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Classification of plant leaf diseases using deep neural networks in color and grayscale images

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Abstract

For a long time, plants have shown a crucial role in our life, manufacturing and industry. However, a large number of diseases have significantly affected to the production of plants. The detection and diagnosis of the diseases are necessary to improve the production of plants. In recent years, the automatic classification of plant diseases using artificial intelligence and computer vision have attracted a huge number of researches. The paper presents a classification method of plant leaf diseases using various Deep Neural Networks (e.g., Alexnet, Resnet-50, Densenet-121). The color features have significantly affected the classification accuracy. Therefore, we analyzed and compared the classification accuracy on two public datasets (Plant village leaf datasets) that consist of color and grayscale images. The method obtained the classification accuracy of 98.08% and 92% on color and grayscale images, respectively. The obtained results showed the effectiveness of the method. Based on the obtained results, the impact of color features to the classification accuracy of various Deep Neural Networks is analyzed in the paper. Moreover, the paper compares the performance of various optimization algorithms during the training process of deep neural networks to classify leaf diseases.

Keywords: Artificial Intelligence, Classification of plant leaf diseases, Deep neural networks, Machine learning

1. Introduction

For decades, plants have shown an important role in our life and industrial fields. However, several kinds of diseases have significantly reduced to the production of plants (Abd Algani et al., 2023). The detection and diagnosis of the diseases are necessary to improve the production of plants. In recent years, with rapid advances in artificial intelligence (AI) and computer vision fields, the classification of plant diseases has attracted a large number of researches (Sachdeva et al., 2021). Among the existed methods, the automatic detection of plant diseases using the classification the plant leaf images is considered as an efficient way (Zhao et al., 2022). The classification of diseases in grayscale plant leaf images is more challenging compared to that in color images. In grayscale images, the regions of plant diseases are difficult to detect because of the blur and shadow properties.

Traditional methods investigated the handcrafted feature extraction and machine learning classifiers to discriminate diseases in plant leaf images. In recent years, Deep Neural Networks (DNNs) have shown the promising performance for the classification diseases in plant leaf images (Zhao et al., 2022). The paper presents a classification method of plant leaf diseases using various Deep Neural Networks. The color features are essential for the classification of diseases in plant leaf images. Therefore, we analyzed and compared the classification accuracy of diseases in plant leaf of color and grayscale images. Moreover, we also analyzed the performance of various DNNs for the classification of diseases in leaf images using different solver algorithms. The application of powerful solver algorithms is an efficient way to improve the classification accuracy of DNNs (Abdulkadirov et al., 2023; Iqbal et al., 2021).

Following the introduction, the next section reviews and analyses related works of the classification of diseases in leaf images. Section 3 presents the proposed method of classification of diseases in color and grayscale leaf images. The experimental results and the comparison of the performance of the proposed and existed methods are presented in Section 4. Finally, conclusions of the method are summarized, and some future research directions are recommended in Section 5.

2. Literature review

In last decades, a large number of researches have been proposed to solve the classification of plant diseases (Suwais et al., 2022). In the section, we review and analyze significant studies of classification of leaf disease images. Traditional approaches focused on the extraction of visual features (e.g., color, morphology, texture) of leaf images. After that, the extracted features are combined with machine learning classifiers to categorize leaf images (Javidan et al., 2023). Javidan et al. (2023) applied the image processing, principal component analysis and the K-means and support vector machine (SVM) to classify leaf disease images. Hossain and Amin (2010) extracts morphological features of leaf images. Then, the work applied the probabilistic neural network to classify leaf images. The method was evaluated on the small datasets that consist of 1200 images. The method obtained the classification accuracy of 91.41% of leaf images. Chaki et al. (2020) proposes the feature extraction based on shape and color. Then, a neuro-fuzzy classifier is applied to classify leaf images.

