ISSN 2228-9860 eISSN 1906-9642 CODEN: ITJEA8

International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies

http://TuEngr.com

Early Plant Disease Detection Using Gray-level Co-occurrence Method with Voting Classification Techniques

Alaa O. Khadidos[1*]

[1] *Information Systems Department, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, SAUDI ARABIA.*

**Corresponding Author (Email aokhadidos@kau.edu.sa).*

Paper ID: 12A13H

Volume 12 Issue 13

Received 23 June 2021
Received in revised form 26 September 2021
Accepted 07 October 2021
Available online 14 October 2021

Keywords:
Computer Vision Systems; Agriculture 4.0; Smart agriculture; Precision agriculture; Digital agriculture; Color image segmentation; Voting Classification

Abstract

Early detection of plant disease is a primary challenge in smart agriculture. Image processing can be used for detecting plant disease. When it comes to detecting plant disease, a variety of algorithms are built around these four stages. The performance of earlier designed algorithms is computed with regard to different parameters such as accuracy, recall, etc. In this paper, we propose a machine learning approach that will process images captured from an IoT camera-based approach that periodically sends photos. The proposed approach uses a voting classifier for determining if a plan is healthy or not. The voting classifier was compared against the SVM and provided 26% better accuracy and precision and 27% better recall.

Disciplinary: Plant Science and Digital Image Processing.

Cite This Article:

Khadidos, A. O. (2021). Early Plant Disease Detection Using Gray-level Co-occurrence Method with Voting Classification Techniques. *International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies, 12*(13), 12A13H, 1-15. http://TUENGR.COM/V12/12A13H.pdf DOI: 10.14456/ITJEMAST.2021.260

1 Introduction

The issue of successfully protecting plants is directly related to the issues of climate change and sustainable agriculture. The results of many pieces of research show that climate change may modify stages and the scales of pathogen growth. It can also alter hot resistance causing physiological variations of host-pathogen relations. A fact that makes the situation more complicated is that the global rate of disease spread is simpler in the current scenario than ever before. Novel infections can occur in areas where they were earlier unknown and, naturally, where local expertise is not available to fight them [1]. The use of pesticides by inexperienced people can lead to the development of long-standing opposition to pathogens, gravely decreasing their capability to retaliate [2]. An important pillar of precision agriculture is the accurate and timely detection of plant infections. Preventing redundant wastage of financial and other resources contributes significantly to obtaining a healthy yield, by dealing with the issue of the long-standing pathogen resistance development, and mitigating the adverse effects of global warming. The proper and earlier disease detection, particularly with regard to timely prevention has been made even more important in this changing environment. The plant pathologies are detected using different methods. Some disorders have no symptoms, or the effect is too late to be effective, necessitating a more in-depth examination. However, the majority of diseases cause some sort of visual manifestation; therefore, naked-eye inspection by a trained practitioner is a popular method for detecting plant disease. A plant pathologist must have good observational skills for recognizing the symptoms so that the plant diseases could be diagnosed accurately. Alterations in symptoms represented by diseased plants can initiate an inappropriate diagnosis because incompetent horticulturists and hobbyists may face more challenges determining it than a trained plant pathologist [3]. A computer-aided system designed to facilitate the identification of plant diseases based on the view and visual signs of plants will significantly assist hobbyists in the planting process as well as qualified practitioners as a confirmation system of disease diagnosis [4].

Advances in computer vision provide an incentive to innovate and improve precision agricultural conservation practices, as well as to widen the demand for precision agriculture computer vision applications [5]. Color analysis and threshold are two popular digital image processing schemes used to diagnose and identify plant diseases. Image processing-based plant disease detection entails several phases, including image collection, preprocessing, segmentation, feature extraction, and classification [6]. Figure 1 depicts the overall mechanism of detecting plant diseases.

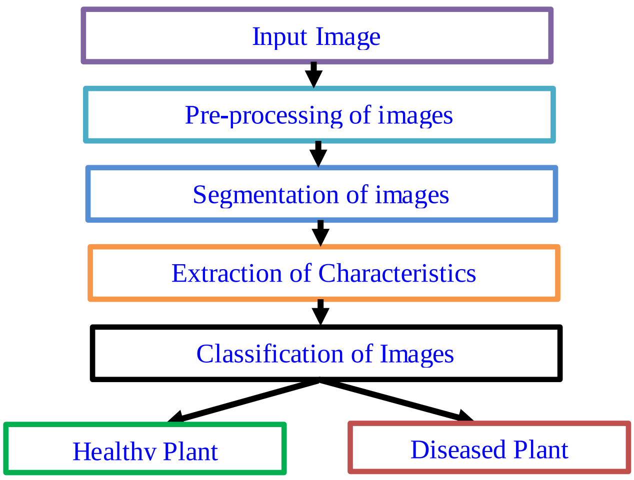

Figure 1: Image-based plant disease detection.

All steps including image processing-based plant disease detection are

1.1 Image Collections

To create a powerful detection model, images of plants are collected in a variety of biological situations. The collection contains a variety of photos with varying resolutions. Plant photos are captured using a variety of instruments, including cell phones, tablets, and regular RGB cameras. Lighting conditions at the time of image capture, atmosphere, and geographic location are all factors that influence dataset gathering. The photos were taken at different stages of the plant's development.

