Comparison of Crop Disease Detection Methods - An intensive analysis

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ABSTRACT

Farmers already have a diversified portfolio of crops on their farms. And they're also trying to grow more kinds of crops on their farm. Farmers are often responsible for enormous losses because they do not anticipate crop diseases at an early stage. This kind of 'experimental farming' mentality. Learning from past experience has been more costly for them. Therefore, automatic diseases and diseased sections in the leaf images need to be systemized. Leaves together effects on reduction in crop quantity and quality. In the battle against serious threats, detection of diseases of plant leaves is a crucial function precisely. This survey explores in depth different crop diseases and the detection methods.

Keywords

Crop diseases, Image processing, Machine Learning, Prediction, Support Vector Machine.

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Introduction

In underdeveloped nations, such as India, the market is primarily based on agriculture. Due to plant diseases the performance and amount of agricultural products will be reduced. Plant diseases primarily arise from erratic fungi, bacteria and the microorganisms' life cycle. Some plant diseases are not evident in the early stages. It occurs only in the final stage. Agriculture is not only meant to feed rising people, but also a significant energy source and solution to the climate crisis. In order to treat and monitor the disease, plant disease diagnosis is very important in earlier stages. Plant conditions lead to a major production and economic disruption and a decrease both in agricultural products value and in quantity. Monitoring for the identification of diseases has gained greater interest in agriculture. There may also be significant decreases in both the quality and quantity of crops.The central technique acknowledged in training for identification and discovery of plant infections is naked eye surveillance of specialists. This problem involves continuous monitoring and consultation of experts in large fields that are excessively expensive. It is too costly and time-consuming for farmers to travel a long distance in many countries to visit specialists. Farming land can often be much larger and every plant can not be observed by farmers every day. This is a crucial activity for farmers as they also need to pay attention to crop growth for higher yields. The main objective of agricultural diseases and insect pests is to achieve the control of knowledge and IOT collection of diseases and insect pests. The programmed methods used in the prevention of crops are important for accuracy to detect plant infections early. Automatically recognise signs of disease as soon as they appear on plants to detect and identify a rapid method. The detection process includes multiple stages, such as image acquisition, image pre-processing, segmentation, mining and neural network-based classification. Diseases are perceived on the leaves or branches of the vegetable.

Therefore, many efforts are carried out in identifying the crop disease types and analyzing its machine learning detection methods.

The main contribution of this work is

- Categories of crop diseases and roadmap of recent machine learning approaches into disease detection are explained.

- A standard comparison chart of various machine learning approaches of crop disease detection is proposed.

The above-said points clearly distinguish this work from other recent works related to crop disease detection. It gives the detail as broad as earlier works. The organization of paper as follows: Section II brief the crop disease types. Section III describes the proposed comparison chart of machine learning approaches of crop disease detection. Section IV summarizes the current work.

CROP DISEASES AND ITS RECENT STUDY

2.1 Fungal Diseases

Fungal diseases of plants are fungal diseases. Fungi can be single or multicellular; however, they can kill plants in either way by stealing nutrients and destroying tissue. In plants, fungal diseases are the most widespread infection. Fungal infections may be described as signs, such as spots in plant leaves, leaves yellowing, or bird-eye spots in berries. In fact, with certain fungal diseases, the organism itself can be seen as a mould, mildew or spores on the leaves. These can occur on stems or the underside of leaves as growths or malformations. Such overt observations of the disease-causing body are referred to as symptoms of infection.

2.2 Bacterial Diseases

Bacteriums are prokaryotic single-celled species. Bacteria are everywhere and many can help, but in humans and in plants, other bacteria can cause illness. Bacterial signals, since bacteria are microscopic, are often more difficult to detect than fungi. A milky white fluid, known as bacterial ooze, can appear when an infected stem is cut. A bacterial infection is suggested by this. Wet patches on leaves that are oozing bacteria are other signs of water-saken injuries.The lesions gradually enlarge and render the leaves reddish-brown spots as the disease grows. Bacterial infection usually occurs in leaf spots or fruit spots. These veins, as opposed to fungal patches, are also present on the blade. If the spots advance rapidly, parts of the plant spot, wilt and ulteriorly die, it can be recognised as a blight. Bacteria also grow cancers that are sunk in malformed regions on branches or roots. During the season, bacterial cancers can ooze, while fungal cancers can grow fruits.

2.3 Viral Diseases

Viruses are contagious particles that are too small for a light microscope to identify. They invade host cells and hijack host machinery, causing millions of copies of the virus to be produced by the host. There are no signs of viral diseases in plants, because a light microscope does not even reveal viruses.However, the trained eye is able to observe certain signals. A mosaic pattern, yellowed or shrinkled leaves is characteristic of the viral infection.This typical pattern of discoloration is the name of many plant viruses, including the tobacco mosaic virus. Small plant growth is typically widespread in viral infections. The mosaic pattern of coloration in the leaves can also be seen in the fruit. In berries, where discoloration occurs in rings, close to leaves, ring spot signs can also be present.

