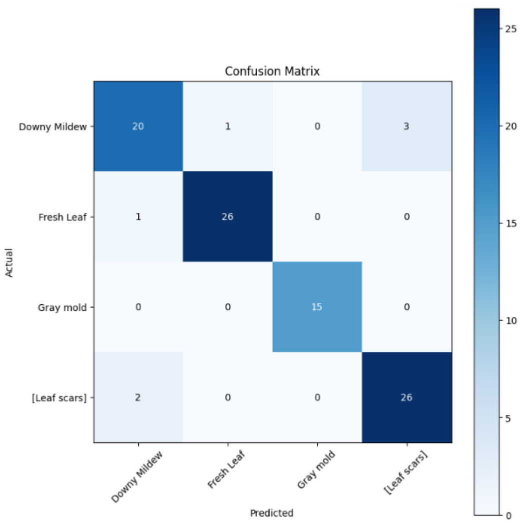
In this section, the confusion matrix obtained as a result of deep learning, Training loss and Training accuracy are given.



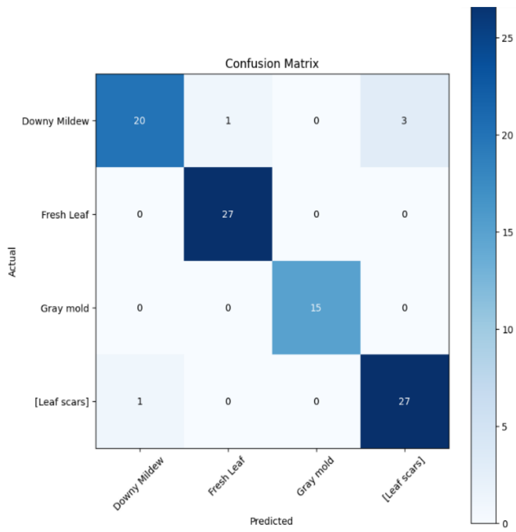
(a)Resnet101 Original



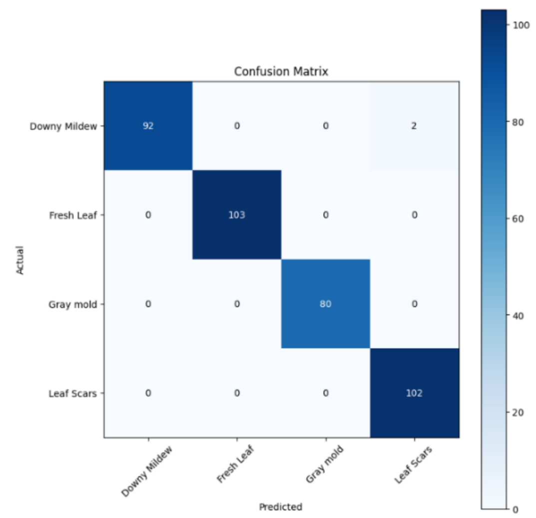
(b) Se-Resnet101 Original



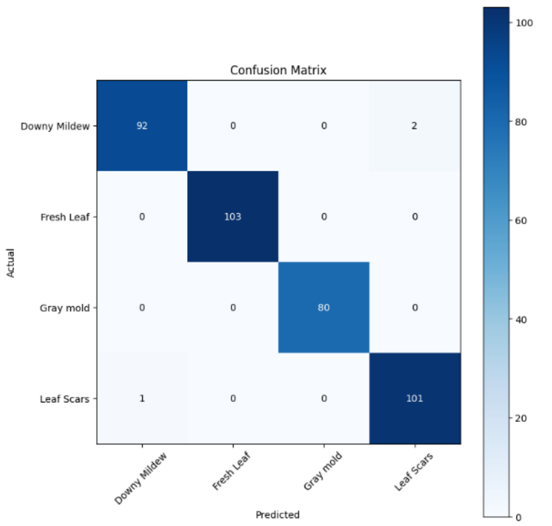
(c)ResNext101 Original



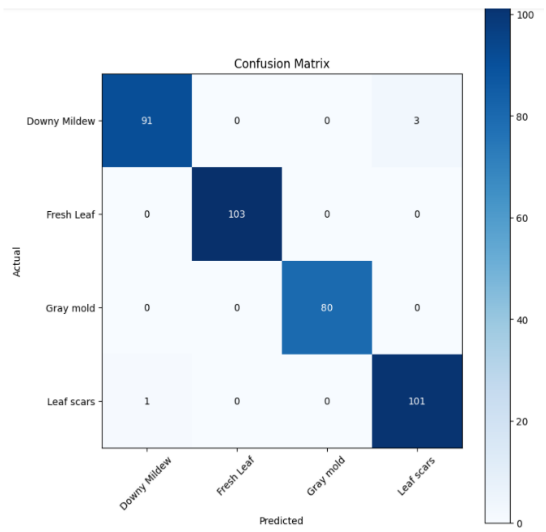
(d) SE-ResNext101 Original



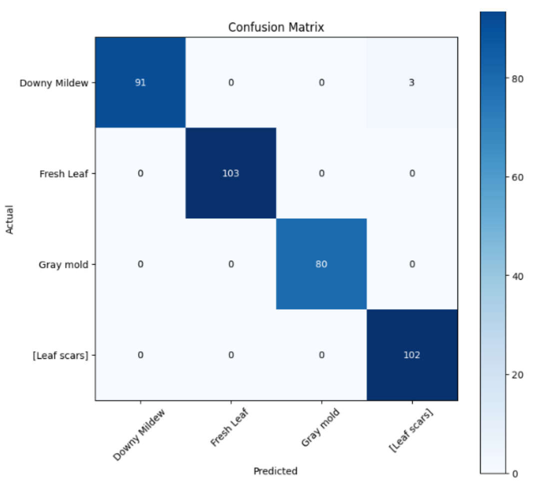
