International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-9 Issue-4, November 2020

Potato Leaf Disease Diagnosis and Detection System Based on Convolution Neural Network

Samer I. Mohamed

Abstract*—For decades, agriculture has been an essential food source. According to related statics, over 60% of the total earth population mainly depend on agriculture's sources for their primary feed. Unfortunately, one of the disaster problems that affect badly on agriculture production is plant diseases. There are about 25% of agriculture production lost annually because of plant diseases. Late and Early Blight diseases are one of the most destructive diseases that infect potato crop. Although, the late and inaccurate detection of plant diseases increases the losing percentage for the crop. The main approach of our proposed system is to detect early the plant diseases to decrease the plant's production losses by using a diagnosis and detection system based on the Convolution Neural Network (CNN). We used CNN to extract the diseases features from the input images of the supported training dataset for classification purposes. For model training, 1700 of potato leaf images were used, then the testing process is done by using approximately 300 images and 100 images for fine tuning and parameters calibration against any biased data. Our proposed CNN architecture archives 98.2% accuracy, which is higher compared with other approaches run on the same dataset.

***Keywords*: Plant Disease Detection, Plant Disease Diagnosing, Plant Disease Classification, Deep Learning, Convolution Neural Network (CNN).**

I. INTRODUCTION

A plant disease is the change that affects or modifies its vital functions. It is mainly caused by bacteria, fungi, microscopic animals or viruses, and has a strong impact on agricultural yields. The main objective from the proposed system is to help in solving one of the most significant problems that face Egypt's economy and cause environmental problems. As the world depends on agriculture before any evaluation until now, there are around 60% of the earth's population depends on agriculture as the primary source of food. According to Food and Agriculture Organization (FAO), the world population is on continuous growth, the food source from agriculture must also increase 70% to cover this increase. However, there are about 25% of agriculture production losses due to the plant diseases that harm the different crops, and this percentage is equivalent to the food consumption of 600 million people. Leaf diseases in plants cause most of the food production and economic losses. Potato is one of the important crops locally (in Egypt) and globally as it used for local consumption and exportation. There are around 8961 thousand acres planted, 215 thousand acres of it cultivated with potato, producing around 2.2 million tons of potato with average 11.3 tons per acre, which makes Egypt as the largest potato producer in Africa [2]. However, that is not enough for future population need according to [3] the Egyptian consumption of potatoes increasing to 115.3% within the last 13 years. One of the proposed solutions to control this production loss was to detect the disease that infects the plant at early stages and learn how to stop or avoid them. There are different reasons behind this loss in crops as the absence of enough knowledge about plant diseases and human errors or limitation for diseases diagnosing. Controlling and early detecting will reduce crops losses. Most of potato diseases have visual symptoms and sensitive to environmental changes. One of the most common potato diseases is Early Bligh (EB) and Late Blight (LB), which have visual symptoms. The traditional way used to detect and diagnose plant disease is using eye observation by experts, which is not very accurate, expensive, and need a long time for a large area [4]. There are a variety of other approaches used for automatic detection of plants leaf diseases. Some of them used the basic machine learning techniques with image processing, while others used the deep learning techniques for object detection tasks. In [5], a multi-layer perceptron method was utilized for automatic detecting of three of Phalaenopsis or orchids diseases, and the achieved results for classification is 89.6 %. Early detection of plant disease symptoms is one of the main challenges in protecting crops and increase its productivity. Automatic recognition of plant diseases by image processing represents a promising solution to overcome this problem and reduce the lack of expertise in this field [5]. Deep Learning techniques, including Convolutional Neural Networks (CNN), have emerged as one of the most promising approaches given their ability to learn reliable visual characteristics and features from the image itself, the thing that help in detecting specific symptoms in the plan disease like those appear in the potato Early Blight and Late Blight.

