Review Article

Automated Detection of Plant Diseases- A Promising Tool for Smart Agriculture

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ABSTRACT

Smart agriculture utilizes modern technologies to increase crop productivity. The productivity of agricultural crops has to be elevated for food security for the ever-increasing global population. The production of agricultural crops is largely affected due to increasing infestation of diseases and pests in addition to abiotic stresses. Early detection and management of diseases hold key to tackling the challenge. The disease pest infestation can be controlled by applying pesticides and insecticides. But numerous negative health effects that have been associated with chemical pesticides have been well documented. The increasing computational technology and recent advances in deep learning have paved the way for rapid disease diagnosis and management. Here we have discussed the automatic detection and classification of plant diseases as well as their severity through Image Processing. The detection of disease and its degree of severity from images is based on colour, texture and shape and gives a fast and accurate solution through the use of smart computational tools. DNNs (Deep Neural Networks) and CNNs (Convolutional Neural Networks) are effective in the detection, recognition and classification of plant diseases towards an automated solution for the large-scale agricultural industry.

Keywords: Smart agriculture, Automated detection, DNNs, CNNs.

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INTRODUCTION

Agriculture plays the most pivotal role in providing global food security to both humans and animals. To cope with the increasing global population, growth in the agricultural field has become a prerequisite for compensating for global hunger.[1] Along with food security, agriculture plays a crucial role in supporting the global economy also. In earlier days, agricultural production was increased by the use of new high-yielding varieties, improved farm types of machinery, inorganic fertilizers and pesticides. But extensive use of these chemical compounds and the farm types of machinery caused severe damage to environmental resources like land, water and air. The excessive and continuous use of chemical pesticides and herbicides causes some physiological changes in the pest and weeds to make them resistant to the chemicals.[2]

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In this present scenario, increasing agricultural land to increase production is next to impossible. So, the main concern of scientists is to increase the productivity of food crops without causing damage to environmental resources. The rising cases of plant biotic and abiotic stress are an alarming risk to global food security. Plant biotic stressors, i.e., viruses, bacteria, fungi, nematodes, insects etc. are the leading threat to crop production.[3] Plant diseases affect the quality and yield of food crops. More than 50% of crop loss is caused globally per year due to disease pest infestation. The agro-ecosystem is continuously hampered by the extensive use of pesticides to control disease pest infestation.[4] For increasing production, the usage of chemical compounds beyond the permeable limit causes chemical toxicity to the product. While consuming the food, humans and animals become affected by the presence of chemical residues in the food crop. Consumers are conscious of the negative impacts of the extensive use of chemical fertilizers and pesticides. For this reason, the market value and demand for organically produced food crops are rising day by day. The only way to minimize the usage of harmful chemical pesticides is the early and précised detection of disease causing pathogens.[4]Plant diseases are being identified through serological methods, molecular methods and biomarker-based methods for past several decades.[5] Immune fluorescence (IF), ELISA, PCR, RT-PCR, Flow Cytometry, DNA microarrays, FISH, DNA and RNA sequencing, infrared spectroscopy, fluorescence spectroscopy, multispectral imaging, hyperspectral imaging, X-ray imaging, and NMR etc. are the widely used technologies for identifying disease pests.[5]

The necessity of the hour will be for smart agriculture. Smart agriculture or precision agriculture includes the use of technologies like the internet, sensors, robotics, GPS and artificial intelligence in the agriculture sector for improving the quality and quantity of production in a sustainable way by maximizing the usage of resources and minimizing environmental hazards. Smart agriculture is an automated machine-based system that precisely monitors and analyses the need for resources at the time of crop production. Disease detection through automation is the most important component of smart agriculture.[4] An automated disease detection system has been developed in recent years for the proper diagnosis of plant diseases. This is a consistent, precise, efficient, strong, and productive strategy for the early detection of diseases.[5] This system is mainly an image-based computational detection technology where plant images are acquired from the field through the camera and/or sensors and then pass-through pre-processing of images, segmentation of images, feature extraction from the segnmented images, selection of features and the classification processes for detection.[6]

IPT and MLA have become potential tools for prompt and precise detection and recognition of pathogenic diseases.[4,7,8] Through IPTs plant diseases can be quickly and accurately recognized based on photographs of different plant parts such as stems, fruits, flowers and/or leaves captured by using sensors operating under visible light, infra-red light and/or different bands of the electromagnetic spectrum though cameras and imaging devices. The deep learning (DL) approach, a sub-category of machine learning (ML), together with visualization technology is used widely to identify disease pest infestation in the agricultural field.[9,10] One of the most effective yet expensive technologies for diagnosing, classifying, differentiating, identifying, and characterising diseases is hyperspectral imaging.[11,12] The non-parametric methods that are used to identify the spectral signatures of a diseased plants are like PCA, SVM, Fuzzy logic, CA, PLS, artificial intelligent nose and Neural Networks (NNs) are implemented nowadays.[1] But neural networks have the most precise discrimination capability for plant diseases among these technologies.[1] In this paper we have discussed the past, present and future trends of disease detection and different kinds of non-parametric approaches to automated disease detection with special emphasis on neural networks.