(e) Resnet101 Agumented



(f) SE-Resnet101 Agumented



(g) ResNext101 Agumented

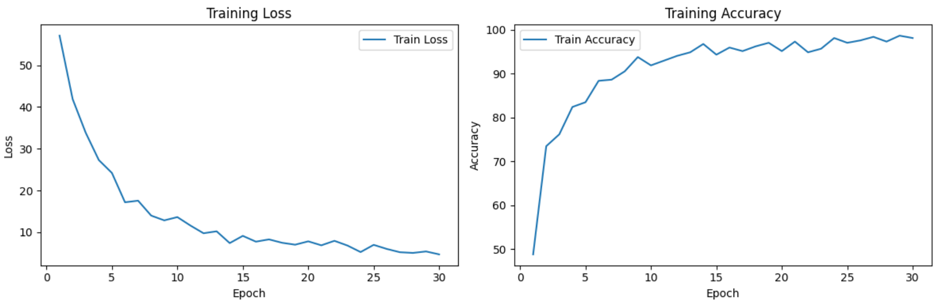


(h) SE-ResNext101 Agumented

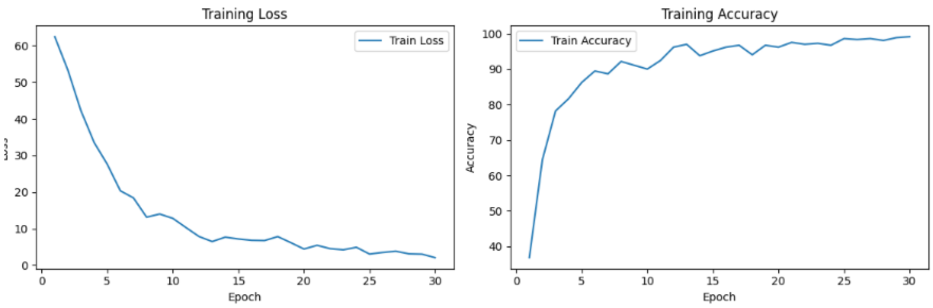
Figure 4. Confusion matrix graphics of original and augmented images (a) Resnet101 original, (b) SE-ResNet101 original, (c)ResNext101 original, (d) SE-ResNext101 original, (e) Resnet101 agumented, (f) SE-ResNet101agumented, (g) ResNext101 agumented, (h) SE-ResNext101 agumented

