International Journal of Research in Advanced Engineering and Technology
www.allengineeringjournal.in
ISSN: 2455-0876
Received: 26-03-2026, Accepted: 26-04-2026, Published: 11-05-2026
Volume 12, Issue 2, 2026, Page No. 11-16

Identification of plant diseases using deep learning

Ibrahim Aliyu Yabo[1], Hudu Burah[1], Mohammed Adamu Sule[1], Kadawa Ibrahim Ali[1], Sabiru Sarki Tudu[1], Abubakar Abubakar Aliyu[2]

[1] Advanced Aircraft Engineering Laboratory, Gusau. National Space Research and Development Agency, Nigeria

[2] Department of Computer Engineering Technology, Federal Polytechnic Kaltungo, Gombe State, Nigeria

Abstract

The agricultural sector plays a vital role in the economy of country. Agricultural output is very vital in many developing countries. Increase in population and increase in the life expectancy is pressurizing the agricultural sector to come out with new types of high yielding crops. The diseases in the plants are common, early detection and control increases the yield of a crop. The problems of leaf in plants are often dangerous and they usually shorten the lifespan of plants. Leaf diseases are mainly caused by three types of attacks including viral, bacterial or fungal. Diseased leaves reduce the crop production and affect the agricultural economy. Since agriculture plays a vital role in the economy, thus effective mechanism is required to detect the problem in early stages. This research developed a scheme for identification of plant diseases using deep learning which utilizes transfer learning using pre-trained Convolutional Neural Network (CNN). The developed scheme uses images obtained from developed dataset of two different plant leaves images from KSUSTA, called the KSUSTA dataset. Denoising, downscaling operation and RGB conversion applied on the acquired image to reduce the cost incurred in using the original image. The developed scheme was based on current image processing and computer vision techniques, to accurately detect and identify the healthy and non-healthy plant leaves from a given image of the plant leaf with less false positive prediction. The experimental result shows that the developed scheme outperformed the existing one with a large margin.

Keywords: Plant disease, downscaling, fungal, bacterial and deep learning

Introduction

There has been a lot of research around identifying and classifying the disease in a plant using image processing. The researches include the use of various Machine Learning and Deep Learning strategies to complete the task. Machine Learning approaches include image segmentation (Bagde S., *et al,* 2015) [1], shape-only features for plant leaf identification, Support Vector Machines (SVM's), using shape features and K-Nearest Neighbors (KNN), K-means and Artificial Neural Networks (ANN) and Probabilistic Neural Networks (PNN).

First digital images are acquired using digital camera. Then image processing techniques, such as image enhancement, segmentation, color space conversion and filtering, are applied to make the images suitable for the next steps. Then important features are extracted from the image and used as an input for the classifier (Pantazi, *et al.,* 2018).

The overall classification accuracy is therefore dependent on the type of image processing and feature extraction techniques used (Pujari JD., *et al,* 2013). However, latest studies have shown that state of the art performance can be achieved with networks trained using generic data. Deep Learning based plant disease classification models includes the use of variety of CNN models such as AlexNet, GoogleNet, modified GoogleNet, LeNet, Caffe and Deconvolutional Network, and VGGNet. There have been implementations of ResNet model for many applications such as Paying more Attention, Large-Scale Plant Classification and ImageNet classification by ResNet50. CNNs are multi-layer supervised networks which can learn features automatically from datasets. For the last few years, CNNs have achieved state-of-the-art performance in almost allimportant classification tasks. It can perform both feature extraction and classification under the same architecture (Atabay 2016) [3].

Identification of plant diseases from an image is a very difficult task as the image contains a lot of noise which reduces its quality. Machine learning techniques such as Support Vector Machines (SVM), Artificial Neural Network (ANN) and Random Forest are the most widely used for image classification. There is still some weakness shown in the previous studies by some classifiers such as Support Vector Machines (SVM) and Random Forest in identifying healthy and damaged leaf by performance evaluation using an F-Score, but the Artificial Neural Network, Particularly Multilayer Perceptron (MLP) has resulted the highest F-Score performance in several studies (Han Han, & Wang Zhai, 2003). With SVM when the data set has more noise, i.e. the target classes are overlapping, it does not perform very well in detecting and identifying the classes of an image. With Random Forest when the data increases a large number of trees makes the algorithm too slow and ineffective for real-time predictions.