Recently, with the advances in computing technologies, the Convolutional Neural Networks (CNNs) are fine-tuned to classify leaf diseases efficiently (Zhao et al., 2022). Particularly, after several large datasets of leaf images were published, the CNNs are widely investigated for the classification (Wu et al., 2007). Compared to traditional methods, the CNNs allow to obtain higher performance in the classification issue (Szegedy et al., 2014). However, CNNs require a large numbers of leaf images to train the models efficiently. Zhao et al. (2022) has generated unhealthy leaf images to increase the number of images the training datasets using the DoubleGAN network. Then, various CNNs including VGG16, Resnet and Densenet-121 have been investigated to categorize leaf disease images. Wagle et al. (2022) uses the transfer learning technique of CNNs to classify leaf images in a small dataset. Elfatimi et al. (2022), the Mobilenet-v2 model is applied to classify bean leaves in an efficient way. The Mobilenet model was trained on the dataset with 1296 bean leaf images. The obtained classification accuracy of 97% on the dataset that consists of bean leaf images is reported in that work. Ma et al. (2018) focused on the recognition of cucumber diseases using DNNs. The obtained accuracy is at 93.4% on cucumber leaf images datasets. Chen et al. (2019) aimed to classify diseases of tea leaves using a CNN. The application of the CNN model allows to gain better classification accuracy of plant leaf diseases compared to traditional methods. Shijie et al. (2017) applied the VGG network to classify 10 diseases of tomato leaves. Chouhan et al. (2021) investigated and compared the performance of CNN and Support Vector Machine (SVM) for the identification of rice leaf images. The existing methods of the classification of leaves may obtain high accuracy of specific leaf images in small datasets. Most of the methods have been proposed for color images. In the paper, we propose and evaluate various CNNs to classify both grayscale and colored images. Moreover, during the training of the DNNs, we analyze different solver algorithms that affected the classification accuracy of plant leaf diseases.

3. Proposed method

The overall steps of our proposed method are shown in Figure 1. Firstly, the data augmentation based on image processing is proposed to increase and balance the number of images. We applied several image processing (e.g., noise addition, rotation and transition) to increase the number of input images. The data augmentation played an important role to improve the performance of DNNs (Zhao et al., 2022). Then, we employ different deep neural networks (DNNs) to classify leaf diseases. In the paper, various DNNs are optimized to improve the accuracy of the classification of diseases. Concretely, we fine-tuned the Alexnet (Krizhevsky et al., 2012), Residual Network (Resnet-50) (He et al., 2016) and Dense convolutional networks Densenet-121 (Huang et al., 2017). During the training of DNNs, we investigated different optimization algorithms to improve the performance of the DNNs.

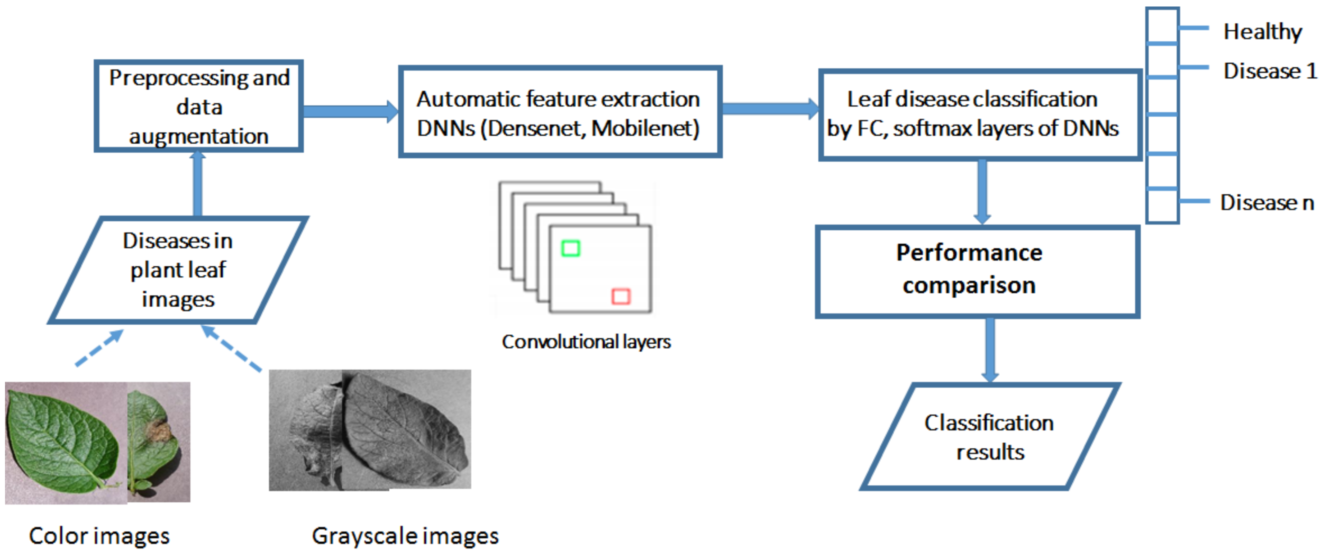


Figure 1. Overall steps of the proposed method to classify plant diseases

The Alexnet has commonly applied to solve the image classification task. The structure of the network consists of eight layers. The size of input leaf images are normalized at [227x227x3]. Table 1 shows the structural information of the Alexnet.