II. LITERATURE REVIEW

In [6] Support vector machine (SVM) method was used for brown and angular leaf spot diseases which threaten cucumber plants, and 83.3% was the accuracy achieved. The authors in [7] utilized Artificial neural networks (ANN) for classification, with K-means for clustering tasks to detect and classify leaves diseases, the resulted classification accuracy is 94.67%.However, most of these approaches based on the feature extractions techniques, which achieved limited accuracy than others, and customized feature extraction techniques need to reconfigure if the plant type changes or the disease change. Recently, Convolutional Neural Network (CNN) achieved significant better results in computer vision tasks, like image classification and object detection. CNN is a multi-layer and a feed-forward neural network with one or more convolutional layer followed with fully connected layers.

Revised Manuscript Received on November 20, 2020.

Associate Prof. Samer I. Mohamed, October University for Modern Sciences and Arts MSA, saibrahim@msa.eun.eg

One of the attractive features of CNNs is that it can automatically extracts features from images for classification purposes through the learning process. Although all these advancements in the disease's detection, accuracy, scalability and operability remain as challenges for wider solutions in many countries suffer from crops production losses.

Complex CNN ReLu and overlapping pooling [14], have become a prevalent feature in new architecture. Such developments have helped to reduce training time and error rate [11]. In 2019, Wu et al., compared ResNet to VGGNet, GoogLeNet, and DenseNet, finding that ResNet produced the best results in classifying grape leaf diseases [16]. In modern research; architectures including AlexNet, LeNet and GoogleNet, are commonly incorporated into the backbone of custom builds [17]. Data set processing is important to a model's performance. Viral, bacterial and fungal infections can be difficult to distinguish, due to sharing an overlap of symptoms. These symptoms can be with measurable difference in color, shape which result as the plant responds to the pathogen [20]. Because of this complexity, it is preferable to use RGB data [10]. This produces clear, noise free images which may take longer than greyscale data to train, but overall are more common for plant disease identification models [22]. Early and accurate diagnosing of LB and EB diseases will prevent the disease from spreading on the potato fields, which decrease the losses and make disease controlling easier than the traditional approaches. For our proposed system, CNN will be utilized for early diagnosing for two of harmful and effective diseases, LB and EB diseases of potatoes through leaf images. The CNN model is designed in the proposed system to achieve high detection accuracy, and flexible with small changes which make the detection process more reliable. The CNN system input is an image of potato leaf in order to check if the leaf is infected or is it healthy and classify disease type. The learning processes done using images dataset contains healthy leaf images and infected leaf images. The diagnosing result as system output shared with the user/farmer to take actions that help with disease management. The objectives of this study are to diagnose the LB and EB diseases at the early stages based on leaf images with high accuracy, Better usability by the farmers and ability to be used on wider scale with different other crops and diseases. Since growers cannot be able to detect early and late blight diseases at its early stages because of limit experience and the hardness of continuous and precision monitoring of field about disease symptoms and the hard to gather the data at large areas this leads to the increase in crop losses, which raise the cost of the crop. The aim of our project is to design sensitive and accurate system that (i) detect and classify the potato leaf diseases based on leaf images from the field ;(ii) disease forecasting or disease warning system for predict the diseases that help farmers to control the plant environment before disease appears; (iii) and real-time monitoring of the weather on the field.

III. THE PROPOSED SYSTEM FOR PLANT DISEASE DIAGNOSES

The detailed block diagram shown in *Fig. 1* consists of three phases the first phase is for data collecting and sending, this phase is mainly responsible for collecting the data from the sensors of (humidity, soil moisture, and temperature, etc.) and images from the digital camera. The sensors will be at the potato's field to get real-time and accurate data from the field not from the weather stations. Microcontrollers collect the data from the sensors through the analog and digital sensors and then send it to the gateway using the nRF24L01 module, which is connected to the Arduino kit. Then the data will go through the gateway will be stored on the storage of the cloud server that constitute phase 2. The cloud storage system contains the data from the plant environment using sensors, forecasting data from weather forecasting platforms using APIs, historical data, and images from the camera. There are many weather forecasting APIs like Yahoo weather or Google weather, the forecasting will be during the next seven days, and this part is called the proactive part. A historical dataset from weather forecasting station in Cairo for the **proactive** functions will be environmental data for five years or more to train the system, and for the **reactive** part, there will use around 3000 images to train the system. Then the frontend phase which interfaces with the end user/farmer with push notifications and dashboard on the overall farm state. The Frontend interface is linked with the actuators or pumps to control the environmental parameters to prevent the perfect conditions for the disease formation.