For the purpose of effectively and accurately identifying the healthy and un-healthy leaves from any image irrespective of the complexity of the background, there is a need to achieve at least a human level accuracy. This can be achieved by using a deep CNN framework that utilizes a deep feature extraction technique via transfer learning approach. This is necessary in order to improve the identification rate while reducing the rate of achieving false positive results.

Hear are some reviewed similar works that have been carried out in the area of plant disease identification and identification. This review is carried out to understand the extent of research in this area, as well as tools and approaches used. The knowledge gained facilitated this research work by using different tools and approaches to get better result.

Adnan *et al.,* (2019) [5], proposed Plant Disease Identification Algorithm using CNN and Remedy, they employed preprocessing and Training the model (CNN). The database is preprocessed such as Image reshaping, resizing and conversion to an array form. Similar processing is also done on the test image. A database consisting of about 32000 different plant species is obtained, out of which any image can be used as a test image for the software. The trained database is used to train the model (CNN) so that it can identify the test image and the disease it has. CNN has different layers that are Dense, Dropout, Activation, Flatten, Convolution2D, and MaxPooling2D. After the model is trained successfully, the software can identify the disease if the plant species is contained in the database. After successful training and preprocessing, comparison of the test image and trained model takes place to predict the disease.

Aravindhan *et al.,* (2019) [6], developed a Plant disease identification and classification system using dCNN. The dataset used in their study is called the PlantVillage Dataset and was obtained from SP
Mohanty's Git-Hub repository. The dataset comprised of raw images, data distribution for SVM
and other useful data. The raw images consisted each of color, grayscale and segmented images.
Each category resulting close to 55k images which includes 38 different classes. Altogether there
are 38 classes present in the dataset their models were trained on 29 classes, and selection was
done by selecting classes with at least one disease and one healthy class each, so that the model learns to distinguish the disease. Colored (RGB) images were used in this study to train and classify
the diseases. Hence the selected dataset comprises of 29 classes and 36k images. Hierarchical
division is done on the selected dataset and resulting into 8 superficial classes. Now the dataset is
split into training and validation sets with 80% and 20% of the dataset respectively. Thus, we have 28938 and 7210 images for training and validation sets respectively.

Kapilya *et al.,* (2019) [7], developed classification and functional analysis of major plant disease using various classifiers in leaf images. According to (Kapliya *et al.,* 2019) In their system they follow the normal Image processing techniques to analyze and detect the plant disease. The methodologies that they have adapted are as follows Image Acquisition, Preprocessing or Enhancement, Segmentation, Feature Extraction of the Image and Classification of diseases. They presented the flow of Basic Image Processing Methodologies in the developed system. The system also follows trained and tested Images for classification. For training phase, the captured region of the image
i.e., the leaf portion is taken and preprocessed by applying the required method like Image Smoothing/Noise reduction by applying the filter and it is corrected according to the requirement and segmentation method will be applied to it where spotting of the diseased region would be performed by separating the background with error portion. Feature Vector mechanism will extract the region of interest and used for training the Classifier. In the testing phase, Image is passed through preprocessing, segmentation process and the feature extraction process, where the diseased area would be spotted and it would be identified through the trained classifiers. The Evaluation of the system is estimated through the accuracy of the output.

Kim *et al.,* (2009) have classified the grape fruit peel diseases using color texture features analysis. The texture features are calculated from the Spatial Gray-level Dependence Matrices (SGDM) and the classification is done using squared distance technique. Grape fruit peel might be infected by several diseases like canker, copper burn, greasy spot, melanose and wind scar
(Kim *et al*., 2009).

Methodology

The conversion of colored images to gray level images can be done using either the average method or the weighted method. The average method is considered the easiest of the two as it simply calculates the average of the three colors as given by (Saravanan, 2010):

$$\text{Grayimage} = \frac{R+G+B}{3} \quad (1)$$

Where R, G and B represent Red, Green and Blue channel of the RGB image respectively. However, the problem with this method is that, the output might produce a dark image instead of a grayscale one. This is because, the three different colors have different wavelengths and each of these colors contribute to the formation of the image. When calculating the grayscale value, the average will be taken withrespect to each individual color contribution to the image (Saravanan, 2010).