Table 1. Structural information of the Alexnet (Krizhevsky et al., 2012)

Layers of Alexnet
Convolution 1
Maxpooling
Convolution 2
Maxpooling
Convolution 3
Convolution 4
Convolution 5
Maxpooling
Classification layer
Total: 8 layers

The Resnet-50 has shown high performance in image classification tasks (He et al., 2016). The network consists of 50 layers. The structure of the network consists of five blocks. Table 2 shows the structural information of the Resnet-50. The size of input images of the network is normalized at [224x224x3].

Table 2. Structural information of the Resnet-50 (He et al., 2016)

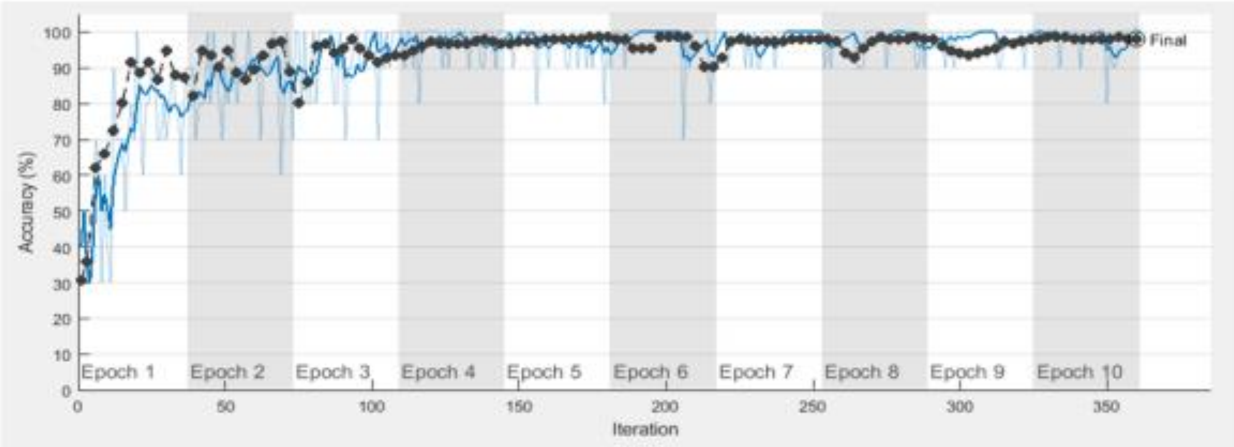
Layers of Resnet-50
Block 1
Block 2
Block 3
Block 4
Block 5
Classification layer
Total layers: 50

In recent years, the Densenet-121 has emerged as a high-performance neural network that has been popularly applied for the image classification task. The network consists of 121 layers and the input images are normalized at the size of [224x224x3]. The network consists of four dense blocks and three transition layers. Table 3 shows the structural information of the Densenet-121.

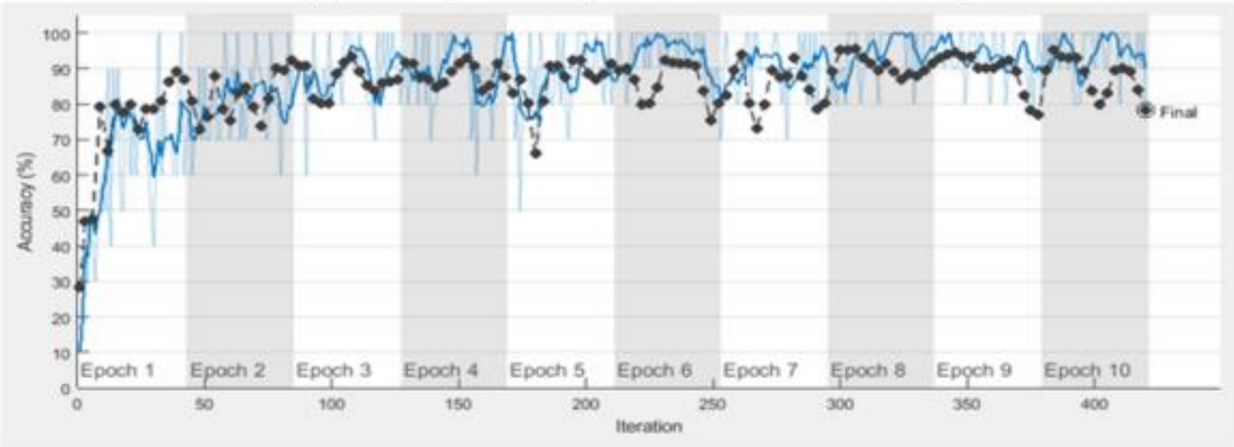
Table 3. Structural information of the Densenet-121 (Huang et al., 2017)

