Critical Review of Deep Learning Algorithms for Plant Diseases by Leaf Recognition

Article *in* Journal of Contemporary Issues in Business and Government · January 2021

DOI: 10.47750/cibg.2021.27.05.044

Journal of Contemporary Issues in Business and Government Vol. 27, No. 5,2021
https://cibg.org.au/

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

Critical Review of Deep Learning Algorithms for Plant Diseases by Leaf Recognition

M. Jaithoon Bibi[1], Dr. S.Karpagavalli[2] and A. Kalaivani[3]

[1] Research Scholar, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore, &Assistant Professor, Department of Multimedia and Web Technology,
KSG College of Arts and Science, Coimbatore, Tamilnadu, India

[2] Associate Professor and Head, Department of Computer Science,
PSGR Krishnammal College for Women, Coimbatore, Tamilnadu, India

[3] Research Scholar, Department of Computer Science,
PSGR Krishnammal College for Women,Coimbatore, &
Assistant Professor, Department of Computer Technology,
Nallamuthu Gounder Mahalingam College, Pollachi (India)

1 jaithoonchella@gmail.com, 2 karpagavalli@psgrkcw.ac.in, 3 kalaivanivijayan19@gmail.com

ABSTRACT

The identification and classification of the crop leaf diseases plays an essential role in the cultivation. Plants are the livelihood. Peoples depend entirely on crops for the breathing of their daily lives. Thus, suitable crop caring should take place. Most research suggests that the quality of agricultural commodities can be restricted depending on different factors. Crop diseases include microorganisms and pathogens. The leaf diseases not only reduce crop growth, the cultivation is also destroyed. Several researchers have been identified crop leaf diseases using image processing algorithms but it take more time for detection. Therefore, advanced algorithms are required to identify and classify the crop leaf diseases automatically with higher accuracy. There are different deep learning algorithms using crop leaf images developed for automatically detecting the crop leaf diseases in an efficient manner. In this article, a survey on different deep learning algorithms using image processing for detecting and classifying the crop or plant leaf diseases is presented. Also, the merits and demerits of the surveyed algorithms for crop leaves diseases identification are addressed in a tabular form. Finally, a comprehensive analysis is concluded and future directions are suggested to increase the accuracy of leaf diseases classification.

Keywords—Crop pathology, Leaf diseases, Image processing, Deep learning, Disease classification

Journal of Contemporary Issues in Business and Government Vol. 27, No. 5,2021
https://cibg.org.au/

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

I. INTRODUCTION

Cultivation plays a major role to increase the economic system of each country. In this context, plants have become an essential source of energy and a basic part for solving the global warming issue. But, there are many diseases that affect the crops with the possibility to cause economic, social and biological losses. Crop diseases are not only the risk to food security at the global level, but can also have devastating effects for smallholder cultivators whose source of revenue depend on healthy crops. Crop disease contributes 10-16% losses in the global harvesting. According to the Food and Agriculture Organization (FAO) report, world population is expected to reach 9.1 billion in 2050. Thus, agricultural manufacture needs to be increased up to 70% for satisfying the food demands of a gradually increasing population [1].

Alternatively, plentiful utilization of chemicals such as bactericides, fungicides and nematicides for controlling the crop diseases has been causing undesirable effects in the ecosystem. Leaves are crucial since they are the major source of photosynthesis which is how crops feed themselves.Presently, there is a necessity for effective early disease detection methods for preventing the crop diseases to satisfy the food security and sustainability of ecosystem. It is very complex to the cultivators for diagnosing the diseases only with the aid of forecasting. Detection of diseases of crop leaf is a very crucial and challenging process [2]. To overcome this problem, a system has been developed for detecting and classifying the crop leaf disease in agriculture.

Research in agriculture has the key objective towards increasing the food quality and productivity with increased revenue. Cultivators have wide range of varieties for choosing fruit and vegetable crops. Conventional techniques for detection of diseases on various crop is easily exposed eye observation with the support of experts, but this needs continuous forecasting which consumes more time. Simultaneously, cultivators do not have precise solution and facilities due to high cost and time consumption. As a result, advanced computing systems such as deep learning with image processing algorithms [3-4] are used to detect the diseases using infected images of different leaf spots. A large amount of diseases can be appeared on the leaves. So, identification of such disease on a specific crop with their solution is very required.Numerousalgorithms with promising solutionshave been accountedfor detecting the crop pathologiesusing leaves images and preventing crop loss due to diseases. This paper discusses different image processing with deep learning algorithms for crop leaf disease identification and classification using crop leaf images. It also focuses on the merits and limitations of those algorithms and displays them in tabular form.