The weighted method was developed to solve the problem of different wavelengths associated with the average method. Since the Red (R) color has the highest wavelength of the RGB colors and the Green (G) has the least (with a soothing effect to the eyes), the contribution of the red color is reduced while that of green is increased. Thus, given a colored input image, the grayscale image can be obtained by (Saravanan, 2010):

$Grayscale = (R \times 0.299 + G \times 0.587 + B \times 0.114)$ (2)

where R, G and B represent Red, Green and Blue components respectively.

The methodology adopted in carrying out the research work are itemized as follows:

- Development of the KSUSTA plant leaves image dataset
- Development of the dCNN-based plant disease identification system
- Testing of system developed in 2 with datasets of 1
- Comparison of results obtained in iii above with results obtained from the scheme developed by Kapilya *et al.,* (2019) [7] using the performance metrics of identification rate, precision, recall and recognition accuracy**.**

Development of KSUSTA Image Dataset

In this research work, images of two different plant leaves namely spinach and bitter leaf were captured using a digital camera. These images are captured at a resolution of 300 x 1508 pixels with a Nikon D40 camera specification, under different environment and light conditions.

a. Image Acquisition

The acquired images obtained as listed in Table 1: are grouped into 5 categories namely B1, B2, B3, B4 and B5 based on the following conditions: day, night, images with single and multiple plant leaves and images affected by reflection. A sample of the dataset is shown in table 1. The number of images obtained is based on available vehicle images.

Table 1: Description of the KSUSTA Dataset

Dataset	Image Group	Scenes Description	No of Images
KSUSTA	B1	Images taken at night	45
KSUSTA	B2	Images taken in sunny weather	105
KSUSTA	B3	Reflected images	25
KSUSTA	B4	Multiple leaves images	15
KSUSTA	B5	Images captured under the rain	25

The plant leaf disease identification scheme starts with the image acquisition, after which the acquired images are pre-processed. The developed datasets contain images captured at a very high resolution (3000 x 1508) which increases the computational complexity of the scheme; some preprocessing techniques are then applied to help reduce the computational cost associated in using the original images and increases the performance of the system.

The original colored image was downscaled to reduce the computational complexity. The scaling factor used for the operation is determined by the width and height of the characters on the Plant Leaf Disease region as given in equations (2.1) and (2.2): The width and height of the Plant Leaf Disease region were measured to be 60cm by 20cm to match the actual size of a standard number plate. The scale used was 3 and 2 respectively for the height and width of the plant leaf. This is because the width is always greater than the height.

Noise Elimination

In this research work, the noise in the input image was remove using a 3×3 median filter this is because median filter preserves the edges of the image and produced edged images with fine details. However, Plant Leaf Disease s are known to be corrupted by salt and paper noise hence using a median filter completely eliminates the noise without blurring the rest of the objects in the image.

Development of the Deep Learning Based Plant Leaf Diseases Identification Scheme. The processes involved in the development of the plant leaf diseases identification scheme are discussed in details in the following sub-sections. The plant leaf diseases identification scheme was developed using current image processing and computer vision techniques, which are Sobel edge detector, edge density filtering, connected component analysis and the geometric characteristics of the plant leaf and lastly a pre-trained deep convolutional neural network (ALEXNET)) to extract features and classify the extracted plant leaf candidates. The flow chart of the processes carried out is described in Figure 1, and a detail description of the steps involves for development of the scheme are also discussed.