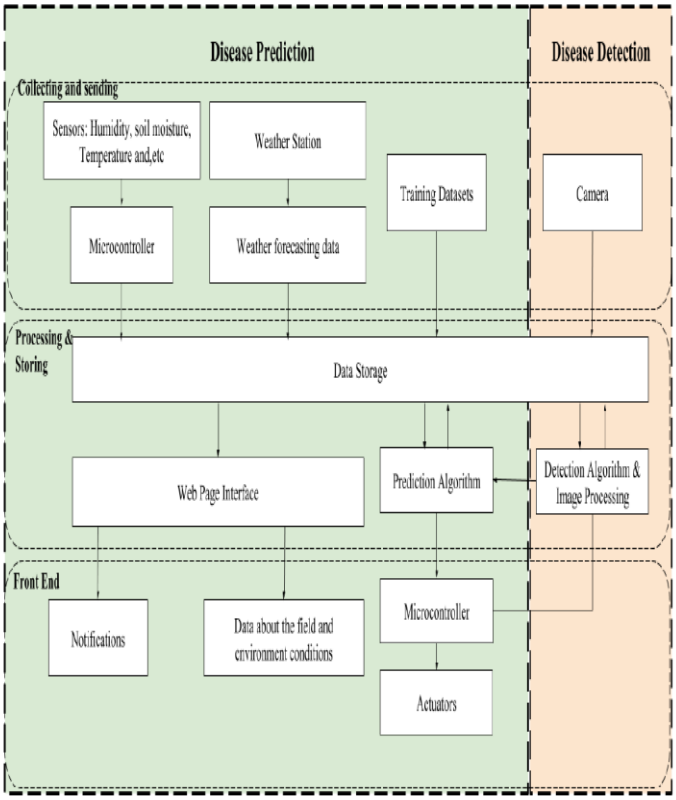

Fig. 1. Proposed Warning system block diagram

In order to achieve the early detection of LB and EB diseases, CNN will be used based on leaf images.