Layers of Densenet-121
Convolution 1
Pooling
Dense block (1)
Transition layer (1)
Dense block (2)
Transition layer (2)
Dense block (3)
Transition layer (3)
Dense block (4)
Classification layer
Total layers: 121

In the training process, we have set the parameters of the networks to optimize the classification accuracy. In the work, the learning rate is set at 0.0001. The stochastic gradient descent (SGD) algorithm (Simonyan and Zisserman, 2015) is applied to minimize the loss values during the training process of the DNNs. The value of momentum is set as 0.9 for the SGD algorithm. The accuracy and loss values during the training of Alexnet on colored and grayscale images are shown in Figure 2 and 3, respectively. As shown in the Figures, the accuracy values increase and the loss values decrease. The values show the efficient training of the DNNs.



(a) Accuracy of training the Alexnet with colored images



(b) Accuracy of training the Alexnet with grayscale images

Figure 2. Accuracy of training the Alexnet with color (a) and grayscale (b) images

One of the key factors that significantly affect the performance of the DNNs is the application of the optimization algorithms. The optimization algorithms allow the DNNs to minimize the loss values during the training process. During the training process, the DNNs require to adjust a huge number of parameters. In the work, we examine the Root mean square propagation (RMSProp) (Mukkamala and Hein, 2017), Adaptive moment estimation (Adam) (Kingma and Ba, 2017) and Stochastic gradient descent (Murphy, 2012) optimization algorithms. The RMSProp allows to obtain the highest accuracy. The Adam and SGD allow to obtain a lightly lower accuracy. However, it takes RMSProp algorithm the longest time to train DNNs. Input leaf images are resized and normalized to train and test the DNNs. The initial learning rate is set as 0.001. During the training process, the SGD algorithm selects a specified learning rate for all parameters of DNNs. Meanwhile, RMSProp and Adam adjust the learning rates that are adaptive for parameters of DNNs.