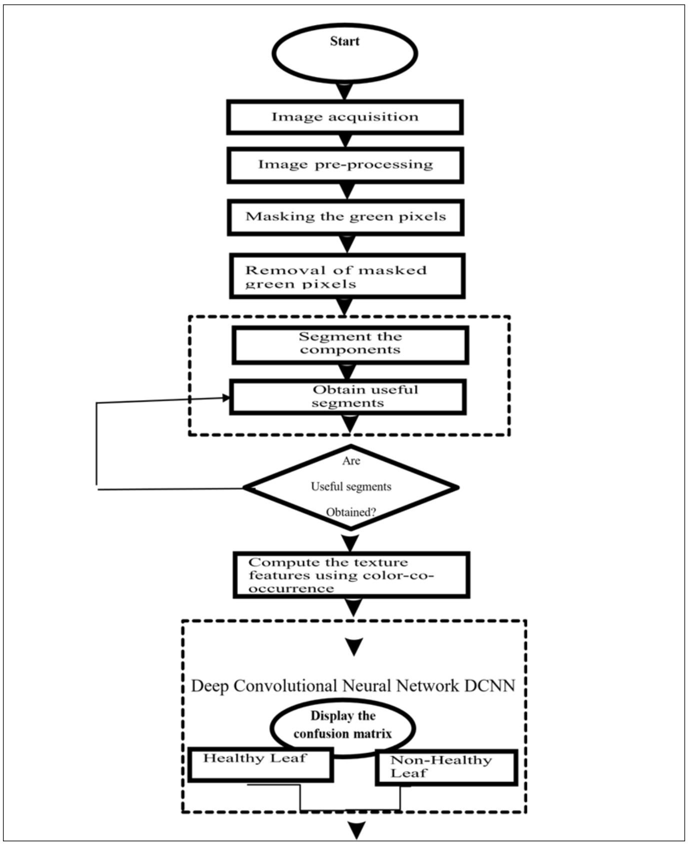


Fig 1: Flowchart of the developed Scheme

Useful Components Segmentation

ALEXNET pre-trained model has been trained on over a million images IMAGENET and has
learnt rich features from the wide range of images. In this work, instead of training the entire network from scratch, features from the already trained network are exploited to extract an initial set of feature representation which was used in the classification of the new dataset. The derived representation was transferred into a supervised neural network classifier.

Modification of The Identification and Output Layer

The last three layers of the pre-trained network are configured for 1000 classes, these layers depicted as layer 23-25 in Figure 2 consist of the FC8, the softmax layer and the classification output layers respectively. The earlier layers of the ALEXNET are fine-tuned to coincide with the new dataset instead of training the entire network. During the fine-tuning process the fully connected layer named as (fc8) is replaced with a new layer (A single layer neural network) having the same number of outputs as the number of classes of the new dataset. While the softmax layers which outputs the probability of the predicted label is removed since the expected output is not a probability distribution but class labels. The final classification output layer is responsible for classifying the new dataset and then predicts the resultant output of the new dataset.

Transfer Learning and Retaining the Model

The following steps were carried out during transfer training process

Specify the dataset for the training and testing images: The training and testing images are the extracted images. The size of the training data required by the ALEXNET model is 227 by 227 RGB image. Therefore, since the input is grayscale, it is converted to RGB image by replicating the single channel to obtain a 3-channel RGB image

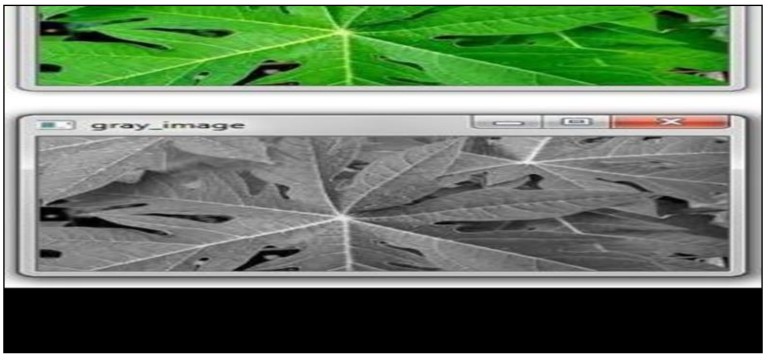


Fig 2: RGB to Grayscale conversion of a Leaf

Identification of the Output

In this work the main goal of the identifier is to compare the representation of plant leaf image with those of the training set templates, and determine the categories to which each extracted image belongs, the fully connected layer on the ALEXNET model identifies the output of the 1000 object classes of the ImageNet data repository, however, seems there are only two labels to be classified in this work, a the single layer neural network is a binary classifier used to identify the predicted class of either a healthy leaf and non–healthy leaf.