1.2 Pre-processing of Image

The pre-processing image aims to improve the visual quality of plant images [7]. Image pre-processing can have a significant positive impact on the efficiency of feature extraction and the outcomes of image analysis. In this stage, various tasks such as glamour elimination, image intensity stabilization, and artifact removal, etc. are carried out. The pre-processing of the image improves the image data before the computational processing of images [8]. For the reduction of noise from photographs or other artifacts, various preprocessing methods are employed. Image cropping is used to delete unwanted image sections and acquire the requisite portion of the leaf image. For image smoothing, this procedure also uses a smoothing filter. The image-enhancement method improves image contrast [9].

1.3 Segmentation of Images

Segmentation of images is a critical step in the extraction of features and the detection of plant diseases in photographs [9]. The most crucial task in the complex environment is the segmentation of images to localize and detect diseased plant leaves.

As a result, image segmentation is concerned with distinguishing symptom information from background information [10]. An image is decomposed into several non-overlapping, meaningful, and similar nature of the region in this method. The infectious area of plant leaves is of particular relevance when it comes to infections. The essential principle step in recognizing the illness image and the type of the disease is to segment the leaf disease image. Image segmentation has a direct effect on successive image processing and even regulates its success or failure. It is not possible to ignore the threshold in image processing.

1.4 Extraction of Characteristics

Extraction of features is a critical stage in detecting plant diseases. Many problems have arisen when harvesting functionality for the identification of plant diseases [11]. Image properties such as textures, structure, color, and motion-related attributes are critical for disease feature extraction [12]. The accurate classification of plant disease depends on the features of the leaf to a great extent. For the extraction of insightful features, Hu moments and Haralick texture features are usually used.

1.5 Classification of Image

Picture classification is the process of taking an input and determining a class or a probability that it belongs to a specific class. Classification techniques are similar to detection techniques in that they aim to identify and label the pathology that affects the plant rather than simply trying to find a single ailment among a multitude of diseases and symptoms. Classification approaches, like quantization, usually begin with a segmentation step, followed by the extraction of several types of features that will be fed into a classifier model of some sort [13]. The techniques in the following sections are divided into categories based on the categorization method used.

2 Literature Review

Marzouf et al. [14] proposed a mechanism for identifying plant illnesses based on DL (Deep Learning) systems and ANN (artificial neural network). In addition to the ResNet, this approach used CNN (convolutional neural network) to detect plant illnesses in the early stages. The researchers used an updated data set that included photos of healthy and diseased leaves. The photos might be classified as diseased or normal using this method. Finally, Anaconda 2019.10 was used to compare the proposed strategy to others. The results showed that the proposed approach outperformed the existing model in detecting plant illnesses [15,16].

CNN (convolutional neural network) was created by Ferentinos et al. [17] to detect diseases in plants. Clear images of plant leaves were used in these models. To identify the infection, deep learning algorithms were used to classify these images as normal and infected. To train these models, researchers used a publically available database including 87,848 images. Twenty-five different plants were represented in this database. The testing of multiple models was done in order to achieve a 99.53% success rate in plant disease identification. This model could be tweaked to aid in the identification of integrated plant infection in real-time crop growth conditions. There is still room for precision to be improved to optimal levels.

Using the CNN and LVQ algorithms, Sardogan et al. [18] devised a method for identifying and classifying diseases in tomato plant leaves. The attributes were extracted, and categorization was done automatically using a CNN model. Three RGB-component-based channels were used to apply the filters. The convolution part's output feature vector was used to train the network using LVQ (Learning Vector Quantization). Experiments showed that the proposed method was flexible in detecting the four different types of tomato leaf diseases.

Cap et al. [19] developed a leaf localization technique for detecting plant diseases. For this, photos of leaves acquired on-location with a high-resolution camera were used. A deep learning strategy was employed in conjunction with the recommended approach. This research resulted in a simple and accurate system for detecting leaf area. This approach was very comparable to other disease diagnosis mechanisms that were accessible. The F1 score for the suggested technique was 0.78. Almost every healthy leaf photograph was used in this project. The recommended techniques would be investigated and evaluated in a real-time scenario with numerous sick leaves in the future. In real-time circumstances, the recommended procedures were not used.

Militante et al. [20] developed a method for identifying illnesses in a wide range of plant species, including tomato apple, grapes, maize and potato. The DL (deep learning) system was trained using a dataset of more than 30000 photos of healthy and diseased plant leaves. The absence or presence of illnesses in plants was discovered and recognized using this method. The developed system has a 96.5% accuracy in detecting the plant and a 100 percent accuracy in recognizing the type of plant and disease that happened in the plant.

Apple Leaf Disease Dataset (ALDD) was created by Jiang et al. [21] to detect diseases in apple plant leaves. Images from laboratories and complicated backdrops were used to build this data set. This study proposed a new apple leaf disease detection model based on this dataset.

Deep convolution neural network (DCNN) models were used in this model. In addition, by starting with the GoogleNet Inception module and including the Rainbow concatenation [22], a new deep CNN (convolution neural network model) was created. INAR-SSD [23] was the name given to this model. The primary goal of this approach was to improve multi-level infection object identification and less infectious item identification performance. On the generated data set, the recommended model had a detection accuracy of 78.80 percent map, according to the results. This model also diagnosed diseases at a fast rate of 23.13 frames per second. The results showed that the recommended model correctly identified illnesses in the apple plant at an early stage. Precision and speed could be enhanced [24,25], but this was not taken into account in this study.