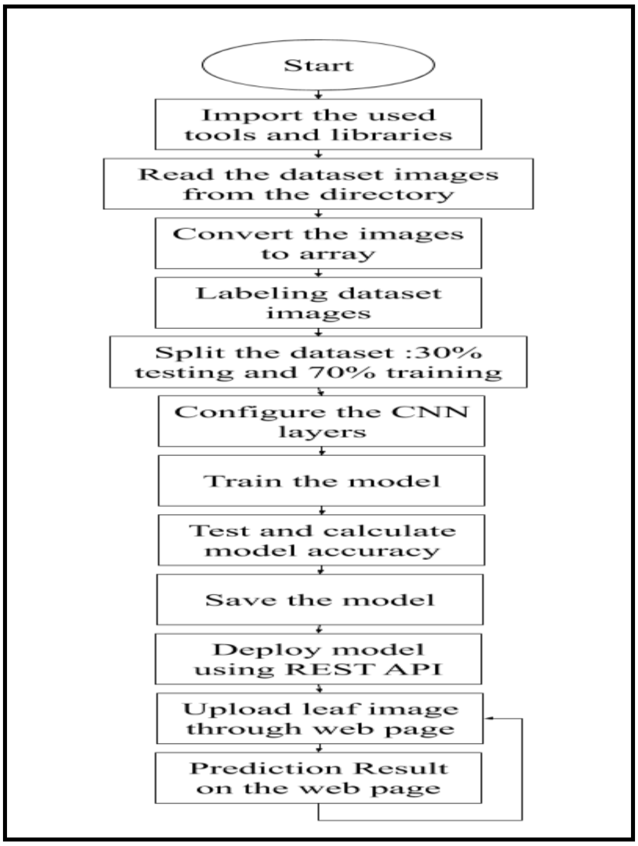

Fig. 2. Proposed Warning system flow chart

First, the model architecture was designed to achieve high accuracy. Second, selecting and preparing the dataset used for the learning processes. Third, train the model using the training dataset. Fourth, with testing or validating the model accuracy using different images. Ended by deploying the model on a web page for using. The flowchart of the system is shown in Fig. 2. Thus, the output system data will have feedback using the image processing results, to increase the accuracy and see if the symptoms are appearing in the leaf of the plant and take the right action. The image will come from the field using a digital camera to be uploaded to the cloud to run the CNN algorithm which results if the plant is healthy or infected and classify the disease and help the farmer to take the proper action based on the disease type.

A. *CNN Model*

The CNN model is used for disease detection and classification, the model includes an Input layer, Convolutional layers, Pooling layers, fully connected layers, and output layer. The model is implemented using python programming language and Tensorflow library, which “is an interface for expressing machine learning algorithms, and an implementation for executing such algorithms” [8]. The used model for the detection system is shown in Table I and Fig. 3.

TABLE I THE CNN MODEL DETAILS

Layer Type	Weight filter Size	Output Shape
Input Layer	-	3×256×256
Convolutional layer 1	7×7	32×250×250
Pooling Layer 1	3×3	32×83×83
Convolutional layer 2	5×5	32×79×79
Pooling Layer 2	2×2	32×39×39
Convolutional layer 3	3×3	64×37×37
Pooling Layer 3	2×2	64×18×18
Convolutional layer 4	3×3	128×16×16
Pooling Layer 4	2×2	128×8×8
Fully Connected Layer 1	-	128
Fully Connected Layer 2	-	128
Output Layer	-	3

The model architecture consists of four convolutional layers. The convolutional layer is a core layer on the CNN, and it is the reason behind the CNN name. The convolutional layer used to extract the feature map form the input image, then creating a new matrix with a smaller size using filters [9]. In the proposed model, the first layer uses a 7×7, which is the largest filter size on the model to represent the general features from the input image. The second convolutional layer uses a 5×5 filter, then in the last two layers,3×3 filter used. The ReLu activation function was used after the matrix convoluted through all convolutional layers. The pooling layer condenses the output matrix from the previous convolutional layer. Max pooling function used at each pooling layer. The first pooling layer filter size is 3×3, and the next pooling layers use 2×2 filters. The dropout function utilized in the model to avoid model overfitting [10]. Lastly, there is one fully connected layer with 128 neurons, activated using ReLu activation function. Lastly, the output layer is activated using the Softmax function, which contains three neurons. For design and implementation of the model architecture, TensorFlow and Keras libraries were used, which based on python programing language. The model architecture was implemented on the cloud-based kernel to achieve high computing power and graphical computing power.

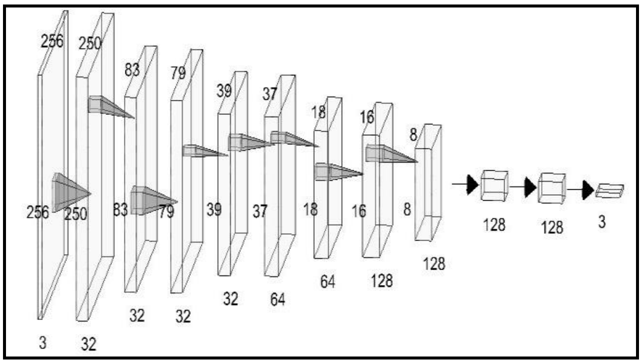

Fig. 3. The CNN model architecture

B. *Dataset*

The dataset used in this study consist of potato leaf images from PlantVillage dataset [11]. The dataset consists of 38 image classes; in this study, only three classes used for classification. The three leaf image classes used for disease classification system are infected by Late Blight, infected by Early Blight, and healthy potato leaves. Fig. 4. shows samples of infected leaves and not infected leaf from the dataset. The used dataset for the proposed system consists of 2150 colored or RGB leaf images with resolution 256×256 pixels. There are 1000 leaf images with LB, 1000 leaf images with EB, and 210 images of an uninfected or healthy leaf.