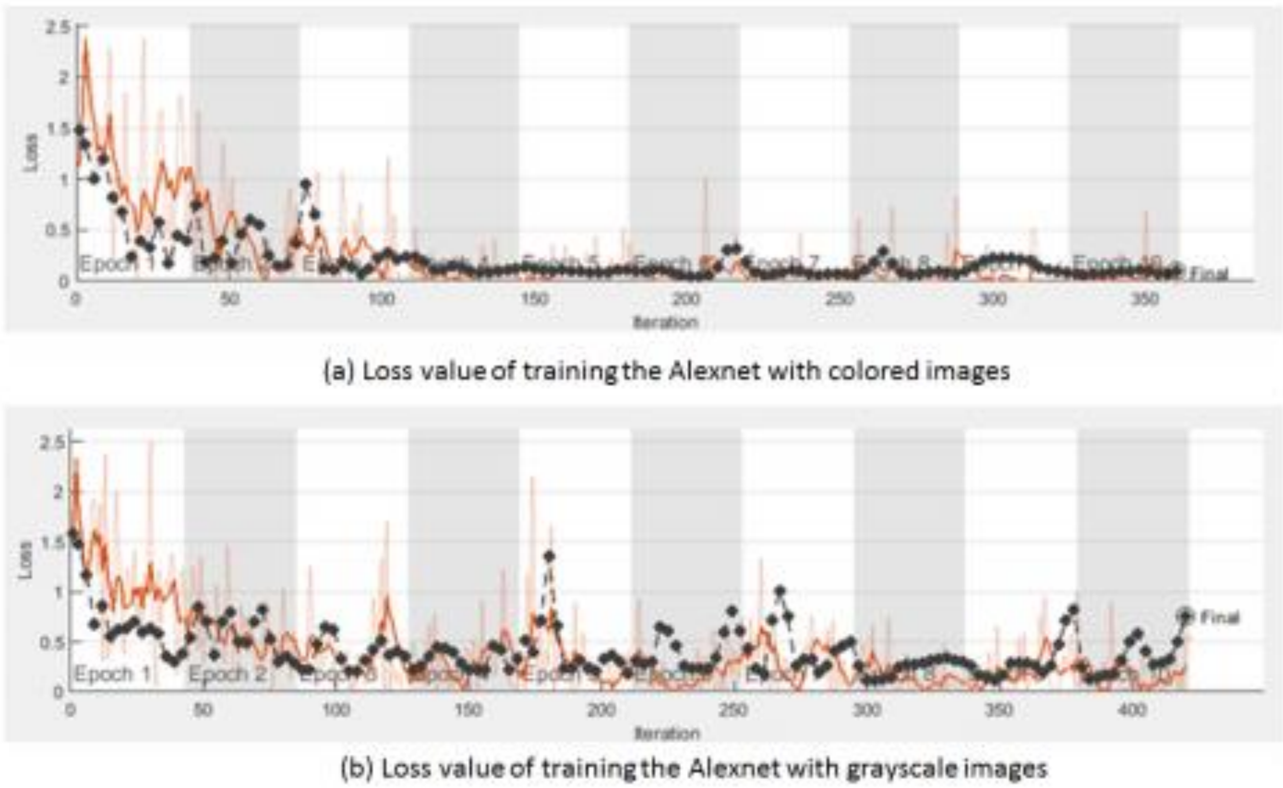


Figure 3. Loss value of training the Alexnet with color (a) and grayscale (b) images

4. Experimental results

4.1 Dataset and evaluation metrics

The public datasets of leaf diseases of apple and potato (Hughes and Salathe, 2015) have been used to evaluate the proposed method. A large number of color and grayscale images were collected in the public datasets. Table 4 shows the number of images that are used for the evaluation. Figure 4 demonstrates examples of diseases in color and grayscale plant leaf images in the dataset. The color images are stored at 8.8 KB and the grayscale ones are at 8 KB. Eighty percent of the images are used to train and twenty percent of them are used to test the DNNs.

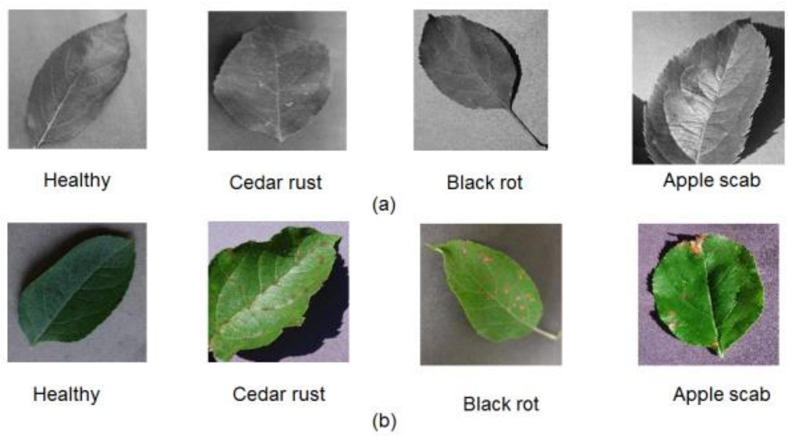


Figure 4. Examples of diseases in color and grayscale apple plant leaf images (Hughes and Salathe, 2015)

Table 4. Statistic information of apple and potato leaf disease datasets (Hughes and Salathe, 2015) after applying the data augmentation

Dataset description	Number of leaf images
Early blight of potato	1000
Late blight of potato	1000
Healthy potato	1000
Black rot of apple	1600
Black scab of apple	1600
Cedar rust of apple	1600
Healthy apple	1600

The Precision (P), Recall (R) and F1 (Simonyan and Zisserman, 2015) score metrics have been widely applied to evaluate the image classification task. In the work, the evaluation metrics are applied to evaluate and analyze the performance of the proposed method.