Zhang et al. [26] proposed a new Internet of Things-based plant sick leaf segmentation and detection technique (Internet of things). Super-pixel, K-mean, and pyramid of histograms of orientation gradients (PHOG) approaches were all found to be appropriate. Using super-pixel clustering, the sick leaf image was first separated into several compressed super-pixels. The segmentation of the lesion image was then performed using K means clustering. This procedure removed all super-pixels from the image [27]. Finally, the PHOG properties were extracted using three color elements from each fractional (segmented) lesion image and its grayscale version. The integration of four PHOG descriptors was done in the form of a vector in this case. On the two datasets of plant infected leaf pictures, several tests were conducted. The suggested technique was found to be extremely effective in the tests [28]. This research presents a real-time method for segmenting damaged leaf images and detecting leaf infections. To evaluate the proposed strategy, only small data sets containing one or two disorders were used.

An unsupervised feature learning approach using a convolutional autoencoder was developed by Pardede et al. [29] to detect plant illnesses. This approach did not require handmade attributes because the network was capable of learning how to produce discriminative qualities.

This technique was carried out without supervision, and it was not necessary to label the data. To diagnose plant diseases automatically, the autoencoder's output was used as input to SVM-based classifiers. When compared to a typical autoencoder with more hidden layers, the established algorithm performed better.

Singh et al. [30] described an image segmentation technique for automatically detecting and classifying plant leaf diseases. Various plant disease detection and classification techniques were also examined. The image was segmented using a GA (genetic algorithm) in this study. The use of image segmentation in illness identification was crucial. The recommended algorithm was put to the test on ten different species of plants. Furthermore, the infections of these plants were exploited as a means of detection. The proposed method produced optimal results with minimal computation. These findings demonstrated the effectiveness of the suggested method for detecting and classifying plant leaf diseases. This program could also detect plant illnesses in their early stages, which was even another advantage.

Tetila et al. [13] analyzed different network weights so that the infection in soybean leaves could be detected robotically. These weights were implemented to the different leaf images of the soybean plant. These images were directly collected from a small and cheap UAV (unmanned aerial vehicle). The evaluation of four deep neural network models was carried out for achieving a high accuracy level. For this purpose, several metrics for fine-tuning (FT) and transfer learning were used in this work for the training of these models. To eliminate the issue of overfitting, the training of the network was carried out using data augmentation and abandon. The recommended approach used the SLIC method for segmenting the images of plant leaves captured from the high altitude. A dataset used in this work was generated from real flight researches. The testing of this dataset was performed using a computer vision tool. The achieved outcomes revealed that fine-tuned metrics could efficiently enhance detection precision. The proposed approach was tested only for simple datasets including only one or two diseases.

Following are the various research gaps of the literature survey.

1) Existing plant disease identification methods are focused on segmentation. The segmentation strategies are incapable of identifying the type of disease, which has an impact on the model's results.
2) In certain circumstances, the execution also falls short of delivering accurate results. More fine-tuning is required.
3) There are only a few infections that have been covered. As a result, the scope of the project must be expanded to include more diseases.
4) The techniques which are designed in the previous work use the single classification models. Due to the single-use of the classification model accuracy is low for plant disease detection.
5) To improve accuracy for the plant disease detection technique of feature extraction needs to be applied with the hybrid classification models.

A new approach for automated identification and classification of plant leaf diseases based on hybrid classification models has been suggested to fill these research holes.

The benefits of the suggested algorithm are

1. The intended approach employs hybrid classification models to increase the precision of plant disease identification.
2. The use of estimators for automated cluster center initialization, eliminates the need for user feedback during segmentation.

3. The proposed approach is completely automated, while current approaches require user feedback to choose the right segmentation of the input image.

Image processing is a technique for handling visual data in the form of pixels. Owing to the complexity of the data used; detecting plant diseases is a big difficulty in image processing. The solution to the plant disease detection problem lies in the fundamental steps of the image process. Image input, pre-processing, segmentation, area of interest collection, feature extraction, and classification are among these processes. Textural feature analysis is a technique that may be used to examine several types of textural information in an input image. The implementation of the classification technique to determine the disease type from the input image is the final stage. The type of disease that can be detected from an input image is determined by the image, textural features, and classification algorithm. The chief inspiration of this research work is to accurately detect the disease type from the input image. The standard approach implements linear SVM for the detection of diseases. The linear SVM can simultaneously detect two diseases which in turn affect the efficiency of the system. As a result, there is a need for an effective method that can forecast more than two diseases at the same time without compromising the performance of the classifier model. The identification of plant diseases becomes more effective as the input image is correctly identified. A larger number of diseases should be used to increase the effectiveness of the plant disease identification framework.

The primary goals of this work are

- To study and investigate a variety of plant disease identification methods,
- Develop a voting classification system for identifying plant diseases,
- To implement the proposed method and its comparison with standard methods in the context of accuracy precision and recall.

3 Materials and Methods

Plant disease detection refers to the technique of detecting the diseased component of the plant's input leaf image [32]. The scheme initiated in this work for detecting plant diseases consists of many steps. All these steps have been defined in the following:

Pre-processing: As input, this step takes an image dataset. The photos in the dataset were gathered from a trustworthy source. This research makes use of a publicly available plant village dataset. The official website for the plant village gives information about plant and disease types. Images of potato leaves make up the collected dataset. The overall dataset is branched into three sections. The first section includes healthy leaves, the next one includes leaves the images of early blight disease and the last section includes images showing late blight disease. The collected input images are converted to greyscale to make the subsequent processing easy.

Segmentation: The segmentation method is concerned with dividing a digitized image into many sections. The chef's concept of segmentation is to identify objects or derive details from images. This step makes the image analysis process easy. Image segmentation is used to identify the area of interest and the bounding line of images. All pixel in an image is labelled. Every pixel with the same labeling has different features. This dissertation employs K-means clustering to segment images of plant leaves. The key impression of K-means is that it divides samples into distinct clusters depending on size. The closer the two points are, the more compact and independent clusters they will receive as the closing target. The best value of k which is used as input is 3. The image is segmented in accordance with the value of K. Then, the required part is selected from the diseased part of the input leaf.