Testing of the Developed Scheme on the KSUSTA Dataset

During testing the developed scheme, the following process were carried out

1. **Load the Pre-Processed Image**

The image which have been pre- treated using image processing tools and resized to 227 by 227 which is the desired input size of the ALEXNET model serves as the input to the developed scheme

2. **Perform the Operation in Methodology 3b -3j**

The basic operations which is detailed in methodology 3 is applied to the pre-processed image, these operations are said to be the main functionality of the developed system.

3. **Display 5 Samples of Test Image with Their Predicted Labels**

The 6 randomly selected test images with their predicted label are displayed as depicted in Figure 3

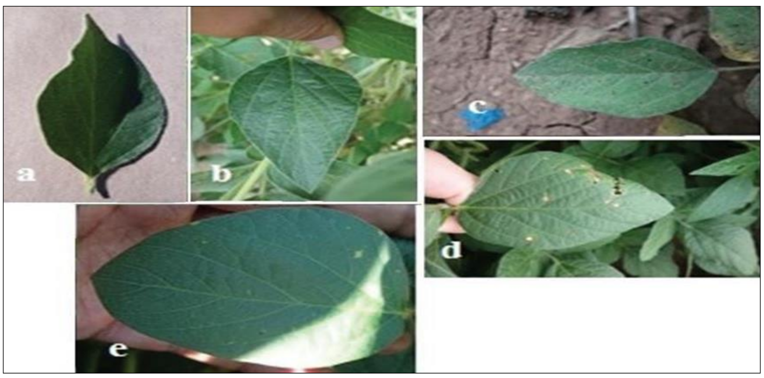


Fig 3: Healthy Leaves Images

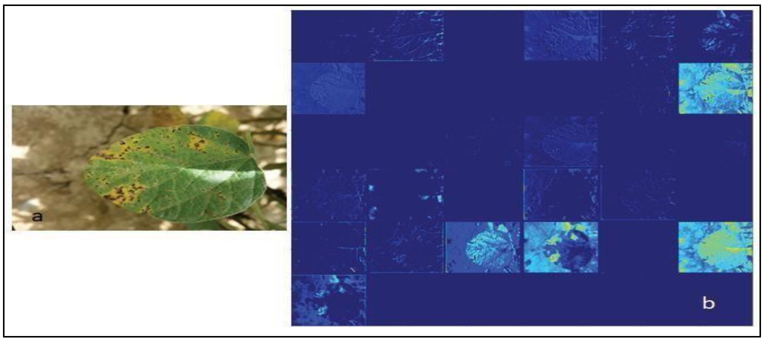


Fig 4: RGB and Converted HIS Image of unhealthy leaf

Result and Discussion

The results obtained from testing the developed scheme are presented and discussed in this chapter. In this research, the developed scheme was tested and evaluated using the developed KSUSTA dataset.

a. Grayscale Conversion of Images for Developed Ksusta Dataset

The acquired images of KSUSTA dataset were converted to grayscale images using equation 2 in order to reduce the processing time of the algorithm. Sample results of the gray conversion of test images from the datasets are presented in Figure 5 The operation eliminated all the color information of the image (chrominance) leaving only the luminance. The significance of this operation is that lesser time is required to process the 8-bit gray channel image than the 24-bit RGB channel.

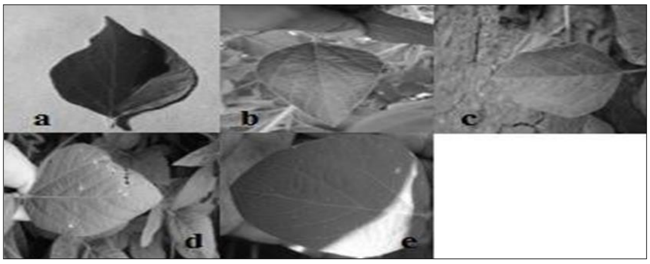


Fig 5: Grayscale Converted Image

b. Analysis of the Developed Plant Leaf Disease Identification Scheme

The testing of the developed algorithm was carried out on 50 randomly selected images of bitter leaves and spinach leaves obtained from the KSUSTA dataset captured under clear conditions and comparison carried out against the existing scheme of Kapilya *et al.,* (2019) [7].