The F1 score can be defined using the Precision, recall metrics as follows (Simonyan and Zisserman, 2015):

$$F1 \text{ score } = \frac{2\times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (1)$$

4.2 Performance evaluation

Table 5 and 6 show the performance comparison of the classification of diseases in plant leaf images. The Densenet-121 obtains the highest scores thanks to the complex structure. The Alexnet obtains the lowest scores. The classification of diseases in colored images is much better than that in grayscale images because the colored features allow to discriminate diseases better. Table 7 and 8 compare the classification accuracy of the DNNs on grayscale images of potato and apple. Compared to the classification using the Inception network (Abd Algani et al., 2023), the Densenet allows to improve the classification accuracy for the task.

Table 5. Performance comparison of the proposed and existed methods of the classification of diseases in color potato leaf images

Model	P	R	F1 score
DenseNet121	99.07%	98.50%	98.78%
ResNet50	99.05%	98.50%	98.77%
Inception_v3 (Abd Algani et al., 2023)	91.52%	90.50%	91.01%
Alexnet	93.50%	92.50%	93.00%
HOG and SVM (Suwais et al., 2022)	89%	87%	87.99%
DWT and kNN (Suwais et al., 2022)	85%	83%	83.99%

Table 6. Performance comparison of the proposed and existed methods of the classification of diseases in color apple leaf images

Model	P	R	F1 score
DenseNet121	98.08%	97.50%	97.79%
ResNet50	98.04%	97.50%	97.77%
Inception_v3 (Abd Algani et al., 2023)	89.60%	88.50%	89.05%
Alexnet	91.50%	90.40%	90.95%
HOG and SVM (Suwais et al., 2022)	84%	81%	82.47%
DWT and kNN (Suwais et al., 2022)	82%	80%	80.99%

Table 7. Performance comparison of the proposed and existed methods of the classification of diseases in grayscale potato leaf images

Model	P	R	F1 score
DenseNet121	94.50%	90.50%	92.46%
ResNet50	92.60%	89.40%	90.97%
Inception_v3	84%	83%	83.50%
Alexnet	83%	80%	81.47%
HOG and SVM (Suwais et al., 2022)	89%	87%	87.99%
DWT and kNN (Suwais et al., 2022)	85%	83%	83.99%

Table 8. Performance comparison of the proposed and existed methods of the classification of diseases in grayscale apple disease images

Model	P	R	F1 score
DenseNet121	92%	90.50%	91.24%
ResNet50	91.60%	89.40%	90.49%
Inception_v3	83%	82%	82.50%
Alexnet	81%	79%	79.99%
HOG and SVM (Suwais et al., 2022)	87.4%	85.4%	86.44%
DWT and kNN (Suwais et al., 2022)	84.4%	82%	83.18%

Figure 5. shows that the RMS solver algorithm allow to obtain the highest accuracy of the classification compared to Adam and SDGM algorithms

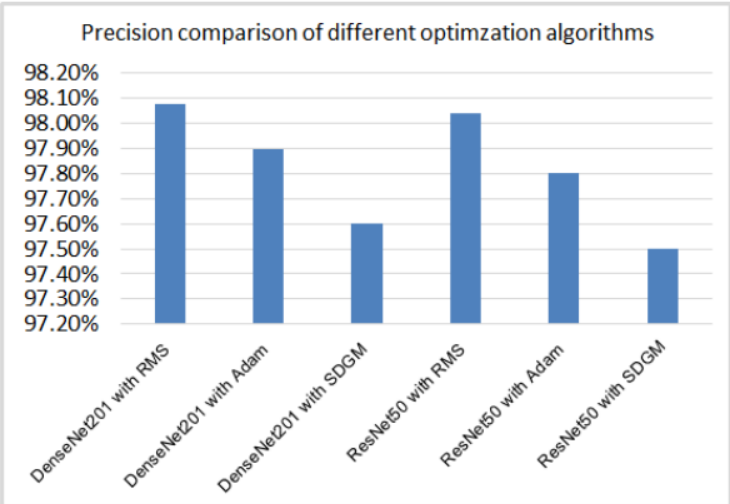


Figure 5. Comparison of the accuracy of different DNNs using various optimization algorithms for the classification of leaf diseases

To compare the classification accuracy of the diseases, we evaluated the classification using the DNNs with the handcrafted feature extractions methods. Table 6 - 8 demonstrate that the classification of the diseases using the handcrafted feature extractions methods obtain lower results compared to those of DNNs. Compared to existed method (Suwais et al., 2022), the use of DNNs in the work extracted visual features more efficiently. The handcrafted feature extraction techniques using the Histogram of gradient (HOG) and Discrete Wavelet Transformation (DWT) obtained lower accuracy compared to those of DNNs.