II. SURVEY ON CROP LEAVES DISEASESIDENTIFICATION AND CLASSIFICATION ALGORITHMS

Sladojevic et al. [5] proposed a novel method by using Deep CNN (DCNN) for classifying the plant diseases. At first, the images of plant's leaves were collected independently for various plant diseases. Then, the collected images were pro-processed to get the Region-Of-Interest (ROI) of plant leaves and augmentation was used for removing the unwanted distortions. After that, the DCNN was trained for classifying the leaf diseases into healthy leaves and diseased leaves.

Journal of Contemporary Issues in Business and Government Vol. 27, No. 5,2021
https://cibg.org.au/
P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

Singh et al. [6] proposed an algorithm for automatically detecting and classifying the plant leaf diseases. At first, pre-processing was applied for eliminating the unwanted distortions from the input leaf inputs. The interested image region was obtained by performing the clipping of the leaf image and the smoothing filter was applied to smooth the image. After that, the green colored pixels were masked by computing the threshold value. Then, the masked cells in the edges were eliminated and the useful regions were segmented using Genetic Algorithm (GA). Further, the obtained segments were used for classifying the leaf diseases.

Cheng et al. [7] proposed a pest detection scheme by using fine-tuning method. In this scheme, CNN and deep residual learning were constructed a framework to detect the agricultural pests diseases using the pest image samples captured from the farmland with complex background.Ferentinos [8] suggested the CNN framework for detecting and diagnosing the plant diseases using leaves images of healthy and diseased plants. In this framework, several leaves images of healthy and diseased plants were used for CNN training and testing.

Sharif et al. [9] proposed a hybrid technique for detecting and classifying the diseases in citrus plants. This technique consists of two processes such as detecting the lesion spot on the citrus fruits and leaves, classifying the citrus diseases. At first, the citrus lesion spots were extracted by an optimized weighted segmentation scheme which is applied on an enhanced input image. Afterwards, color, texture and geometric features were combined in a codebook. Moreover, the optimal features were chosen by using a hybrid feature choice scheme which has Principal Component Analysis (PCA) score, entropy and skewness-based covariance vector. The selected features were given to the Multi-class Support Vector Machine (M-SVM) for final classification of citrus diseases.

Wang & Zhang [10] proposed a technique for segmenting the corn leaf diseases on the basis of Fully CNN (FCNN). Initially, pre-processing and data enhancement were carried out on the obtained images for establishing the training and testing datasets. Then, the training centralized image was given as input to the FCNN and the feature map was upsampled for obtaining the feature map of similar size as the input image. At last, the resolution of the segmented image was reconstructed by the deconvolution process and the segmented outcome was obtained by classifying the upsampled feature map pixel-by-pixel.

Sun et al. [11] proposed a novel image segmentation and classification model on the basis of multiple linear regression that identifies the plant diseases. In this model, an improved histogram segmentation technique was used to automatically compute the threshold values for segmenting the leaf images. Also, the regional growth method and true color image processing were combined to extract the features such as color, textures and shape features. Further, multiple linear regression classifier was applied for identifying the leaf diseases.

Khan et al. [12] proposed an automated system based on Correlation Coefficient and Deep Features (CCDF) for detecting the different fruits diseases. This system consists of infected regions identification, feature extraction and classification processes. At first, contrast of

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

input image was enhanced by using the hybrid method followed by the CC-based segmentation scheme which partitions the infected regions from the background. After that, two deep pre-trained frameworks, namely VGG16 and caffeAlexNet were used for extracting the features of selected diseases. Besides, parallel features fusion process was embedded for combining the extracted features prior to max-pooling process. Moreover, the most discriminant features were chosen by using GA and the final stage of classification was performed by the M-SVM classifier.

Ma et al. [13] proposed a DCNN for performing symptom-wise detection of four cucumber diseases such as anthracnose, downy mildew, powdery mildew, and target leaf spots. Initially, the symptom images were segmented from cucumber leaf images which are captured under field conditions. Then, data augmentation was used for avoiding the overfitting problem and enlarging the datasets formed by the segmented symptom images. Further, the DCNN was trained by using the augmented datasets for classifying the cucumber diseases.