Modern methods have been used to improve the identification rate and the accuracy of disease detection, such as machine learning and deep learning algorithms. Various experiments have been performed with machine-learning for plant diseases identification and diagnosis, including random forests, artificial neural networks, SVMs, fugitive logic, the K-means algorithm, CN networks, etc. Figure 1 demonstrates the fundamental architecture to detect crop diseases.

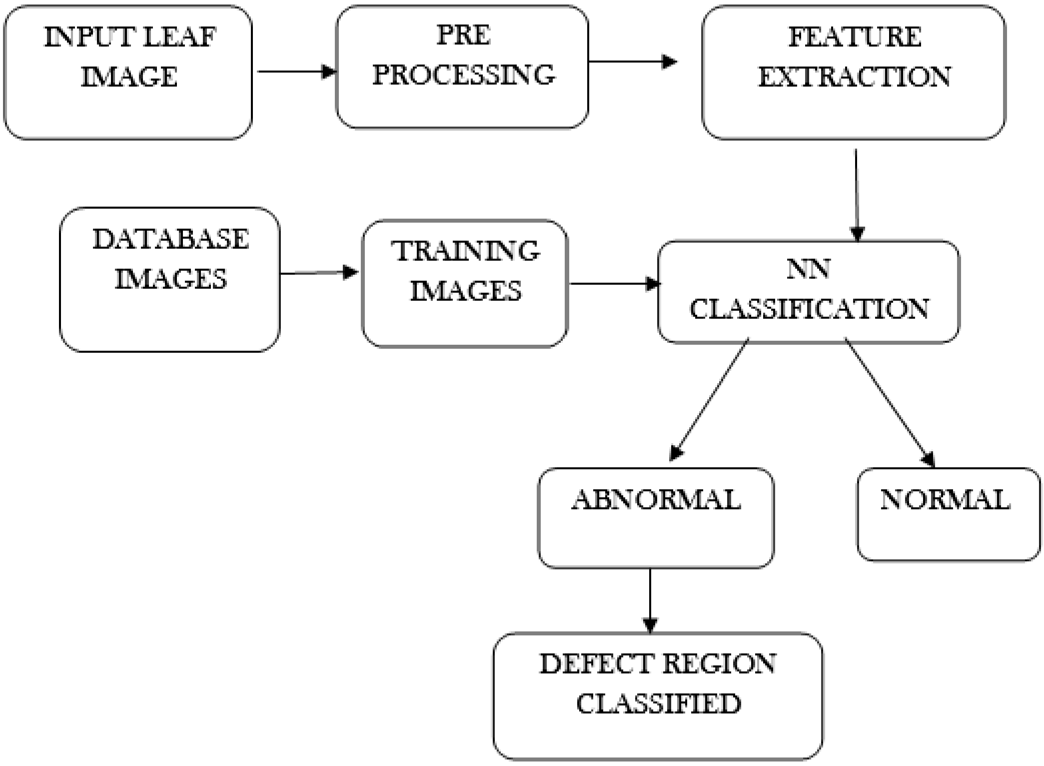

Figure 1. Crop Disease Detection Architecture

According to some research papers, new/modified ML architectures have been introduced to achieve better/transparent plant disease detection. In comparison to AlexNet and VGG, Zhang et al.[2018] presented an improved model GoogLeNet and Cifar-10. Improved versions of these state-of-the-art models give a remarkable 98.9% precision. Liu et al.[2017] , A new DL model was developed to achieve more accurate identification of plant diseases in comparison to SVM, AlexNet, GoogLeNet, ResNet-20 and VGG-16 models. This model achieved 97.62% accuracy in the classification of apple plant diseases. The data collection has also been extended in 13 different directions (90°, 180°, 270° rotation and mirror symmetry, contrast change, sharpness and luminosity). In addition, the whole dataset has also been converted to Gaussian noise and PCA flashes. The dataset choice was also explained with the help of graphs to show how necessary it is to extend the data set. Chen et al.[2019], The new LeafNet CNN model for classifying tea leaf diseases achieved greater precision than the SVM and Multi-Layer Perceptron support systems. The LeafNet model is a new one (MLP). Kamal et al.[2019] implemented two DL models, MobileNet upgrade and MobileNet downgrade, which were identical to the VGG model; MobileNet's downgraded classification was actually 98.34% accurate and had fewer parameters compared with VGG, saving time in model training.A state-of-the-art PlantdiseaseNet DL, which is surprisingly suitable for the complex climate of an agrarian region, was suggested at Arsenovic et al.[2019]. Jiang et al.[2019] classified and detected five types of apple plant diseases, a state-of-the-art CNN model called VGG-inception architecture. Multiple DL architectures like AlexNet, GoogLeNet, several ResNet and VGG were out of efficiency. It also incorporated simulation and activation of inter-object/ class detection; for its clear vision of plant diseases, it was also identified.

