An Enhanced Plant Disease Classifier Model Based on Deep Learning Techniques

Madallah Alruwaili, Sameh Abd El-Ghany and Abdulaziz Shehab

Abstract*: Plant disease detection is used to detect and identify symptoms of plant diseases. Detection of plant diseases through the naked eye is ineffective, especially because there are numerous diseases. Therefore, there is a need to develop low-cost methods to improve rapidity and accuracy of plant disease diagnosis. This paper presents an effective model for plant disease detection by using our developed deep learning approach. Extensive experiments were performed on the PlantVillage dataset, which contains 54,306 images categorized between 38 different classes containing 14 crop species and 26 diseases. Our proposed model demonstrated significant performance improvement in terms of accuracy, recall, precision, and F1-score compared with the existing model used for plant disease detection.

Keywords* : Deep learning, Curl virus, feature extraction, AlexNet, plant diseases.

I. INTRODUCTION

As a result of the rapid technological development in machine learning algorithms, artificial intelligence, and digital image processing techniques, there is an urgent need to integrate this modern technology into the development of modern methods to help farmers identify diseased plants during early stages. It is evident that spreading of plant pests and diseases leads to a loss in the overall crop yield.

Plant diseases affect the shape, color, and texture of the leaves, flowers, and fruits. This makes it difficult for farmers to distinguish between the symptoms of different diseases with their naked eyes because of the similarity between the nature of some diseases. In addition, some farmers may not have sufficient experience dealing with diseases. Therefore, there is a need for automated techniques that will help the farmers in early diagnosis of plant diseases and provide suggestions and solutions on how to deal with these diseases. The advantages of automatic disease detection methods over traditional methods include less effort, less time, and high accuracy. Automatic methods for plant disease detection and recognition majorly involve a sequence of steps including image collection, preprocessing, segmentation, feature extraction, and disease classification. Image collection involves either of the two methods, using a public image dataset such as PlantVillage or taking image samples of diseased plants from the field using a digital camera or drones. This step can affect the quality of the disease diagnosis system because the model trained for image classification is affected both negatively and positively by the image quality. Preprocessing involves improving the accuracy of the model used for disease classification.

Preprocessing of raw data can involve several steps such as resizing the image, noise removal, background isolation, and spatial filtering. Image segmentation is a process of grouping similar regions of an image to extract the infected region in the image. Currently, there are many methods for image segmentation ranging from pixel classification to edge detection. Feature extraction is considered one of the most important steps to diagnose and identify diseases. Choosing the right method for extracting features is a challenge because it affects the overall system performance to diagnose diseases. Several methods can be used to extract the most significant features. Color, shape, and texture are the features used. One or more methods can be combined to identify plant diseases. In addition, the use of informative features is necessary to improve the classification accuracy and reduce computational time. Disease classification is the final step in the disease classification system. Here, a classification model is used to determine whether the plant is diseased or not. The model is trained using different machine learning algorithms, such as naïve Bayes, decision tree, K-means, support vector machine (SVM), and random forest, and training sets with diseased plant samples. However, these algorithms depend on the complexity of image preprocessing and feature extraction processes that can reduce the accuracy of the model used for disease detection and diagnosis. Modern deep learning (DL) techniques have proven successful in recognizing different patterns efficiently. DL is one of the most impressive examples of machine learning with the ability to automate feature extraction. In addition, it reduces the error rate and computational time as compared to those in other traditional machine learning approaches as well as achieves high accuracy on classification tasks. In this paper, a DL model using the Alex Net architecture is customized and employed to detect different plant diseases in an efficient manner. The proposed model outperforms other techniques because of its efficient parameter selection during transfer learning and the use of new data augmentation methods. The calculated accuracy, recall, precision, and F1-score for the proposed model shows promising results. This paper contains five sections. Section 2 describes a literature review for existing models for plant disease classification.

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The details of the proposed model using the AlexNet architecture and data augmentation are presented in Section 3. In addition, a pilot outline for the framework of the system is provided in this section. The dataset description, experimentation details, results, and comparison to existing methods are given in Section 4. Lastly, Section 5 concludes the work and expected future work.