(a) (b) (c)

Fig. 4. Samples of potato images ;(a) Early Blight (b) Healthy (c) Late Blight

The dataset needed preprocessing and preparing before the training and testing processes start. First, reading the images from the dataset was needed, so the images with the same class were gathered in a single file named by the class name. Second, the images resized to 256 by 256 pixels using the OpenCV library. Third, the read images were converted to arrays because the input layer of the model entered the model as an array. Fourth, the labeling process was done using the Skikit-learn machine learning library, by creating the label of each class based on the file name, which represents the class name of each image. Finally, the dataset split for training and testing.

C. *Testing and Training Method*

In the CNN model, the training process is an essential and core step. In the learning process, the network adapts itself with the input dataset to output the corresponding label. The images dataset split to 70% for training, 20% for testing and 10% for model tuning. The model trained using 70% of the dataset, which is around 1700 images, through 80 epochs. One Epoch means one forward pass of all the training dataset and one reverse pass. After each epoch the testing data enter the model, then validation accuracy of the epoch calculated. Finally, after finishing all epochs the total training accuracy and validation accuracy calculated. The hardware used for model training is a four CPU cores 16 Gigabytes of RAM.

The model coded in Python language. To implement the model there are different libraries used like: "Numpy" to deal with arrays. "Pickle" to save and load the model after training with a simple way for save and load the model. "CV2" or "Opencv2" to deal with images, it is the most popular and has a very helpful documentation. "SKlearn" for labeling which it is suitable for the dataset used. "Keras" for CNN model design, "Keras" is an open-source neural-network library written in Python. It can run on top of "TensorFlow". Keras is used because it was designed to enable fast experimentation with deep neural networks, it focuses on easy to use, modular, and extensible.), "Matplot" for plotting and visualize the data.

To run the algorithm code Kaggle kernels was used because of high computing power and high GPU. Kaggle Kernels technical specification:

- 9 hours of execution time
- 5 Gigabytes of auto-saved disk space
- Gigabytes of temp, scratches disk space
- 4 CPU cores
- 17 Gigabytes of RAM
- 2 CPU cores and 14 Gigabytes of RAM for GPU

D. *Model Deployment*

After the model training, the CNN network wights were saved to be used in different devices and reduce the computing power needed to use the model. The saving and loading of the model done using "Pickle" library. After the model saved, it downloaded on the personal computer with four Gigabytes of RAM and two CPU cores. The model was loaded on the PC, then the model was deployed as API on the webpage, then on the web page the uploaded image was converted as a POST request and the prediction appears on the page using the GET request.

IV. PROPOSED MODEL VALIDATION AND TESTING

To make sure that the proposed CNN model achieves the desired performance accuracy, the model was validated using around 430 leaf images, which are different images than the images used for the training process includes 30 healthy leaf images, 200 infected by LB, and 200 infected by EB For model testing, the process started with testing data entered to the model then followed by step to be classified. The testing data pass into the model every epoch to calculate the validation accuracy. In Fig. 5, the validation and training accuracies through 50 epochs were represented. After finishing from all epochs, the total validation accuracy will be calculated. The total accuracy for the proposed model is 98.2%.