COMPARISON ANALYSIS

Table 1. Comparison chart of various machine learning approaches in Crop disease detection

No	Author	Methodology	Dataset Used	Remarks
1	Davoud et al.[2016].	Gaussian process regression and	ASD spectroradiometer dataset	PLSR revealed the determination coffector (R2) at the leaf and canopy values of

		support vector regression (ν-SVR)		0.98 (RMSE = 0.6) and 0.92 (RMSE = 0.11). In leaf (R2 = 0.98, RMSE = 0.05) and in canopy (R2 = 0.95, RMSE= 0.12) SVR showed R2 and RMSE near the PLSR scale. GPR suggested R2 values in leaf and canopy scale 0.98 (RMSE = 0.03) and 0.97 (RMSE = 0.11), respectively.
2	Uday Pratap Singh et al.[2019]	Multilayer Convolutional Neural Network (MCNN)	real-time dataset captured at the Shri Mata Vaishno Devi University, Katra	Compared to other state-of - the-art methods for its accuracy, the higher quality of the proposed study is verified with 97.13 percent accuracy.
3	Noa Schor et al.[2015].	principal component analysis (PCA) and the coefficient of variation (CV)	PM database	PCA-based leaf vein removal classification achieved maximum accuracy in classification (90%), while the CV approaches were high in precision as well (85 percent, 87 percent). PM pixel-level recognition based on PCA was high (95.2%) while leaf-like accuracy (64.3%) was poor as measured on the upper side of the leaf while symptoms of disease start on the lower side of the patient.
4	Wenjiang Huang et al.[2014].	RELIEF-F algorithm	Canopy Spectral Data	The identification accuracies of these latest indices were 86.5 percent, 85.2 percent, 91.6 percent, and 93.5 percent. We also applied these NSIs for non-imaging winter wheat canopy data, and it was promising to classify the results of various diseases.
5	George Deroco Martins et al [2 0 17].	RapidEye multispectral sensor.	Hyperspectral data	The spatial distribution for healthily, moderately infected and severely infected coffee plants was defined in the multispectral classification with a total precision of 78 percent and a coefficient of 0,71 Cappa.
6	Haiguang Wang, et al.[2012].	BP networks and PCA.	ColSha or dimension reduced Tex	Grape diseases were produced with 100 percent fitting precision and 97.14 percent prevention precision and 100

				percent fitting precision and prediction precision for wheat diseases
7	Kutty et al.[2013]	SPSS, Neural Network Pattern Recognition	The basic digital color image.	The overall performance is shown with a 0.5 AUC value of the ROC curve.The true result of the category also shows the value of 75.9%.
8	Rothe et al.[2015]	Active contour model, Snake segmentation	The images are acquired using a digital camera.	The algorithm of snake segmentation is an efficient method to isolate sick spots but is an extremely slow operation. On other crops like orange, citrus fruits, wheat or maize, etc. The average rating accuracy was found to be 85.52 percent. The same work can be done to classify diseases.
9	Melike Sardogan, Adem Tuncer, Yunus Ozen & 2018.	Convolutional Neural Network (CNN), Learning Vector Quantization (LVQ)	Plant Village dataset	The average classification accuracy is found to be 86%.
10	Robert et al.[2018].	RCNN	Developed the Plant Server and User View using phpMyAdmin to handle MySQL server administration .	80 percent of confidence was obtained by the F-RCNN-qualified model for anomaly detection, while 95.75 percent were accurate in the method for the transfer of learning disease. In reality, the automated image capture software was introduced and 91,67 percent of tomato plant diseases were accurately identified.

CONCLUSION

This paper explores and summarises crop disease forms and comparisons of different methods of image processing. SVM, Fuzzy logic, ANN and K mean clustering, etc. are techniques very widely used. In addition, many performance metrics are used for these methods to be compared. A detailed explanation of machine learning models used to visualise different crop diseases is given in this study.

REFERENCES

[1] Agrawal, Nitesh & Jyoti, Singhai & Agarwal, Dheeraj. (2017). Grape leaf disease detection and classification using multi-class support vector machines. 238-244. 10.1109/RISE.2017.8378160.