Liang et al. [14] presented a robust image-based Plant Disease Diagnosis and Severity Estimation Network (PD^2SE-Net) by using the residual structure and shuffle units. The main objective of this algorithm was designing the most powerful and practical diagnosis system for estimating the plant disease severity. Also, the data augmentation and visualization of CNNs were used for increasing the accuracy and accelerating the well choice of hyper-parameters during the training process.

Sun et al. [15] proposed a novel algorithm by combining Simple Linear Iterative Cluster (SLIC) with SVM for extracting the tea plant leaf disease saliency map under complex backgrounds. Initially, super-pixel block was obtained by SLIC algorithm, significant point was identified by Harris algorithm and the fuzzy salient region contour was extracted by applying convex hull method. After that, the 4D texture features of super-pixel blocks in salient regions and background regions were extracted. Besides, the classification map was obtained by classifying the super-pixel blocks using the SVM classifier. Finally, the morphological and algebraic functions were executed to restore the classified super-pixel blocks for obtaining the precise saliency map of tea plant leaf disease image.

Dhingra et al. [16] proposed a new fuzzy set extended form neutrosophic logic based image segmentation method for segmenting the ROI of leaf images. The segmented neutrosophic image was discriminated by the fuzzy membership functions such as true, false and intermediate area. Then, the new feature subset using texture, color, histogram and diseases sequence region were obtained on the basis of the segmented regions for detecting the diseased leafs. Further, different classifiers were used to get the final classification.

Yu & Son [17] proposed a novel technique based on the Region-Of-Interest (ROI)-aware DCNN for identifying the apple leaf diseases. At first, two sub-networks such as encoder-decoder network and VGG network were designed in which encoder-decoder network was used for splitting the input images into different regions and VGG network was used for classifying the leaf diseases, accordingly. After that, they were independently trained by the

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

transfer learning with the new training set which has class details in accordance with leaf diseases types and the ground truth images. Further, the predicted ROI feature map was stacked on the top of the input image via a fusion layer for linking two sub-networks and training the linked network in an end-to-end fashion. At last, the stacked feature map was applied to the sub-network for detecting the leaf diseases.

Hang et al. [18] proposed a deep learning-based framework for detecting the plant leaf diseases. In this framework, CNN was integrated into the structure of inception module such as a Squeeze-and-Excitation (SE) module and a global pooling layer for detecting the plant diseases. By using the inception structure, the feature details of the convolutional layer were fused in the multiple scales for increasing the accuracy on the leaf disease dataset. At last, the global average pooling layer was applied instead of the fully connected layer for decreasing the amount of model parameters.

Jadhav et al. [19] proposed an efficient detection of soybean diseaseson the basis of the transfer learning method using pre-trained AlexNet and GoogleNet CNNs. At first, the leaf images were preprocessed and given as input to the pre-trained CNN structure. Then, the last three layers of the GoogleNetstructure were reconfigured and retrained to classify the disease symptoms in the soybean infected leaves.

Dai et al. [20] proposed a new image super-resolution scheme called DATAGAN (Dual-Attention and Topology-Fusion techniques with Generative Adversarial Network) for identifying the crop leaf diseases.Initially, the unclear images were converted into the clear and high-resolution images. Then, the weight sharing method was applied for reducing the amount of parameters and training deeper structures that classifies the crop leaf diseases according to the texture features.

III. COMPARATIVE ANALYSIS

In this section, a comparative analysis of different algorithms for identifying and classifying the crop leaf diseases using leaves images is presented. Table 1 gives the merits and demerits of the algorithms used for crop leaf diseases identification and classification which are studied in above section.

Table 1. Comparison of Different Crop Leaf Identification and Classification Algorithms

Ref. No.	Algorithms	Merits	Demerits	Accuracy
[5]	Pre-processing, Data augmentation and DCNN	Better accuracy.	Pre-processing was not automatically performed.	96.3%
[6]	Pre-processing, Clipping, Smoothing filter, GA-based segmentation	Plant diseases were identified at early stage.	GA was time-consuming and highly expensive for segmenting the ROIs.	97.6%