In Figure 4(a), the Resnet101 model was employed on original images. The confusion matrix reveals accurate classifications of 20 instances and 4 misclassifications for downy mildew. For the fresh leaf class, it correctly identified 26 and misclassified 1. The gray mold class was entirely correctly classified, while for Leaf scars, 25 were correct, and 3 were misclassified. Moving to Figure 4(b), the SE-Resnet101 model on original images showed 22 correct and 2 incorrect classifications for downy mildew. For fresh leaves, it correctly identified 27 and misclassified 1. The gray mold class had 14 correct and 1 incorrect, and for Leaf scars, 24 were correct, with 4 misclassifications. Figure 4(c) illustrates the ResNext101 model on original images. It correctly classified 20 instances of downy mildew and misclassified 4. For fresh leaves, 26 were correct, and 1 was misclassified. Gray mold had 15 correct classifications, and Leaf scars had 26 correct and 2 incorrect. In Figure 4(d), the SE-ResNext101 model on original images correctly classified 20 instances of downy mildew and misclassified 4. Fresh leaves had 27 correct classifications, gray mold had 15 correct, and Leaf scars had 27 correct and 1 misclassification. Additionally, Figure 6 displays training loss and accuracy curves. Moving to augmented images in Figure 4(e), the ResNet101 model classified 92 instances of downy mildew correctly and 2 incorrectly. For fresh leaves, it correctly identified 103, and for gray mold, it was correct in 80 instances. Leaf scars had 102 correct classifications. Figure 4(f) presents the SE-ResNet101 model on augmented images, classifying 92 instances of downy mildew correctly and 2 incorrectly. For fresh leaves, 103 were correct, 80 for gray mold, and 101 for Leaf scars with 1 misclassification. In Figure 4(g), the ResNext101 model on augmented images classified 91 instances of downy mildew correctly and 3 incorrectly. Fresh leaves had 103 correct classifications, and both gray mold and Leaf scars had 80 correct, with 1 misclassification for Leaf scars. Lastly, Figure 4(h) shows the SE-ResNext101 model on augmented images, correctly classifying 91 instances of downy mildew and misclassifying 3. For fresh leaves, 103 were correct, 80 for gray mold, and 102 for Leaf scars.

The training loss and training accuracy graphs obtained as a result of the analysis are given in Figure 5.



(a)



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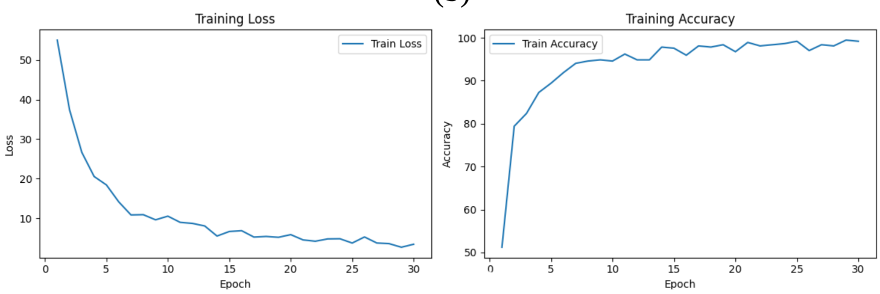
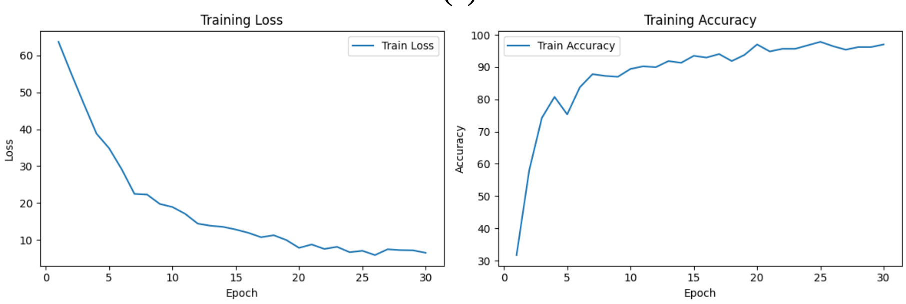


(c)



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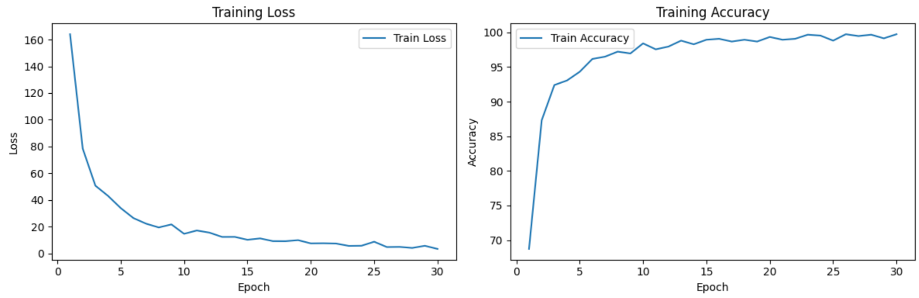
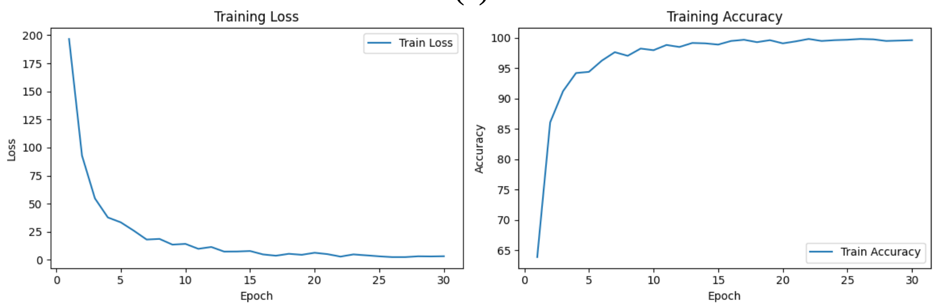
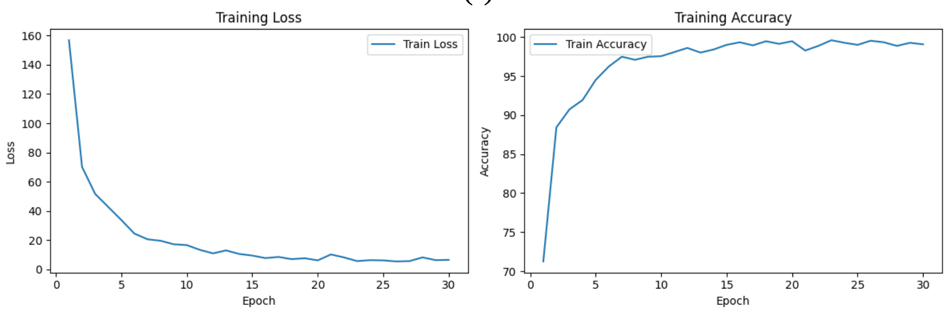