II. LITERATURE REVIEW

Feature extraction plays a major role machine learning. Mohan et al. [1] used SIFT to extract visual features from the paddy plant. To detect diseases and achieve high accuracy, the AdaBoost classifier was used. Finally, the SVM classifier was applied to identify the diseases, and a recognition accuracy rate of 91.10% was achieved. Atole et al. [2] proposed a Conventional Neural Network (CNN) model to categorize 10 classes of common rice diseases. The model was trained on 500 images of infected rice leaves and stems, and an accuracy of 95.48% was achieved. The authors concluded that the CNN model gives a better result than the existing techniques for disease identifying in rice. To detect diseases in the cassava plant, a mobile application using Tensor Flow was proposed in [3]. The main aim of this model is to learn cassava diseases, which achieves an average mean precision of almost 94%. Singh et al. [4] proposed a multilayer CNN to classify mango leaves that are infected by the Anthracnose disease. The proposed model was evaluated using a real time dataset and achieved an accuracy of 97.13% and outperforms other methods, namely PSO, radial basis function neural network, and SVM. In [5], the proposed deep-CNNs model, INAR-SSD, is used for detection of five common apple leaf diseases. This model is proposed by introducing the GoogLeNet Inception structure and Rainbow concatenation. As a result, this model achieves a detection outcome performance of 78.80% mAP. Cruz et al. [6] have proposed a DL model in order to identify the 'quick decline' syndrome of olive, and achieved a rate of detection of over 98%. Mohanty et al. [7] used two pre-trained DL models, namely, AlexNet and GoogLeNet for plant disease classification. The results were validated on a large dataset of 54,306 images from the PlantVillage dataset of diseased and healthy plant leaves and an accuracy of 99.35% was achieved. However, the accuracy decreased to 31% when the original dataset was changed.

III. PROPOSED ALEXNET MODEL

The block diagram describing the steps involved in the DL model is shown in Figure. 1. First, noise from the source images, i.e., PlantVillage (www.PlantVillage.org) dataset, is removed. The images are passed to a median filter to remove noise, after that the image size is reduced to 256 pixels × 256 pixels to decrease computation. Image denoising and resizing are performed as a preprocessing step.

Second, one of the challenges with the PlantVillage dataset is imbalanced data, where some classes have more images than others. Therefore, the problem of overfitting may be arise while training of the Alex Net model. However, collecting various images of diseased plants and labeling it is an expensive task. Data augmentation is a method used to increase the diversity of images before the training process. This technique aims to increase the size of the dataset by applying a set of geometric shifts (resizing, yield, rotation, horizontal reflection) and density shifts (improving contrast, brightness, color, noise), and increasing variations in the images helps reduce overfitting during the training phase. Data augmentation can be used to overcome the overfitting problem while training the CNN.

After data augmentation, the dataset is divided into training and test sets, which include 80% and 20% of the samples, respectively. Finally, the proposed AlexNet model is trained using the images in the training set.

DL is artificial neural network with hidden layers, where the present succeeding layer is based on the output of the preceding layer. Each following layer is connected using neurons, where an activation function is used to introduce non-linearity and without an activation function the network is only a linear combination of the inputs. Weights and biases of the network should be carefully assigned to determine the classification accuracy. As illustrated in Figure. 2, the architecture of our adapted version of the pre-trained AlexNet model used in this study majorly comprises of five convolutional layers, i.e., conv1—5, followed by three fully connected layers (fc6—7), and a linear layer with the Softmax activation function. Layers were interconnected together in a multilayer architecture.

The network was in charge of changing the input visual motivates into non local signals. The abstraction level of the signal became more complex because it is passed through succeeding layers. In the proposed model, in order to overcome overfitting, a "sgdm" method was used. Furthermore, novel regularization methods such as dropout have emerged in order for more overfitting reduction.

IV. EXPERIMENTATION DETAILS

A. Image Dataset

As mentioned above, for analyzing the performance of the proposed model, we have the PlantVillage dataset. This dataset has more than 54000 images of plant leaves for 14 crops. Figure. 3. shows the diseased leaf samples of the plant village plants, including apple, corn, grape, and tomato.

B. Implementation Details and Parameters

The experiments are implemented in MATLAB 2017 (last release) with the machine specifications given in Table I. As stated above, the network was initially trained on the original version of the PlantVillage dataset, then frozen and retrained on the new dataset. The parameters used for model training are summarized in Table II.