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

[7]	CNN and Deep residual learning	Highly effective.	Accuracy was degraded while increasing the depth of CNN.	98.67%
[8]	CNN	High accuracy.	Total training time was very high.	99.53%
[9]	Optimized weighted segmentation scheme, Feature extraction and M-SVM	Better accuracy.	Applicable only for small datasets.	95.8%
[10]	Pre-processing, Data enhancement and FCNN	Better segmentation effect and accuracy.	Training time was high since it takes a long time for extracting the input image.	96%
[11]	Improved histogram segmentation, Regional growth method, true color image processing and Multiple linear regression	Simple and automated system.	Less accuracy.	85.99%
[12]	CCDF segmentation, Hybrid method using VGG16 and AlexNet, M-SVM	Improved accuracy.	It needs to extract the significant features for further increasing theaccuracy.	98.6%
[13]	Segmentation, Data augmentation and DCNN	More robust and can identify the diseases at early stages.	Less accuracy.	92.2%
[14]	Data augmentation and PD^2SE-Net	Improved accuracy.	Overfitting problem can occur due to reasonable splitting of classes in the dataset.	98%
[15]	Harris algorithm, Hull method, SLIC and SVM	Higher accuracy.	Computationally expensive.	98.5%
[16]	Novel neutrosophic logic based image segmentation method	Most effective and high accuracy.	It needs to enhance further accuracy by including feature extraction and feature selection processes.	98.4%

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

[17]	Novel ROI-aware DCNN	Less complexity.	Accuracy was not effective.	84.3%
[18]	CNN with SE module and a global average pooling layer	Reduced training time and the number of parameters.	Less accuracy.	91.7%
[19]	Pre-processing, Transfer learning method using pre-trained AlexNet and GoogleNet CNNs	Better efficiency.	It requires high memory consumption.	AlexNet=98.75%; GoogleNet CNN=96.25%
[20]	Pre-processing, Weight sharing method and DATAGAN	Reduced number of network parameters.	The spatial correlation across the series of observations to the part of image should be learned for increasing the accuracy.	90.52%

V. CONCLUSION

Plant diseases cause many harmful effects to agriculture crops by reducing its growth. To identify such diseases, different image processing with deep learning algorithms have been designed in the past few decades. From this perspective, in this article, a survey on recent deep learning algorithms with image processing for crop leaf disease detection and classification is presented in detail. Also, merits and demerits of these algorithms are discussed to suggest the future directions towards increase the leaf disease identification. From this comparative analysis, it is concluded that the DATAGAN achieves the better classification accuracy while using the least amount of parameters for adversarial training. However, this algorithm could be accelerated highly by devising better schemes for coordinating generator and discriminator. Also, the diseases only affected with the part of leaves or whole image. As a result, the spatial correlation across the series of observations to the part of image should be learned. Therefore, it would require further research to solve these issues by improving DATAGAN algorithm based on evolutionary algorithms that learn the spatial correlation across the series of observations and identify the relationship between the set of pests and diseases efficiently.

REFERENCES

[1] Golhani, K., Balasundram, S. K., Vadamalai, G., &Pradhan, B. (2018). A review of neural networks in plant disease detection using hyperspectral data. Information Processing in Agriculture, 5(3), 354-371.

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

[2] Barbedo, J. G. A. (2013). Digital image processing techniques for detecting, quantifying and classifying plant diseases. SpringerPlus, 2(1), 660.

[3] Saleem, M. H., Potgieter, J., &Arif, K. M. (2019). Plant Disease Detection and Classification by Deep Learning. Plants, 8(11), 468.

[4] Mohanty, S. P., Hughes, D. P., &Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in plant science, 7, 1419.

[5] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., &Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience, 2016.

[6] Singh, V., &Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. Information Processing in Agriculture, 4(1), 41-49.

[7] Cheng, X., Zhang, Y., Chen, Y., Wu, Y., &Yue, Y. (2017). Pest identification via deep residual learning in complex background. Computers and Electronics in Agriculture, 141, 351-356.

[8] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311-318.

[9] Sharif, M., Khan, M. A., Iqbal, Z., Azam, M. F., Lali, M. I. U., &Javed, M. Y. (2018). Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection. Computers and Electronics in Agriculture, 150, 220-234.

[10] Wang, Z., & Zhang, S. (2018). Segmentation of Corn Leaf Disease Based on Fully Convolution Neural Network. Academic Journal of Computing & Information Science, 1(1).

[11] Sun, G., Jia, X., &Geng, T. (2018). Plant diseases recognition based on image processing technology. Journal of Electrical and Computer Engineering, 2018.

[12] Khan, M. A., Akram, T., Sharif, M., Awais, M., Javed, K., Ali, H., &Saba, T. (2018). CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features. Computers and Electronics in Agriculture, 155, 220-236.