Identification Performance on the Dataset

To determine the identification performance, it is considered that the plant leaf is correctly identified as either healthy leaf or non-healthy leaf as shown in Figures 6 to 7. The result obtained from the dataset is as presented in Table.

Table 2: Result of Identification Rate

Dataset	No of Correctly Identified Images	Developed Scheme (%)	Existing Scheme (%)
KSUSTA	49	98	92

The identification result presented in Table shows that the developed scheme achieved a higher identification rate on the test images than the existing scheme. It is evident that the KSUSTA dataset achieved the highest identification rate as a result of its standardized dataset containing less noise.

c. Failed Identification

The experimental results presented in Table 2, shows that the plant leaves were not correctly identified in some of the images. The failed identifications, as depicted in Figure 6, were mainly as a result of the salt and paper noise present in the images, such as reflections, deteriorating state of the plant leaves, etc. which were not completely dealt with during the pre- processing stage or when the plant leaves were not clearly captured or when the distance between the camera and the leaf is very close.

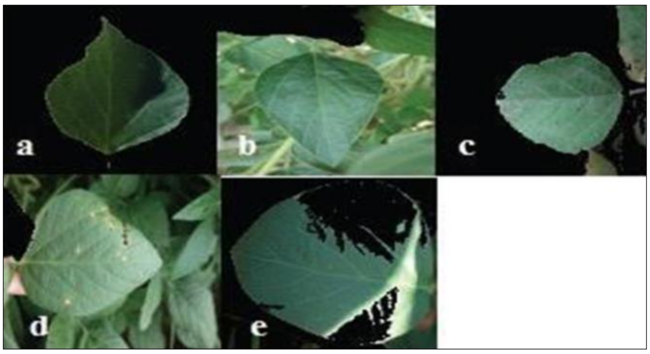
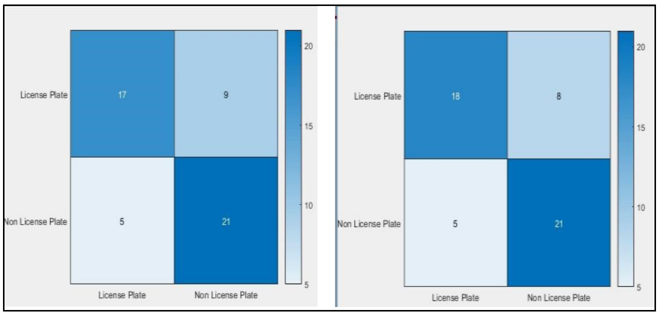


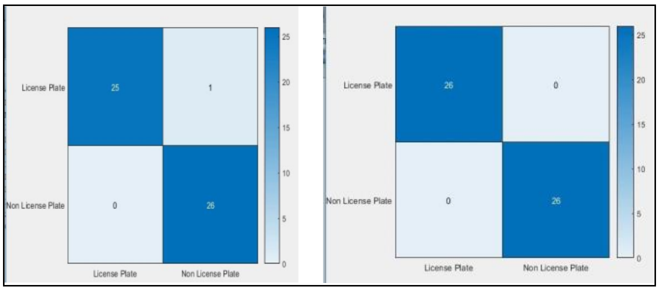
Fig 6: Leaves Image taken in uncontrolled environment/background

d. Confusion Matrix of the Identifier over the Test Set

The result of confusion matrix over the test image are presented in Figure 7. The confusion matrix is generated for both the developed model and the existing scheme.