Feature Extraction: The region of interest (ROI) is the output of image segmentation**.** The main goal of the feature extraction phase is to remove features from the area of interest. Thus, feature extraction is the method of removing a series of values from an image known as features. The features provide a variety of detail about the image that can be used for further analysis. The identification of plant diseases is dependent on a variety of factors, including colors, shape, morphology, and color coherence vector**.** There are various methods for extracting features from the image. A disease detection model can be designed using these features. The most popular feature extraction methods are GLCM, color co-occurrence process; also this could extend to the spatial grey-level dependence matrix, in addition to the histogram-based feature extraction. The GLCM method is a mathematical technique that is for classifying texture features.

Classification of Data: The construction of a classifier model is the final stage in the detection of plant diseases. This process divides the whole dataset into subsets of training and testing. The proportion of the training subset will be more than the testing subset. The implemented classifier model takes input as a training and test set. The division of the complete dataset is carried out in the ratio of 70:30. The 70 percent represents the training set and 30 percent denotes the test set for the disease detection.

Logistic regression is a statistical technique for classifying data into binary categories. The outcome or target variable has a binary nature. It computes the likelihood of an event occurring. Compared to the other supervised classification techniques, like kernel SVM or ensemble methods, logistic regression is reasonably fast and simple. It doesn't necessitate function scaling. For each observation, logistic regression assigns a probability score. Multinomial logistic regression is a logistic regression extension that provides native support for problems with multiple classes. MLR estimates the probabilities lie for the various consequences of a categorically distributed dependent variable by using a combination of independent variables from both classes (e.g., binary, ordinal, continuous). MLR estimates group membership using log odds ratios rather than percentages and an iterative maximum likelihood technique rather than a least-squares strategy to balance the final model. The MLR classifier is best suited for both classification and regression tasks.

The Naive Bayes algorithm is a classification algorithm that uses the Bayes theorem to make decisions. The Naive Bayes Classifier is a simple but efficient classification algorithm that aids in the creation of models capable of making fast predictions. It is a probabilistic classifier, which means it can estimate based on the likelihood of an object and can handle both continuous and discrete data. It is presumed that the occurrence of one function has no bearing on the occurrence of others. NB will converge more quickly than discriminative models such as logistic regression. When compared to the other Algorithms, NB performs well in Multi-class predictions and it can be used for both binary and multi-class classifications.

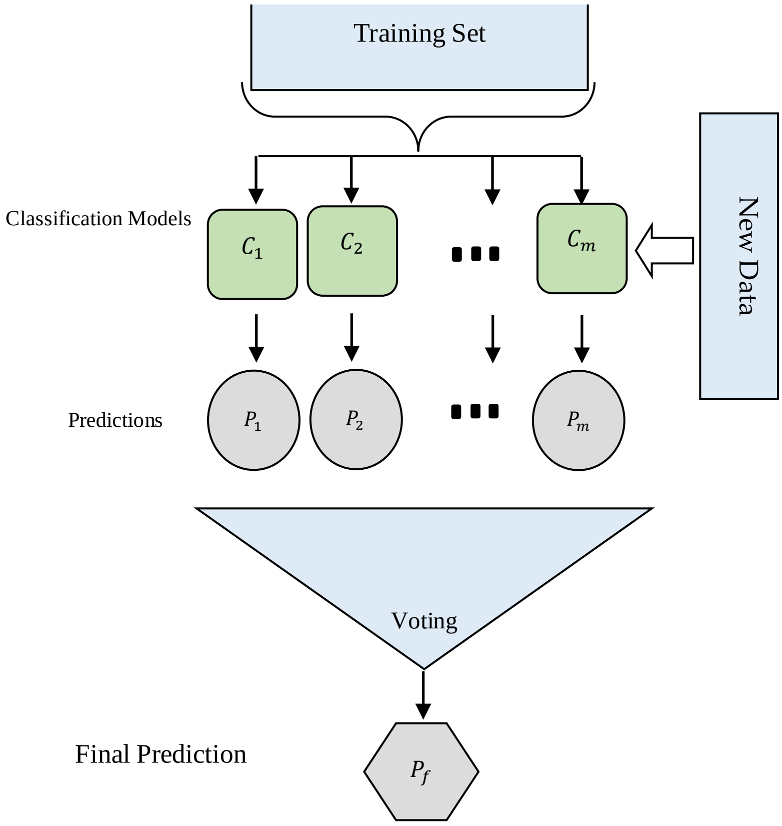

Figure 2: Proposed methodology.

The RF algorithm is a simple machine learning approach that is quick and versatile. This algorithm is made up of several tree predictors. This algorithm almost always yields excellent results. Its performance can't be enhanced easily. This technique can handle a wide range of data formats, including numerical, binary, and nominal information. Several trees are used to create a random forest classifier. These trees are grouped together to provide enough and accurate information. Both classification and regression perform well with the RF method. Classification is a crucial problem in machine learning. It incorporates decision trees and hyperparameters that are similar to those found in bagging classifiers. The fact that random trees overlap in this approach is RF and can be easily examined. Seven random trees, for example, provide information on a variable. Four of these trees are in agreement, while the other three are in disagreement. The majority voting method is used to build the machine learning model. The findings from the random subset of characteristics in the data sets are obtained with more accuracy in the RF.