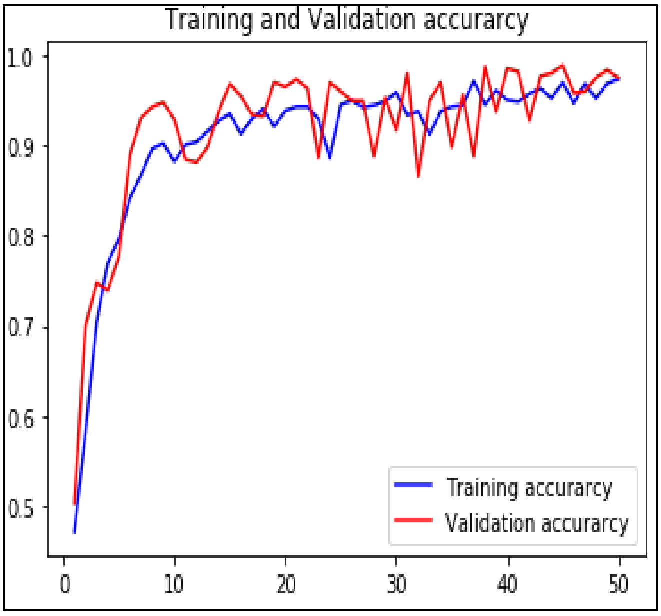

Fig. 5. Plot graph of accuracy on the training and validation datasets over training epochs.

In Table II, a comparison done between different approaches done by [12], [13] and the proposed approach. The First approach proposed by [12] used the SVM method to classify potato leaf images with the same three classes and the same dataset used in this study. In the second system proposed by [13], the dataset used to diagnose LB and EB diseases is formed from the same dataset used in this study besides to other images. Artificial Neural Network (ANN), SVM, and Random Forest (RF) approaches were used. The proposed approach using CNN, achieved higher accuracy than other approaches used for the same diseases.

TABLE II COMPARISON BETWEEN DIFFERENT APPROACHES

Reference	Approach	Accuracy	Dataset
[12]	SVM	95%	PlantVillage
[13]	ANN	92%	PlantVilaage + other images
	SVM	84%	
	RF	79%	
Proposed system	CNN	98%	PlantVillage

From the analysis of the model results, we concluded that Color, shape and texture appear to be important factors in working to extract potato disease features. Color appears to be especially crucial, helping to clearly differentiate similar diseases like EB and LB, by adding an extra dimension of characterization. This explains the importance of RGB data to disease classification tasks. The CNN shows effectiveness in recognizing features. Diversifying the training data to include imagery which has been captured in any uncontrolled environment could stand to strengthen the model immensely. These results signify the importance of developing such resources as part of future research.

V. CONCLUSION

Crop diseases are generally one of the most critical problems that threaten the worlds agricultural, causing large losses in agricultural production of about 25% per year. In this paper, potato leaf diseases diagnosis and detection system are proposed based on the Convolutional Neural Network technology with a customized model architecture. The main aim of the proposed system is to detect early the plant diseases to decrease the plant's production losses due to plan diseases like early and late blight of the potato crops. The model trained and validated using dataset consist of 2210 colored potato leaf images. For model validation, the dataset was split to 70% for training, 20% for testing and 10% for model parameters tuning. The proposed model architecture archives 98.2% accuracy compared with other approaches. The used method is compared with SVM, ANN, and RF techniques using the same dataset where the comparison results shows that our proposed system method outperform the accuracy achieved by the mentioned techniques.

ACKNOWLEDGMENT

This paper and the research behind it would not have been possible without the engagement and support of MSA student Khaled E. Abdallah whom I would like to thank and appreciate all his efforts, insights and expertise that greatly assisted through the course of this research. Finally, it is with true pleasure that I pay my sincere gratitude and acknowledgement for Khaled' contributions to achieve the research objectives as planned.