Table I. Machine specifications

Laptop device	Dell Precision Rack 7910
processor	Dual 8-core Intel Xeon E5-2630 v3
RAM	128 GB
GPU card	NVIDIA Quadro K6000 14 GB

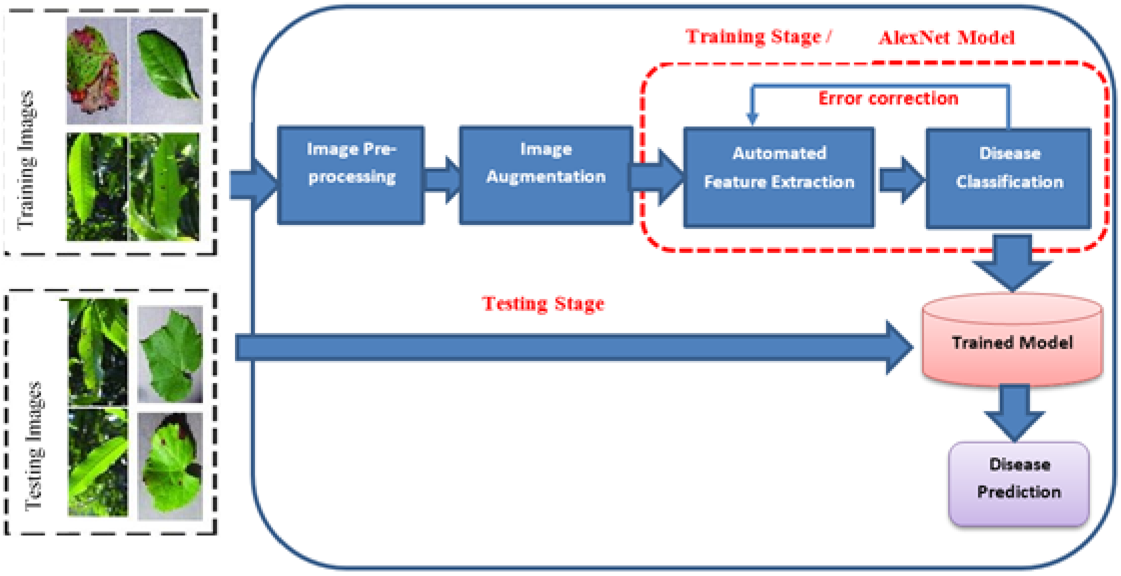

Fig. 1. Block diagram

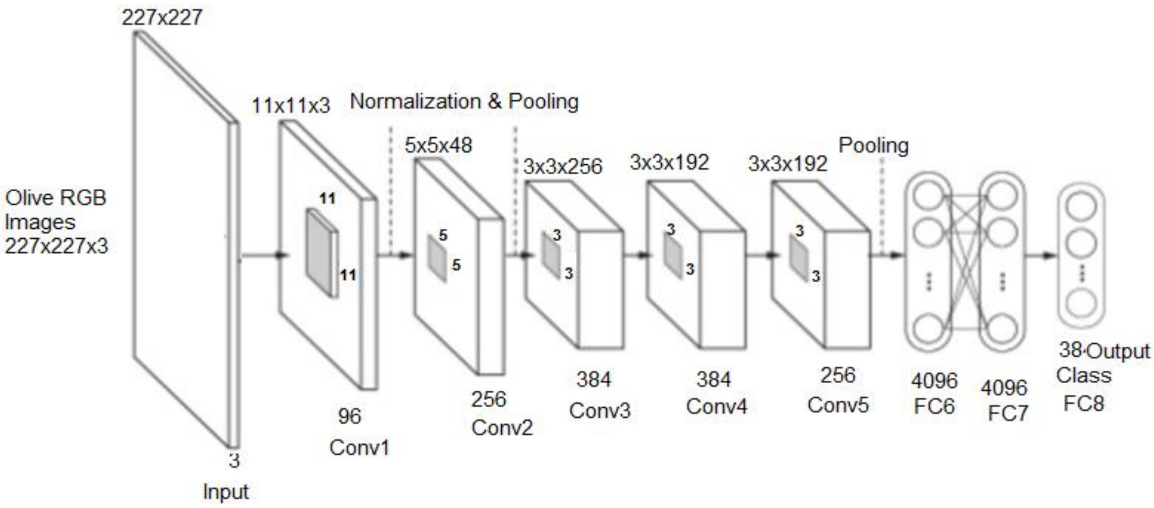

Fig. 2. Structure of the CNN employed in this study.

Table II. Alexnet Parameters.

Factor	Value
'WeightLearnRateFactor'	20
'BiasLearnRateFactor'	20
'InitialLearnRate'	1e-4
'MiniBatchSize'	10
'MaxEpochs'	6
Weight decay	0.0005
Gamma(ϒ)	0.1
Batch size	100

To measure the accuracy of the proposed model, three metrics namely precision, recall and F1-score were calculated. We have conducted 10 trials using random samples from the training and testing sets to train the network to detect and diagnose plant diseases. The network first extracts the features in a fully-automated way and learns on those features. The efficiency of the network to diagnose diseases gradually increases and eventually the network is stable. Table 3 shows the detailed calculated metrics for the 16 selected diseases that were previously shown in Figure. 3.