The output of logistic regression, random forest, and Naive Bayes feeds as input to a voting classifier which can vote between three classifiers and generate ultimate prediction results. As are shown in Figures 2 and 3.

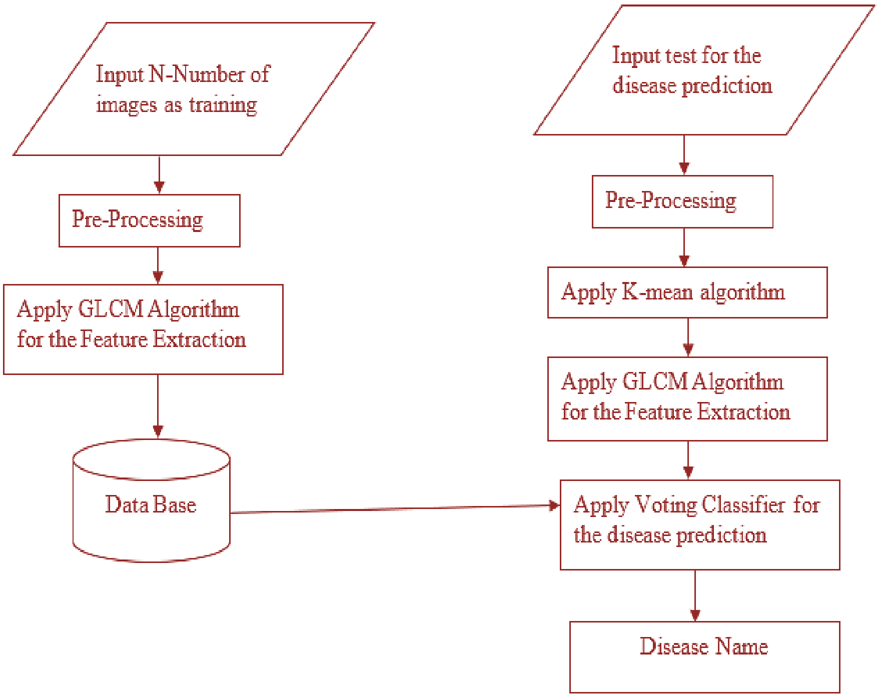

Figure 3: Proposed methodology.

4 Results and Discussion

4.1 Dataset Description

The suggested system's trials are carried out using the plant village dataset. The plant village is an open plate where you may get knowledge on plants and diseases.

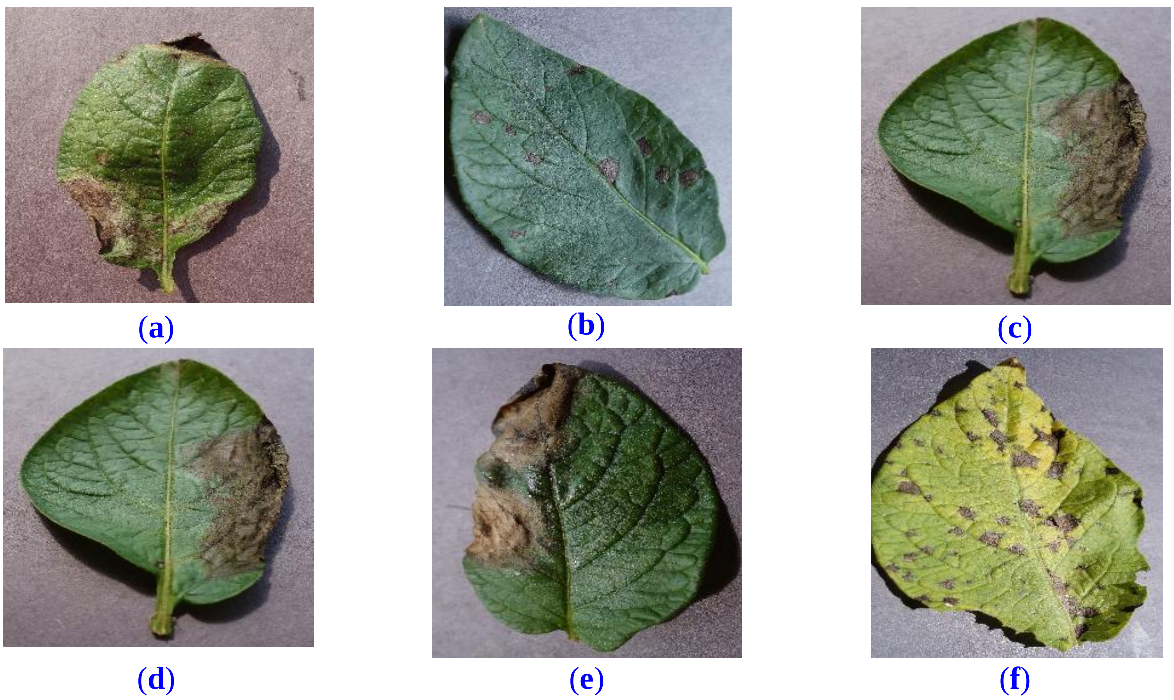

Figure 4: Input images.

Figure 4 represents a plant image that is utilized as input for detecting the disease of plants. This picture was obtained using a database. Pre-processing, feature extraction, and classification are some of the stages in this process.