REFERENCES

1. K. S. Sastry, "Introduction to Plant Virus and Viroid Diseases in the Tropics," *Plant Virus and Viroid Diseases in the Tropics*, pp. 1–10, 2013. W.-K.Chen,*LinearNetworksandSystems*.Belmont, CA, USA:Wadsworth, 1993, pp. 123–135
2. K. A.a., Y. Essa, F. Hashem, and K. Refaie, "*Plant Diseases For Major Crops In Egypt Under Future Climate* Conditions" International Journal of Current Agriculture Science , vol. 6, no. 12, pp. 149–154, Dec. 2016.
3. V. Singh, Varsha, and A. K. Misra, "Detection of unhealthy region of plant leaves using image processing and genetic algorithm," 2015 International Conference on Advances in Computer Engineering and Applications, 2015.
4. K.-Y. Huang, "Application of artificial neural network for detecting Phalaenopsis seedling diseases using color and texture features," Computers and Electronics in Agriculture, vol. 57, no. 1, pp. 3–11, 2007.
5. Z. Jian and Z. Wei, "Support vector machine for recognition of cucumber leaf diseases," 2010 2nd International Conference on Advanced Computer Control, 2010.
6. H. A. Hiary, S. B. Ahmad, M. Reyalat, M. Braik, and Z. Alrahamneh, "Fast and Accurate Detection and Classification of Plant Diseases," International Journal of Computer Applications, vol. 17, no. 1, pp. 31–38, 2011.
7. M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems", arXiv.org, 2019. [Online]. Available: https://arxiv.org/abs/1603.04467. [Accessed: 18- Jun-2019].
8. M. Sardogan, A. Tuncer, and Y. Ozen, "Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm," 2018 3rd International Conference on Computer Science and Engineering (UBMK), 2018.
9. C. Schittenkopf, G. Deco and W. Brauer, "Two Strategies to Avoid Overfitting in Feedforward Networks", Neural Networks, vol. 10, no. 3, pp. 505-516, 1997. Available: 10.1016/s0893-6080(96)00086-x.