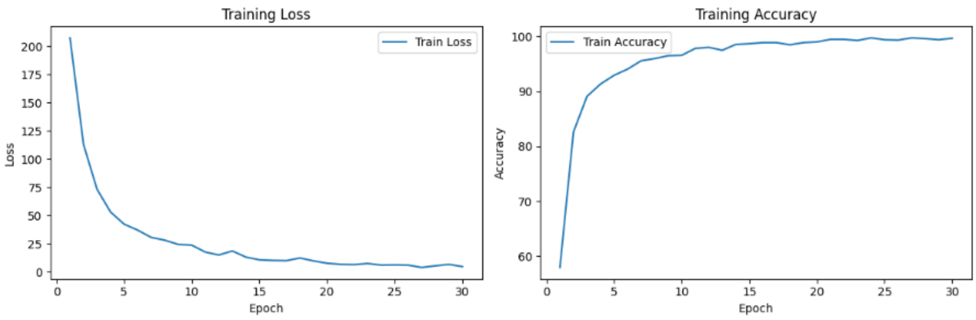
(e)



(f)



(g)



(h)

Figure 5. Training accuracy and training loss graphics. (a) Resnet101 original, (b) SE-ResNet101 original, (c)ResNext101 original, (d) SE-ResNext101 original, (e) Resnet101 agumented, (f) SE-ResNet101agumented, (g) ResNext101 agumented, (h) SE-ResNext101 agumented

Training accuracy and training loss graphs are used to monitor the performance of a deep learning model. These graphs are crucial to evaluate the model's learning performance, overfitting, and underfitting effectiveness [23]. When looking at both the training accuracy and training loss in Figure 5, neither overfitting nor underfitting seems to be observed.

4. Conclusion and Suggestions

Sunflower is one of the important food sources for the world. While its seeds are used as vegetable oil, its stems and leaves are used as animal food. Diseases in sunflower cause significant yield losses. Traditional approaches have a lower success rate and take more time. Computerized detection of diseases, early diagnosis and prevention of these diseases are of great importance in terms of efficiency. In recent years, machine learning and deep learning algorithms have been used frequently in disease detection of various agricultural products.

In this study, some diseases seen in sunflower were classified with Resnet101 and ResNext101 models, which are pre-trained deep learning models, and by adding the SE block to these models, the classification was made separately, and the results were compared. In the analysis, it was seen that pre-trained networks with added SE blocks gave better classification results for this data set.

These proposed models may contribute to more effective classification of diseases in the sunflower industry. It may also be beneficial in the early diagnosis and treatment of diseases seen in sunflower. Identifying the diseases seen in the Sunflower plant reduces time and labor costs by enabling faster and automatic diagnosis of these diseases. As a result, productivity can be increased. Compared to other studies, it is seen that the proposed method increases the classification success. This method can be successful not only in sunflower diseases but also in other plant diseases. As a result, higher quality and safer food products can be offered to consumers. The aim of this article is to automatically and accurately classify sunflower disease varieties based on their visual characteristics. Additionally, the resulting classification models can be used to classify diseases of other agricultural products. Additionally, mobile applications can be developed in this field.

Contributions of the authors

The authors confirm that the contribution is equally for this paper.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics

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