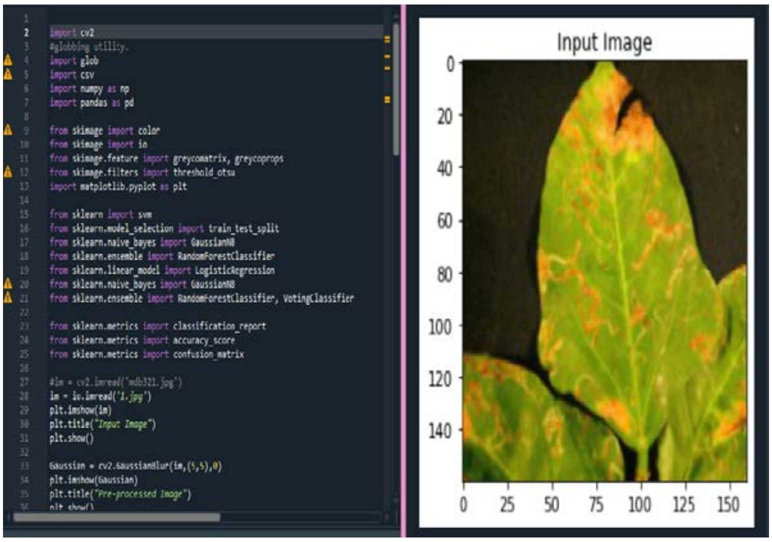

Figure 5: Plant disease detection image.

Figure 5 represents a plant image that is utilized as input for detecting the disease of plants. This picture was obtained using a database. Pre-processing, feature extraction, and classification are some of the stages in this process.

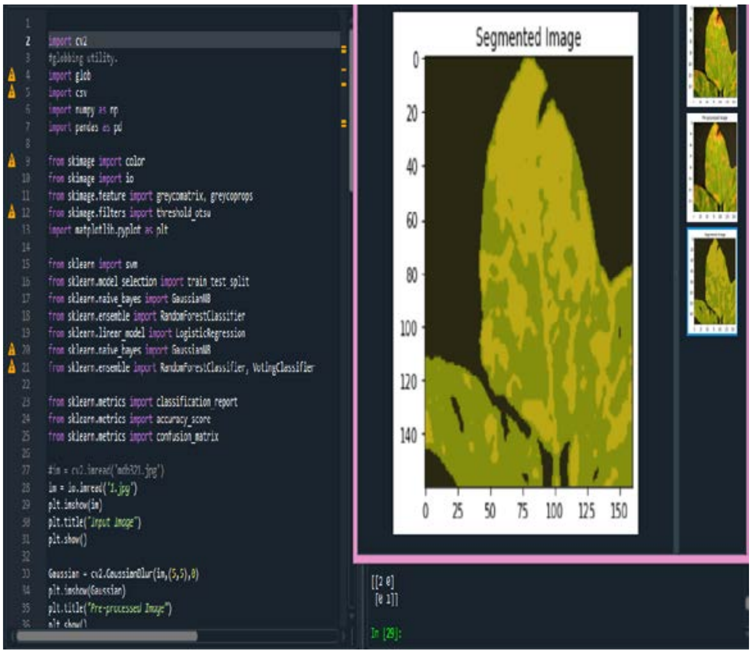

Figure 6: Image segmentation.

Figure 6 shows a particular region of interest that is selected from all clusters. Two major segmentation algorithms are threshold and region-based segmentation. The K-Means algorithm is implemented as Region-based segmentation to segment the image. The amount of segments defines many segments.

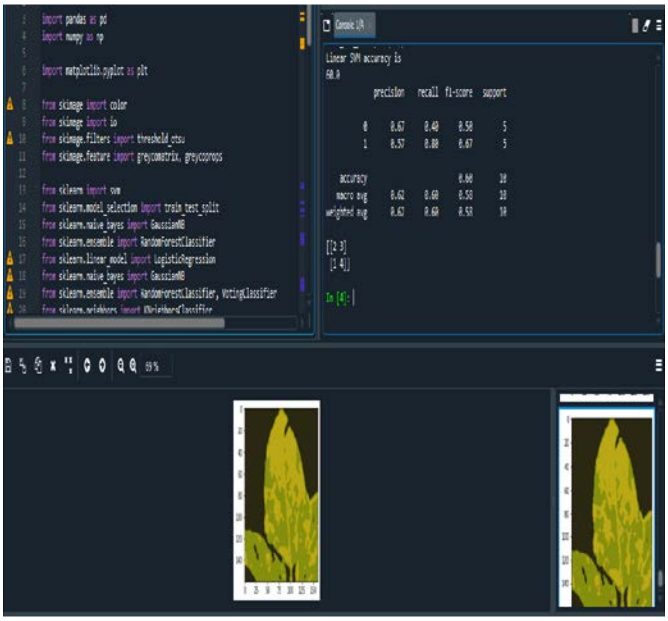

Figure 7: Implement linear SVM classifier.

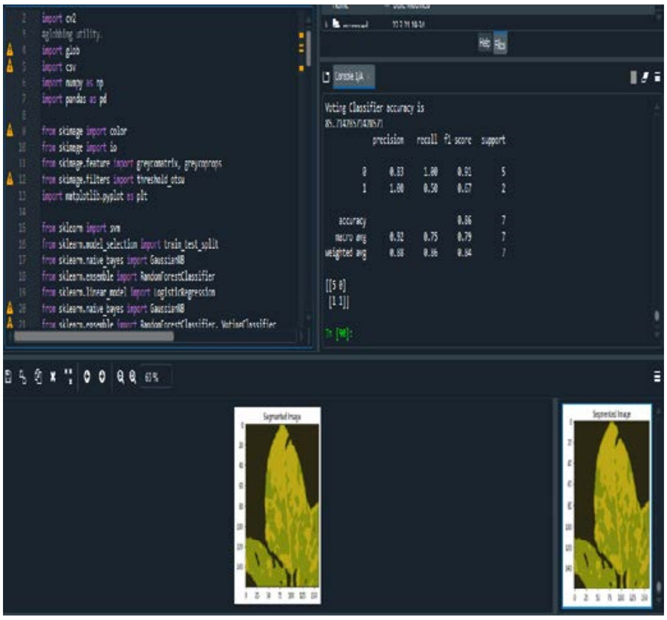

Figure 8: Implement voting classifier.