10. M. Islam, A. Dinh, K. Wahid, and P. Bhowmik, “Detection of potato diseases using image segmentation and multiclass support vector machine,” 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), 2017.
11. P. Patil, N. Yaligar, and M. S. M, “Comparision of Performance of Classifiers - SVM, RF and ANN in Potato Blight Disease Detection Using Leaf Images,” 2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 2017.
12. W.-S. Kang, S.-S. Hong, Y.-K. Han, K.-R. Kim, S.-G. Kim, and E.-W. Park, “A Web-based Information System for Plant Disease Forecast Based on Weather Data at High Spatial Resolution,” The Plant Pathology Journal, vol. 26, no. 1, pp. 37–48, Jan. 2010.
13. J. Zadoks, “EPIPRE: a Disease and Pest Management System for Winter Wheat Developed in the Netherlands,” EPPO Bulletin, vol. 11, no. 3, pp. 365–369, 1981.
14. M. L. Gleason, K. B. Duttweiler, J. C. Batzer, S. E. Taylor, P. C. Sentelhas, J. E. B. A. Monteiro, and T. J. Gillespie, “Obtaining weather data for input to crop disease-warning systems: leaf wetness duration as a case study,” Scientia Agricola, vol. 65, no. spe, pp. 76–87, 2008.
15. M. Jhuria, A. Kumar, and R. Borse, “Image processing for smart farming: Detection of disease and fruit grading,” 2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013), 2013.
16. “Late blight of potato and tomato,” American Phytopathological Society. [Online]. Available:http://www.apsnet.org/edcenter/intropp/lessons/fungi/oomycetes/pages/lateblight.aspx. [Accessed: 18-Jan-2019].
17. Hughes, D.P., Salathe, M. (2015) “An Open Access Repository of Images on Plant Health to Enable the Development of Mobile Disease Diagnostics”, arXiv:1511.08060.
18. https://greenhawksmedia.net/2015/02/11/potatoes-a-fun-option-for-sunny-gardens/ [visited at 5/1/2018]
19. http://www.omafra.gov.on.ca/IPM/english/tomatoes/diseases-and-disorders/early-blight.html [visited at 5/1/2019]
20. http://www.new-ag.info/en/focus/focusItem.php?a=531 [visited at 5/1/2019]
21. http://www.apsnet.org/edcenter/intropp/lessons/fungi/oomycetes/pages/lateblight.aspx [visited at 5/1/2019]
22. https://en.wikipedia.org/wiki/Sigmoid_function [visited at 5/1/2018]
23. https://ml-cheatsheet.readthedocs.io/en/latest/logistic_regression.html [visited at 5/1/2019]
24. https://stackoverflow.com/questions/12836737/how-to-choose-the-degree-of-a-hypothesis-function [visited at 5/1/2019]
25. https://medium.com/@martinpella/logistic-regression-from-scratch-in-python-124c5636b8ac [visited at 5/1/2019]
26. K.-Y. Huang, “Application of artificial neural network for detecting Phalaenopsis seedling diseases using color and texture features,” Computers and Electronics in Agriculture, vol. 57, no. 1, pp. 3–11, 2007.
27. Z. Jian and Z. Wei, “Support vector machine for recognition of cucumber leaf diseases,” 2010 2nd International Conference on Advanced Computer Control, 2010.
28. D. Wu, Y. Wang, S. Xia, J. Bailey and X. Ma, "Skip Connections Matter: On the Transferability of Adversarial Examples Generated with ResNets", arXiv.org, 2020. [Online]. Available: https://arxiv.org/abs/2002.05990. [Accessed: 10- Apr- 2020].
29. M. Ji, L. Zhang and Q. Wu, "Automatic grape leaf diseases identification via UnitedModel based on multiple convolutional neural networks", Information Processing in Agriculture, 2019. Available: 10.1016/j.inpa.2019.10.003.
30. X. Zhang, Y. Qiao, F. Meng, C. Fan and M. Zhang, "Identification of Maize Leaf Diseases Using Improved Deep Convolutional Neural Networks", IEEE Access, vol. 6, pp. 30370-30377, 2018. Available: 10.1109/access.2018.2844405.
31. C. Buche, S. Wallelign and M. Polceanu, "Soybean Plant Disease Identification Using Convolutional Neural Network", 2018. [Accessed 22 April 2020].
32. Isleib, "Signs and symptoms of plant disease: Is it fungal, viral or bacterial?", MSU Extension, 2012. [Online]. Available: https://www.canr.msu.edu/news/signs_and_symptoms_of_plant_disea se_is_it_fungal_viral_or_bacterial. [Accessed: 11- Apr- 2020].
33. P. Sharma, Y. Berwal and W. Ghai, "Performance analysis of deep learning CNN models for disease detection in plants using image segmentation", Information Processing in Agriculture, 2019. Available: 10.1016/j.inpa.2019.11.001.
34. Padmavathi and K. Thangadurai, "Implementation of RGB and Grayscale Images in Plant Leaves Disease Detection – Comparative Study", Indian Journal of Science and Technology, vol. 9, no. 6, 2016. Available: 10.17485/ijst/2016/v9i6/77739.
35. S. Sankaran, A. Mishra, R. Ehsani and C. Davis, "A review of advanced techniques for detecting plant diseases", Computers and Electronics in Agriculture, vol. 72, no. 1, pp. 1-13, 2010. Available: 10.1016/j.compag.2010.02.007.

AUTHORS PROFILE

Dr. Samer Ibrahim was born in Gharbia, in 1976. He received the B.Sc. degree in computer engineering from the Ain Shams University, Egypt, in 1998, and the M.Sc. and Ph.D. degrees in Computer and system engineering from the computer and systems department, Ain Shams University, Egypt 2005 and 2009, respectively. He obtained his fellowship from Higher Education academy (HEA), UK in 2017. He is currently an Associate professor in MSA. Through his journey, Dr. Samer has many publications, patents researches, and books in international conferences and journals. Dr. Samer is a reviewer for many reputable journals and conference world-wide. He is an associate editor in an international journal of computer science and engineering. He has different roles through this journey not only on the academic level but on the industrial level as well. Dr. Samer has 22+ years of IT industrial experience in many international organizations as consultant and executive manager. Being a PMP certified for 17+ and ITIL certified improved his academic, industrial and practical experience in leading and managing critical industrial projects in different technical domains. Dr. Samer traveled several times to foreign countries which offered better understanding of many cultures from east and west, enhanced his ability to get along with different nationalities and ethnic backgrounds. Through this industrial journey, he led many critical and biggest transformation projects/programs that affected the IT industry worldwide in multinational organization like Hewlett Packard with huge record of success stories/records