As we can see in Table 3, most diseases symptoms have a high precision, recall, and F1-score in the diagnosis. However, there are some symptoms where one of the three metrics is lower than usual. Corn northern leaf blight disease, for example, has a recall of 95.46% and an F1-score of 97.67%. In addition, Tomato Bacterial spot disease has a recall of 97.12% and an F1-score of 98.53%. The precision is 100% for all the 16 diseases explored in Table 3, except Corn healthy (C_10) and Grape Leaf blight (C_13). This may be because there exists a similarity in the visual symptoms of this disease with others. Therefore, the proposed system cannot efficiently differentiate between these diseases, resulting in a lower precision, recall, or F1-score. Table 4 summarizes the results of the proposed model compared to other state-of-art models. The proposed model (marked in red) reaches an overall of accuracy of 99%. In addition, the precision is 99.11% whereas the recall and F1-score are 99.49% and 99.29%, respectively. Because of efficient parameter selection during transfer learning, relying on new data augmentation methods, and using fixed number of images in each category, the proposed model

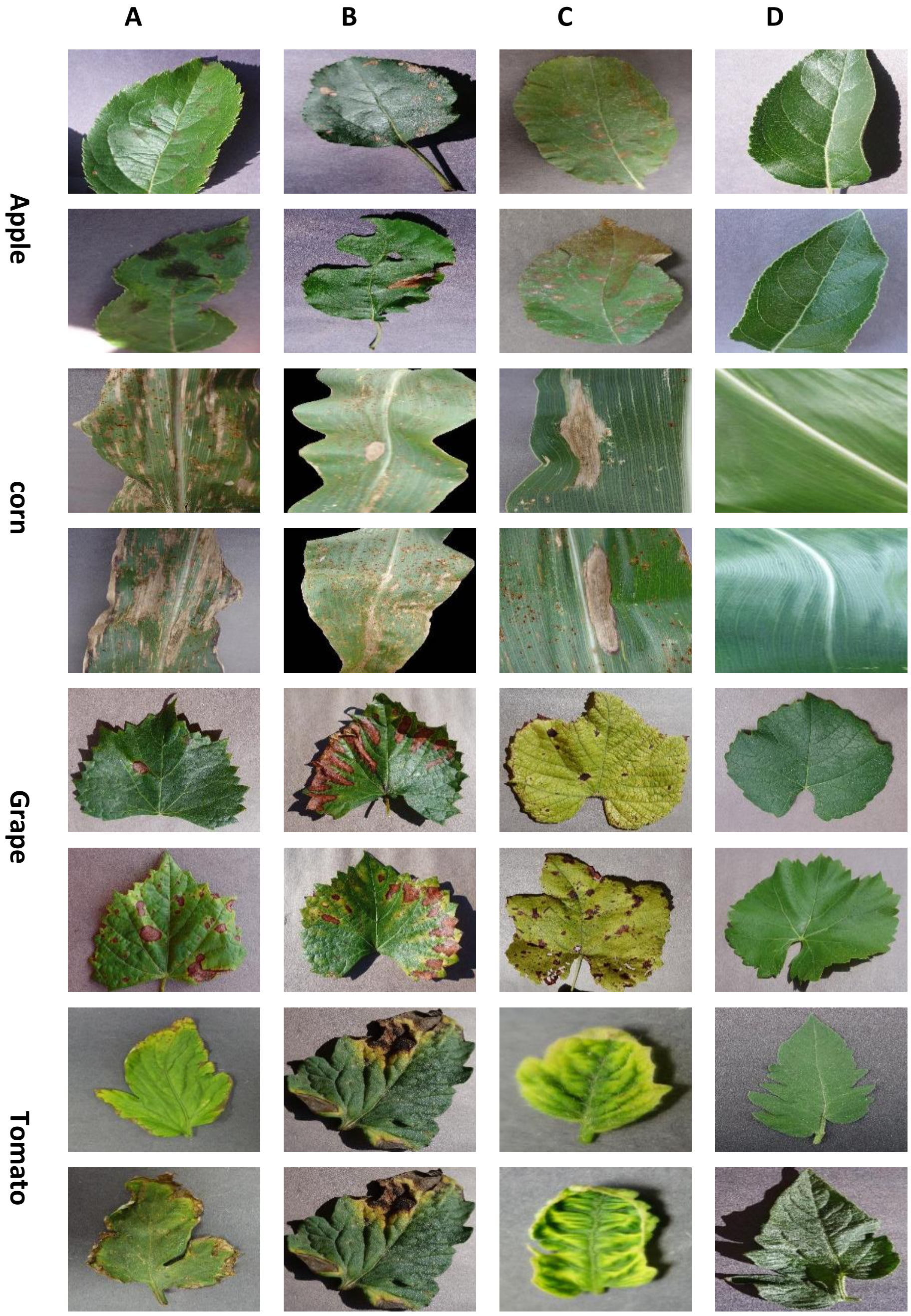

Fig. 3. Sample Leaves images from plant village dataset for crop of Apple, Corn, Grape, and Tomato. From left to right: Apple (A): Apple scab, Apple (B): Apple Black rot, Apple (C): Cedar apple rust, Apple (D): Apple healthy. Corn (A): Cercospora leaf spot (Gray leaf spot), Corn (B): Common rust, Corn (C): Northern Leaf Blight, Corn (D): Corn healthy. Grape (A): Black rot, Grape (B): Esca (Black measles), Grape (B): Leaf blight (Isariopsis leaf spot), Grape (B): Grape healthy. Tomato (A): Bacterial spot, Tomato (A): Early blight, Tomato (A): Yellow Leaf Curl Virus, Tomato (A): Tomato healthy

outperforms other techniques. Conventional models [8, 9] use a small number images, reducing variability in the dataset. As observed in Table 4, over the last year years, DL techniques have shown a remarkable improvement for plant disease detection as compared to traditional approaches [8, 9] such as SIFT, HoG, and SURF because such methods lack the ability of transfer learning, which is used by DL models.

V. CONCLUSIONS