Figure 7 depicts the implementation of the Linear SVM classification algorithm for predicting the disease of the plant. Figure 8 illustrates the voting classification algorithm which is utilized to predict the plant disease.

4.2 Result Analysis

4.2.1 Accuracy

The accuracy is defined as the proportion of correctly classified samples to the total number of samples available for a program$i$. The mathematical representation of this parameter is expressed as

$$\mathbf{A_i = \frac{t}{n} \cdot 100} \qquad (1).$$

In this, t depicts the numbers of samples that are correctly classified and n denotes the number of sample cases.

4.2.2 Execution Time

It is the difference between the end time of an algorithm and its initiation time.

Execution time = algorithm's end time minus the algorithm's start time (2).

4.2.3 Precision

Precision measures the proportion of correctly categorized instances among all positive instances. It is the ratio of positive instances of the overall number of positive instances.

Precision= TP/(TP+FP) (3).

4.2.4 Recall

In the case of imbalanced literacy, recall is commonly used to assess minority class coverage. The recall is calculated by taking the sum of real positive instances and dividing it by the overall number of positive instances.

$$\text{Recall} = TP/(TP+FN) \quad (4).$$

Table 1 shows how the Linear SVM Classifier and the Voting Classifier Algorithm are used to compare the accuracy of input photos. Percentages are used to measure accuracy. In terms of precision, recall, and accuracy for predicting plant disease, the voting classifier strategy outperformed the others.

Table 1: Performance analysis comparison.

Parameters	SVM Classifier (%)	Voting Classifier (%)
Accuracy	60	86
Precision	62	88
Recall	59	86

5 Conclusion

The identification of diseases from plant leaves is the primary goal of this research. Preprocessing, segmentation, attribute extraction, and classification are the four stages involved in plant disease detection models. All approaches based on digital image processing use a digital camera to capture the digital images. Using image processing algorithms on images, the desired results are obtained. For the extraction of textural features, the existing method employs the GLCM algorithm. For segmenting input photos, this study uses k means clustering. Instead of using a Linear SVM classifier, the described technique divides the data into many classes using a voting classifier. For assessing the success of the implemented algorithm, this work takes into account three assessment parameters such as accuracy, precision, and recall. The obtained results show a significant increase in accuracy and a reduction in FPR (False Positive Rate) of up to 10% when comparing the proposed algorithm to the current algorithm.

The futuristic perspectives are that the ensemble classification method can be implemented shortly for improving the presented strategy and the comparison between the proposed and various standard classifier models is possible for making the plant disease detection process more accurate.

6 Availability of Data and Material

Data can be made available by contacting the corresponding author.

7 Acknowledgements

This project was funded by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah, under grant No. J-1440-611-161. The author, therefore, gratefully acknowledges the DSR technical and financial supports.

8 References

[1] Jayme Garcia Arnal Barbedo, "Plant disease identification from individual lesions and spots using deep learning", Biosystems Engineering, Issue 8, pp. 96-107, 2019.

[2] Saradhambal. G, Dhivya. R, Latha.S, R.Rajesh, “Plant Disease Detection and its SOLUTION USING IMAGE CLASSIFICATION”, International Conference on Advanced Computing & Communication Systems (ICACCS), Vol. 119, pp. 879-884, 2018.

[3] Sujatha R, Y Sravan Kumar and Garine Uma Akhil, “Leaf disease detection using image processing”, Journal of Chemical and Pharmaceutical Sciences, Vol.10, Issue 1, 2017.

[4] Nilam Bhise, Shreya Kathet, Mast. Sagar Jaiswar, Amarja Adgaonkar, "Plant Disease Detection using Machine Learning", International Research Journal of Engineering & Technology, Volume 07, Issue 07, July 2020

[5] V Suresh, D Gopinath, M Hemavarthini, K Jayanthan, Mohana Krishnan, “Plant Disease Detection using Image Processing”, International Journal of Engineering Research Technology, Vol. 9, Issue 03, 2020.

[6] R. Manavalan. "Automatic identification of diseases in grains crops through computational approaches: A review", Computers and Electronics in Agriculture, Vol.178, November 2020.

[7] Pallavi. S. Marathe, “Plant Disease Detection using Digital Image Processing and GSM”, International Journal of Engineering Science and Computing, pp. 10513-15, 2017.

[8] Zhongqi Lin, Shaomin Mu, Feng Huang, Khattak Abdul Mateen, Minjuan Wang, WanlinGao, JingdunJia, “A Unified Matrix-Based Convolutional Neural Network for Fine-Grained Image Classification of Wheat Leaf Diseases”, IEEE Access, Vol. 7, 2019.

[9] Abhisha Mano, Swaminathan Anand. "Method of multi-region tumour segmentation in brain MRI images using grid-based segmentation and weighted bee swarm optimisation", IET Image Processing, 2020.

[10] Monishanker Halder, Ananya Sarkar, Habibullah Bahar, “Plant Disease Detection by Image Processing: A Literature Review”, SDRP Journal of Food Science & Technology, Vol.3 Issue-6, 2019.