Moreover, the performance of Support Vector Machine and k Nearest Neighbors (kNN) classifiers are not as high as that of the DNNs. Table 9 shows the comparison of execution time of various optimization algorithms of Alexnet. Adam algorithm obtains the highest execution time compared to other algorithms. Figure 6 shows examples of the classification of diseases in color and grayscale images. The classification of diseases in color images is more accurate than that in grayscale images. Actually, there exist several errors of classification of diseases in grayscale images due to the similarities between shape and size of leaf images.

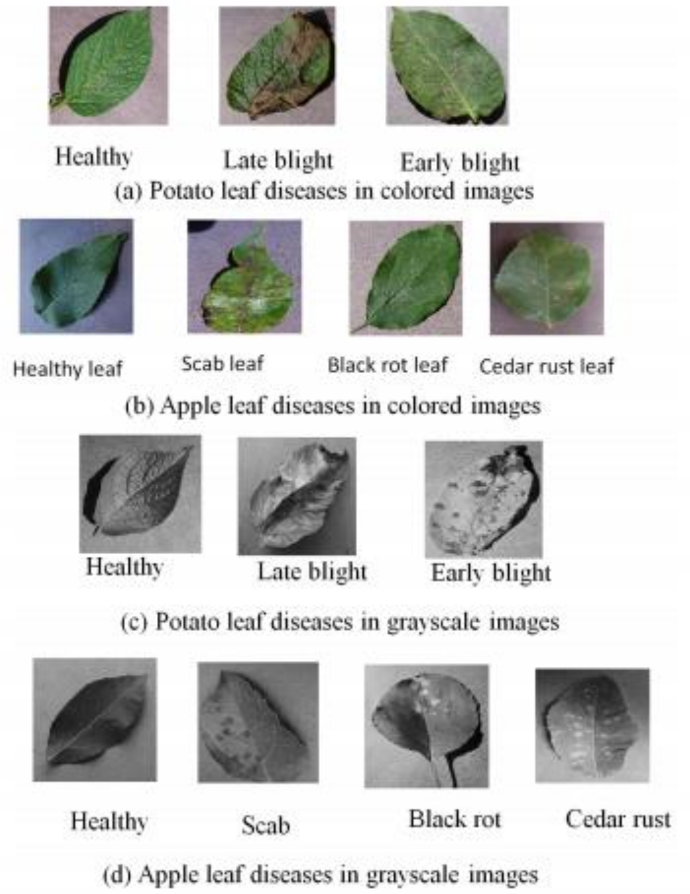
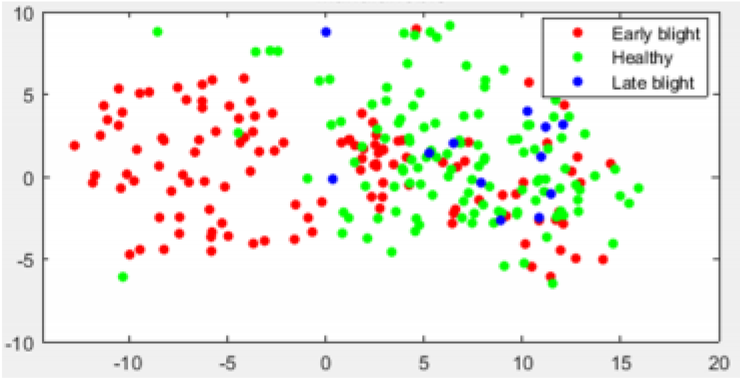