[13] Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z., & Sun, Z. (2018). A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. Computers and Electronics in Agriculture, 154, 18-24.

[14] Liang, Q., Xiang, S., Hu, Y., Coppola, G., Zhang, D., & Sun, W. (2019). PD2SE-Net: Computer-assisted plant disease diagnosis and severity estimation network. Computers and Electronics in Agriculture, 157, 518-529.

[15] Sun, Y., Jiang, Z., Zhang, L., Dong, W., &Rao, Y. (2019). SLIC_SVM based leaf diseases saliency map extraction of tea plant. Computers and Electronics in Agriculture, 157, 102-109.

[16] Dhingra, G., Kumar, V., & Joshi, H. D. (2019). A novel computer vision based neutrosophic approach for leaf disease identification and classification. Measurement, 135, 782-794.

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

[17] Yu, H. J., & Son, C. H. (2019). Apple leaf disease identification through region-of-interest-aware deep convolutional neural network. arXiv preprint arXiv:1903.10356.

[18] Hang, J., Zhang, D., Chen, P., Zhang, J., & Wang, B. (2019). Classification of Plant Leaf Diseases Based on Improved Convolutional Neural Network. Sensors, 19(19), 4161.

[19] Jadhav, S. B., Udupi, V. R., &Patil, S. B. (2020). Identification of plant diseases using convolutional neural networks. International Journal of Information Technology, 1-10.

[20] Dai, Q., Cheng, X., Qiao, Y., & Zhang, Y. (2020). Crop Leaf Disease Image Super-Resolution and Identification with Dual Attention and Topology Fusion Generative Adversarial Network. IEEE Access, 8, 55724-55735.

[21] Jaithoon Bibi. M., &Karpagavalli, S. (2021).Positional-aware Dual Attention and Topology Fusion GAN for Plant Leaf Disease Image Super-resolution and Classification.LinguisticaAntverpiensia, 2021(3), ISSN :0304-2294 Pg.no:(12-25).

Mrs. M. Jaithoon Bibi, Assistant Professor, KSG College of Arts and Science, Coimbatore. She received her M.Phil in the field of Data Mining from Sri Ramakrishna College of arts and Science for Women, Coimbatore. Doing PhD in the field of Data mining from PSGR Krishnammal College for women, Coimbatore. Her area of interest is data analysis and predictive models to reveal patterns and trends in data from exiting data sources. Her teaching experience is 3 year. She has published 03 research papers in international journals and conferences in the area of data mining. She attended various international level conferences, seminars, workshops and technical symposium.

Dr. S. Karpagavalli, Associate Professor and Head, Department of Computer Science (UG), PSGR Krishnammal College for Women, Coimbatore, has 22 years of teaching experience. She has guided 15 MPhil Scholars and currently guiding 4 PhD Scholars in the areas Data Mining, Machine Learning and speech recognition, also has published 42 research papers in International Journals and IEEE, Elsevier, Springer conference Proceedings. She has been acting as reviewer in reputed journals and authored 7 books. She is a member of Computer Society of India (CSI), International Association of Computer Science and Information Technology (IACSIT), International Association of Engineers (IAENG) and Indian Society for Technical Education (ISTE). She is a recipient of **Best Researcher Award** from Indian Academic Researchers' Association (IARA), and **Nation Builder Award** from IQAC and Rotaract club Coimbatore.She has been recognized guide under Bharathiar University to guide MPhil scholars. She have produced **14 MPhil scholars** and currently guiding 1 MPhil scholar. She have authored a book on **Object Oriented Analysis and Design for Beginners** andprincipal investigator of project **Tamil Speech**

P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

enabled interface for children with learning disabilities funded by GRG Trust in August 2017.

Mrs. A. Kalaivani, Assistant Professor, Department of Computer Technology, NallamuthuGounderMahalingam College, Pollachi. She has 8 years of teaching experience. She has been recognized guide under Bharathiar University to guide M.Phil scholars in the area of Data Mining. She received her M.Phil Degree in the field of Data Mining from SreeSareswathiThyagaraja College of Arts and Science, Pollachi and Doing Ph.D in the field of Data Mining from PSGR Krishnammal College for Women, Coimbatore. Her area of interest is Data analysis and Predictive models to reveal patterns and trends in data from existing data sources. She has published 07 research papers in National, International Journals and 2 National Conferences in the area of Big Data Analytics and Data management. She has attended various National Level Conferences, Technical Symposium, Workshops and Seminars.