(a) Confusion Matrix Result of the Existing Scheme



(b) Confusion Matrix Result of the Developed Scheme

Fig 7: Confusion Matrix of the Identifier over the Test

Considering Figure 7 it can be observed that the confusion matrix derived from the developed scheme achieved a better classification task than that of the existing scheme which uses feature descriptor techniques (color silence features) for its feature representation.

e. Evaluating the Precision, Recall, and Identification Accuracy of the Scheme

To evaluate the precision, recall and classification accuracy the confusion matrix result obtained from the test images depicted in Figure 4.3 was used. The matrix consists of the true and false positive and negative prediction for the actual and predicted labels. The confusion matrix derived from the Figure 4.3 are summarized in Tables 3 and 4.. Each of the process were carried out on the dataset (KSUSTA Dataset images), using the number of test images (126). The true and false values obtained from the dataset are also presented.

Table 3: Precision and Recall Rate using the Existing Scheme on the Dataset

Dataset	TP	TN	FP	FN	Precision (%)	Recall (%)	Accuracy (%)
Ksusta	23	22	4	3	97.91	98.29	97.61

From the confusion matrix presented in Table 3, it is observed that using the existing scheme of Kapliya *et al*., (2019) on the KSUSTA dataset obtained a higher precision, recall and accuracy values. This is because the algorithm generalizes well on KSUSTA dataset as a result of the standardized dataset, which results in the minimized training error.

Table 4: Precision and Recall Rate using the Developed Scheme on the Dataset (%)

Dataset	TP	TN	FP	FN	Precision (%)	Recall (%)	Accuracy
Ksusta	23	22	3	3	97.91	98.91	99.97

The results presented in Table 4 shows that the developed scheme obtained higher precision, recall and accuracy rates when compared with the existing scheme. This can be attributed to the utilization of deep learning approach of transfer learning in the developed scheme.

Summary of Research Findings

1. The testing of the developed algorithm was carried out on 50 randomly selected images of bitter leaves and spinach leaves obtained from the KSUSTA dataset captured under clear conditions and comparison carried out against the existing scheme. ii. ii. The identification result presented in Table 2, shows that the developed scheme achieved a higher identification rate on the test images than the existing scheme.
2. It is evident that the KSUSTA dataset achieved the highest identification rate as result of its standardized dataset containing less noise. iv. iv. The algorithm generalizes well on KSUSTA dataset as a result of standardized dataset, which results in the minimized training error.
3. The result presented in table 4, shows that the developed scheme obtained higher precision, recall, and accuracy rates when compared with the existing scheme.

Conclusion

This research work developed a plant leaves disease identification scheme that is capable of detecting and identifying healthy and non-healthy plant leaves from a given image. KSUSTA dataset containing 126 images of vehicle captured under different environmental conditions was developed to validate the performance of the scheme.

The developed scheme was based on current image processing and computer vision techniques, to accurately detect and identify the healthy and non-healthy plant leaves from a given image of the plant leaf with less false positive prediction.

The algorithm was tested on the developed dataset KSUSTA dataset. The experimental result shows that the developed scheme outperformed the existing one with a large margin.

References

1. Bagde S, Patil S, Patil P. Artificial neural network-based plant leaf disease detection. International Journal of Computer Science Mob Comput,2015:4(4):900–905.
2. Pantazi XE, Moshou D, Tamouridou AA. Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers, Computers and Electronics in Agriculture,2019:156:96–104.
3. Atabay. Convolutional Neural Network, feature extraction. 2016 2nd International Conference on Computer Engineering and Applications,2016:20102nd(June):197-201. https://doi.org/10.1001/ICCEA.2010
4. Han *et al*. Image de-noising in digital image processing International Conference on Computer Engineering and Applications, ICCEA,2010:2(June):179-195. https://doi.org/10/1211/ICCEA.2010
5. Adnan *et al*. Plant Disease Identification Algorithm using CNN and Remedy Diagnosis International Journal of Computer Vision,2019:62(3):93-112.
6. Aravindhan *et al*. Plant Disease Identification and Classification System. 2019 International Conference on Machine Learning and Cybernetics (IEEE Cat No.07EX963), 2019, 113-170.
7. Kapilya G, Rosline NG, Dhanasekaran D. Classification and Functional Analysis of Major Plant Disease using Various Classifiers in Leaf Images. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, 2019, 9(2).
8. Kim *et al*. Grape Fruit Peel Disease Identification Using Color Texture. 5733©, 2019, 1-27. https://doi.org/10.1009/TIP/2019.32275