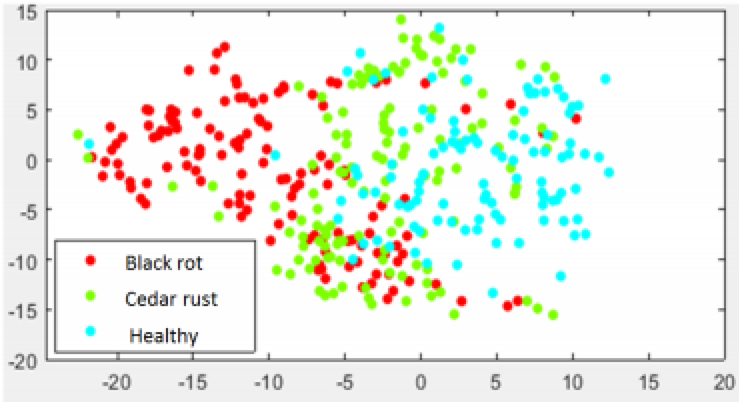
Figure 6. Examples of the classification of diseases in colored and grayscale images

To demonstrate the efficiency of the features extracted by the DNNs, we visualize the extracted features using the dimensional reduction. The t-distributed stochastic neighbor embedding t-SNE (van der Maaten and Hinton, 2008) is applied to map high dimensional data points in the low dimensional space. The distances between the points are respected when we display the points in lower dimensional space. Figure 7 shows that the extracted features are efficient to separate the classes of diseases. The diseases of potato and apple images are represented by the colored points in Figure 7 (a) and (b), respectively. Figure 8 visualizes the extracted features of apple diseases in grayscale images using the Alexnet.

Table 9 compares the running time of the Alexnet with different optimization algorithms. In term of execution time, the SGDM obtains the highest performance compared to Adam and RMS. The execution time of the DNNs and classification methods of plant leaf diseases is evaluated in the Matlab 2021b environment. The running system consists of the 8GB RAM and core-i5 processor with GPU GTX 980.



(a) Feature distribution of potato leaf diseases.



(b) Feature distribution of apple leaf diseases.

Figure 7. The demonstration of the extracted features using the DNN in color images. Features of potato (a) and apple diseases (b) are illustrated in red, green and blue circles, respectively.

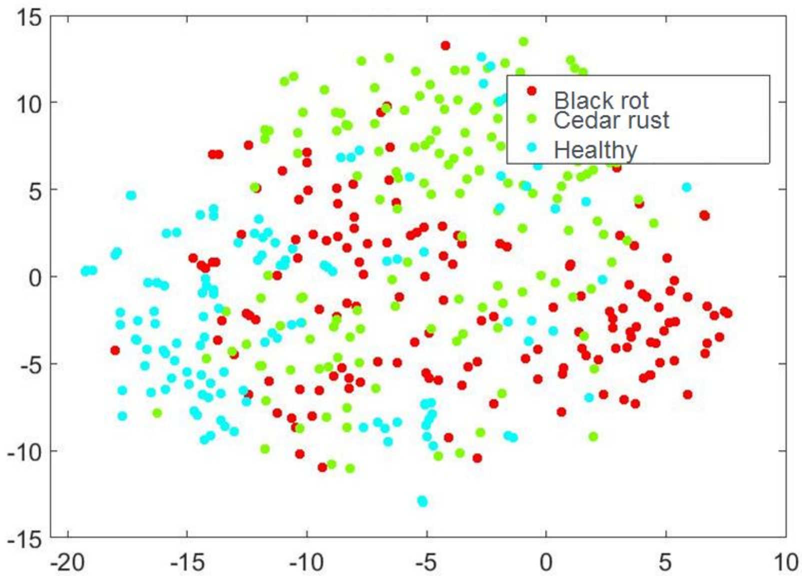


Figure 8. The demonstration of the extracted features using the DNN of apple diseases in grayscale images. Features of apple diseases are illustrated in red, green and blue circles, respectively.

Table 9. Training and testing time of Alexnet model for the classification of diseases using different optimization algorithms

Model	Training and testing time (minutes)
SGDM	35.18
Adam	36.6
RMS	37.2

5. Conclusions

The paper has presented a method of classification of diseases in plant leaf images using various DNNs. The Densenet-121 obtained the highest accuracy of 98.08% for the classification of disease in colored images. The classification accuracy of 92% is obtained on grayscale images. The results demonstrate that the colored features have high impact on the classification accuracy. However, the processing, training and time of grayscale images are better than those of colored images. The use of different optimization algorithms allows to improve the classification performance of DNNs. The RMS optimization algorithm allows DNNs to obtain the highest classification accuracy. In the future, the strategy of using the DNNs with various optimization algorithms can be applied to classify other leaf diseases. Moreover, obtained results can be integrated with the Internet of Things (IoT) systems in smart agriculture applications.

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