Early detection of plant diseases help in better crop quality and increase crop production. Recently, DL techniques have seen a massive rise in popularity in such fields because of the high accuracy and efficiency of these techniques. Compared to other existing methods, the accuracy, precision, recall, and F1-score of our proposed model are 99%, 99.11%, 99.49%, and 99.29%, respectively. The proposed model outperforms other models owing to efficient parameter selection during transfer learning and using new data augmentation methods. Finally, DL algorithms open the door to many research areas such as Internet of Things and robotics to solve future agricultural challenges.

Table III. Metrics of the Plant Diseases

Plant Type	Category No.	Syndrome	Precision	Recall	F_1-Measure
Apple	C_0	Apple_Apple_scab	100	100	100
	C_1	Apple_Black_rot	100	100	100
	C_2	Apple_Cedar_apple_rust	100	100	100
	C_3	Apple_healthy	100	94.74	97.29
Corn	C_7	Corn_(maize)_Cercospora_leaf_spot Gray_leaf_spot	100	100	100
	C_8	Corn_Common_rust_	100	100	100
	C_9	Corn_Northern_Leaf_Blight	100	95.45	97.67
	C_10	Corn_healthy	98.85	100	99.42
Grape	C_11	Grape_Black_rot	100	100	100
	C_12	Grape_Esca_(Black_Measles)	100	100	100
	C_13	Grape_Leaf_blight_(Isariopsis_Leaf_Spot)	98.70	100	99.35
	C_14	Grape_healthy	100	100	100
Tomato	C_28	Tomato_Bacterial_spot	100	97.12	98.54
	C_29	Tomato_Early_blight	100	99.76	99.88
	C_30	Tomato_Tomato_Yellow_Leaf_Curl_Virus	100	100	100
	C_31	Tomato_healthy	100	100	100

Table IV. Proposed Model compared to state-of-art models

	Accuracy (%)	Precision (%)	Recall (%)	F_1-Score (%)
RBF-SVM based on Gabor Energy Filtering with [8].	63.11 ± 11.91	72.44 ± 14.30	65.28 ± 21.74	65.52 ± 15.15
Dense SIFT Features + BoW [9].	87.90 ± 4.44	N/A	N/A	N/A
Different plant species using CNN [10]	92.00 ± 1.35	N/A	N/A	N/A
Mango Leaves diseases using MCNN [4]	97.00 ± 1.21	N/A	N/A	N/A
Apple Leaf Diseases using AlexNet and Google Net[5]	94.85± 0.91	N/A	N/A	N/A
X-Fideo (LeNet deep learning algorithm) [6].	98.60 ± 1.47	98.82 ± 2.63	97.18 ± 2.71	96.89 ± 3.45
AlexNet deep learning algorithm [7].	97.38 ± 1.89	97.42 ± 1.33	97.37 ± 1.45	97.36 ± 2.45
Proposed model	99.11 ± 0.75	99.49 ± 0.83	99.11 ± 1.29	99.29 ± 1.63

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