[2] Arsenovic, M.; Karanovic, M.; Sladojevic, S.; Anderla, A.; Stefanovic, D. Solving Current Limitations of Deep Learning Based Approaches for Plant Disease Detection. Symmetry 2019, 11, 939.

[3] Ashourloo, Davoud & Matkan, Aliakbar & Huete, Alfredo & Aghighi, Hossein &

Mobasheri, Mohammadreza. (2016). Developing an Index for Detection and Identification. IEEE Geoscience and Remote Sensing. 13. 1-5. 10.1109/LGRS.2016.2550529.

[4] Bhimte, Namrata & Thool, V.. (2018). Diseases Detection of Cotton Leaf Spot Using Image Processing and SVM Classifier. 340-344. 10.1109/ICCONS.2018.8662906.

[5] Bodhe, Ketan & Sambare, Ashish & Aote, Nikesh & Naik, Parag & Kale, Deepa. (2017). Implementation of Prototype for Detection and Management of Diabetes using Android Mobile Phone Application and Rule Base System. 10.24001/ijaems.icsesd2017.64.

[6] Chen, J.; Liu, Q.; Gao, L. Visual Tea Leaf Disease Recognition Using a Convolutional Neural Network Model. Symmetry 2019, 11, 343.

[7] Elhassouny, Azeddine & Smarandache, Florentin. (2019). Trends in deep convolutional neural Networks architectures: a review. 1-8. 10.1109/ICCSRE.2019.8807741.

[8] Francis, Jobin & Dhas, Anto & Kadan, Anoop. (2016). Identification of leaf diseases in pepper plants using soft computing techniques. 168-173. 10.1109/ICEDSS.2016.7587787.

[9] Galvez, Reagan & Bandala, Argel & Dadios, Elmer & Vicerra, Ryan & Maningo, Jose Martin. (2018). Object Detection Using Convolutional Neural Networks. 2023-2027. 10.1109/TENCON.2018.8650517.

[10] Huang, Wenjiang & Guan, Qingsong & Luo, Juhua & Zhang, Jingcheng & Zhao, Jinling & Liang, Dong & Huang, Linsheng & Zhang, Dongyan. (2014). New Optimized Spectral Indices for Identifying and Monitoring Winter Wheat Diseases. Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of. 7. 2516-2524. 10.1109/JSTARS.2013.2294961.

[11] Jiang, P.; Chen, Y.; Liu, B.; He, D.; Liang, C. Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks. IEEE Access 2019, 7, 59069–59080.

[12] Kamal, K.; Yin, Z.; Wu, M.; Wu, Z. Depthwise separable convolution architectures for plant disease classification. Comput. Electron. Agric. 2019, 165, 104948.

[13] Khitthuk, Chaowalit & Srikaew, A. & Attakitmongcol, Kitti & Kumsawat, Prayoth. (2018). Plant Leaf Disease Diagnosis from Color Imagery Using Co-Occurrence Matrix and Artificial Intelligence System. 1-4. 10.1109/IEECON.2018.8712277.

[14] Kurale, Neha & Vaidya, Madhav. (2018). Classification of Leaf Disease Using Texture Feature and Neural Network Classifier. 1-6. 10.1109/ICIRCA.2018.8597434.

[15] Kutty, Suhaili & Abdullah, Noor & Hashim, Hadzli & Ab Rahim, A'Zraa Afhzan & Sulinda, A. (2013). Classification of watermelon leaf diseases using neural network analysis. BEIAC 2013 - 2013 IEEE Business Engineering and Industrial Applications Colloquium. 459-464. 10.1109/BEIAC.2013.6560170.

[16] Liu, B.; Zhang, Y.; He, D.; Li, Y. Identification of apple leaf diseases based on deep convolutional neural networks. Symmetry 2017, 10, 11.

[17] Martins, George & Galo, Maria De Lourdes & Vieira, Bruno. (2017). Detecting and Mapping Root-Knot Nematode Infection in Coffee Crop Using Remote Sensing Measurements. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. PP. 1-9. 10.1109/JSTARS.2017.2737618.

[18] V.P.Gladispushparathi & Auxiliaosvinnancy, “Review Study on Machine Learning Impact on Clinical Practice “ Solid state and Technology , Vol64, issue 2 pp: 258-267 , January 2021

[19] V.P.Gladispushparathi & Auxiliaosvinnancy, “An Empirical Analysis of Agricultural Machine Learning - Techniques and Applications “Solid state and Technology , Vol64, issue 2 pp: 245-257, January 2021

[20] V.P. Gladispushparathi,& Thankaramya ,“Deep Learning Driven Image Segmentation in Medical Science - An Intense Learning” Solid state and Technology , Vol64, issue 2 pp: 1725-1734, January 2021