[11] Simranjeet kaur, Geetanjali Babbar, Gagandeep, “Image Processing and Classification, A Method for Plant Disease Detection”, International Journal of Innovative Technology & Exploring Engineering, Vol.8, Issue 9, 2019.

[12] Yan Guo, Jin Zhang, Chengxin Yin, Xiaonan Hu, Yu Zou, Zhipeng Xue, Wei Wang. "Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming", Discrete Dynamics in Nature and Society, 2020

[13] Everton Castelão Tetila, Bruno Brandoli Machado, Gabriel Kirsten Menezes, Adair da Silva Oliveira, Marco Alvarez, Willian Paraguassu Amorim, Nícolas Alessandro de Souza Belete, Gercina Gonçalves da Silva, Hemerson Pistori, “Automatic Recognition of Soybean Leaf Diseases Using UAV Images and Deep Convolutional Neural Networks”, IEEE Geoscience and Remote Sensing Letters, Vol.17, Issue 5, pp. 903-907, 2020

[14] Fatma Marzougui, Mohamed Elleuch, Monji Kherallah, “A Deep CNN Approach for Plant Disease Detection”, 21st International Arab Conference on Information Technology (ACIT), 2020

[15] Robert G. de Luna, Elmer P. Dadios, Argel A. Bandala, “Automated Image Capturing System for Deep Learn-ing-based Tomato Plant Leaf Disease Detection and Recognition”, TENCON, 2018

[16] Adedamola Adedoja, Pius Adewale Owolawi, Temitope Mapayi, “Deep Learning Based on NASNet for Plant Disease Recognition Using Leave Images”, International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD), 2019

[17] Konstantinos P. Ferentinos, “Deep learning models for plant disease detection and diagnosis”, Computers and Electronics in Agriculture, Vol.145, pp. 311-318, 2018

[18] Melike Sardogan, Adem Tuncer, Yunus Ozen, “Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm”, 3rd International Conference on Computer Science and Engineering (UBMK), 2018

[19] HuuQuan Cap, Katsumasa Suwa, Erika Fujita, Satoshi Kagiwada, Hiroyuki Uga, Hitoshi Iyatomi, “A deep learning approach for on-site plant leaf detection”, IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA), 2018

[20] Sammy V. Militante, Bobby D. Gerardo, Nanette V. Dionisio, “Plant Leaf Detection and Disease Recognition using Deep Learning”, IEEE Eurasia Conference on IoT, Communication and Engineering (ECICE), 2019

[21] Jiang, Peng, Yuehan Chen, Bin Liu, Dongjian He, Chunquan Liang. "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks." IEEE, 2019

[22] Khadidos, Alaa O., Adil O. Khadidos, Fazal Qudus Khan, Georgios Tsaramirsis, and Awais Ahmad. "Bayer image demosaicking and denoising based on specialized networks using deep learning." Multimedia Systems, Vol.27, Issue 4, pp. 807-819, 2021

[23] Anwar Rifa’I, Deni Mahdiana, “Image Processing for Diagnosis Rice Plant Diseases Using the Fuzzy System”, International Conference on Computer Science and Its Application in Agriculture (ICOSICA), 2020

[24] Chandan Kumar Singh1, Dr. Sandeep B. Patil2, Dr. Om Prakash Sahu, "Implementation of Plant Leaf Diseases Detection and Classification using Image Processing Techniques", International Research Journal of Engineering and Technology (IRJET), Vol.07, Issue 07, 2020

[25] Paramasivam Alagumariappan, Najumnissa Jamal Dewan, Gughan Narasimhan Muthukrishnan, Bhaskar K. BojjiRaju, Ramzan Ali Arshad Bilal and Vijayalakshmi Sankaran, “Intelligent Plant Disease Identification System Using Machine Learning”, Engineering Proceedings, 2020

[26] Shanwen Zhang, Haoxiang Wang, Wenzhun Huang, Zhuhong You, “Plant diseased leaf segmentation and recognition by fusion of superpixel, K-means and PHOG”, Optik, Vol.157, pp. 866-872, 2018

[27] Marwan Adnan Jasim, Jamal Mustafa AL-Tuwaijari, “Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques”, International Conference on Computer Science and Software Engineering (CSASE), 2020

[28] Mercelin Francis, C. Deisy, “Disease Detection and Classification in Agricultural Plants Using Convolutional Neural Networks — A Visual Understanding”, 2019, 6th International Conference on Signal Processing and Integrated Networks (SPIN), 2019

[29] Hilman F. Pardede, Endang Suryawati, Rika Sustika, Vicky Zilvan, “Unsupervised Convolutional Autoencoder-Based Feature Learning for Automatic Detection of Plant Diseases”, International Conference on Computer, Control, Informatics and its Applications (IC3INA), 2018

[30] Vijai Singh, A. K. Misra, “Detection of plant leaf diseases using image segmentation and soft computing techniques”, Information Processing in Agriculture, Vol.4, Issue 1, pp. 41-49, 2017.

Dr. Alaa O. Khadidos received a B.S. degree from King Abdulaziz University, Jeddah, Saudi Arabia, an M.Sc. from the University of Birmingham, Birmingham, U.K., and a Ph.D. from the University of Warwick, Coventry, U.K. His research interests encompass the areas of Computer Vision, Machine Learning, Optimization, Security and, Image Segmentation, Medical Image Processing, Biomedical MRI, Edge Detection, Feature Extraction, X-ray Imaging, Biomedical Ultrasonics, Cancer, Computerised Tomography, Gradient Methods, Minimisation, nucleus, Ultrasonic Imaging.