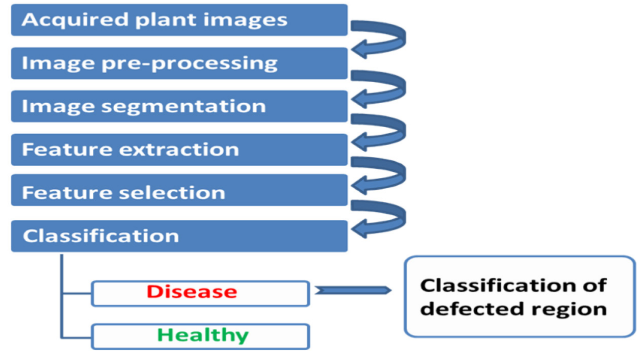

Figure 1: General structure of automated detection of plant diseases.

The proposed methodology consists of six segments, from acquiring images of different plant parts to image pre-processing for segmentation, extraction, and selection of features from segmented pictures and at the final stage classifying the plant whether it is healthy or diseased. Figure 1.

Conventional and molecular methods for disease detection

To control the occurrence and spreading of plant diseases accurate and timely detection of plant diseases is a prerequisite in the agriculture and horticulture field. Plant pathogens are ubiquitous in nature. In most cases, plant diseases are identified by visualising disease symptoms on plants, microscopic evaluation of infected parts to detect causing microorganisms and employing diagnostic methods from molecular, serological, and microbiological sources.[14,15] Traditionally disease pest infestation was identified by the presence of disease symptoms like blight, galls, lesions, tumors, wilts, rots, cankers or damping-off etc. or visible indicators of pathogens like mycelium or conidia of *Erysiphales*. But morphological identification of diseases is not reliable as this method is unable to precisely detect the causal organism. Microscopic methods identify the presence of pathogen spores, mycelium, and fruiting bodies from diseased plant samples. Historically, fungi were recognised by isolating and culturing in selective media. In earlier days bacteria were identified by biochemical assay and viruses were identified by transmission assay.[1] Recent advances in molecular biology techniques allow precise and reliable detection of diseases and disease-causing agents. ELISA, RT-PCR, nested Polymerase Chain Reaction, Co-PCR, M-PCR, DNA fingerprinting, NASBA, RPA, AmpliDet RNA, RT-LAMP, microarrays and FISH, are the widely used technologies for detecting and quantifying pathogenesis as well as identifying pathogen taxonomy.[16-18] All of these technologies have some limitations.

Automated disease detection technologies

These recently developed technologies are revolutionary tools in smart agriculture due to their precision, reliability and sensitivity.[14] Through intensive research, sensor-based methodologies have been developed for the detection, assessment, and characterization of plant diseases.[19-21] These sensors are having the capability to detect early physiological changes in crops due to biotic stress.[20,21] For automated disease detection, at first, the pictures of plant parts have to be captured and then send for image pre-processing to improve image quality by image scaling, processing, histogram equalisation and colour space conversion.[4] The pictures are clicked by using RGB cameras, multispectral cameras and stereovision cameras. Two-fold segmentation of the images is done to recognise plant diseases. First segmentation is implemented to segregate background elements like leaves, stems, fruits, and flowers. Subsequently, second segmentation is used to separate healthy tissues from diseased ones. Image segmentation is done through Delta E (DE). Image pre-processing is done by using RGB (Red, Green and Blue), HSV colour histogram and LBP textural information feature.[22] Comprehensive colour feature (CCF) is used for diseased spot segmentation.

Feature extraction from the segmented image isdone by statistical measures and model-based methods such as Local Binary Patterns (LBP), scale-invariant feature transform (SIFT), Grey Level Co-occurrence Matrix (GLCM), Colour Cooccurrence Matrix (CCM), Spatial Gray-level Dependence Matrices (SGDM), blurred form model (BSM) descriptions, local grey Gabor pattern (LGGP), Spatial Grey Level Dependence Matrix (SGLDM), Otsu method, Auto-Regressive (AR) and Markov Random Field (MRF) models.

For the classification and identification of plant diseases DT, RF, ANN, SVM, PCA, MLC, KNN and NB approaches are used.[7,23-26]

Machine learning technology is becoming the most widely used reliable detector of plant diseases at the very initial stage to minimize the effect of biotic stressors on crop yield. Machine learning algorithms are having vectors that are trained to categorise and classify each and every disease to recognise. The trained algorithms are used to analyse the images taken from the field and classify them based on similarity found by the featured vector.[4,7,27] Multiple learning algorithm can be used simultaneously for training and classification to better identification of plant diseases.[7,28]Training of the images with different algorithms such as K-means Clustering, SVM, and application of the NNs are done for making an image classification model. For the identification of healthy or diseased plants and the name of the disease, the test set will be used for the assessment of the output. Machine Learning techniques are involved at the designing stage for feature extraction.

Optical Sensors for Plant Disease Detection

The selection of a suitable camera for automated disease detection through a machine-learning approach is a tedious procedure due to the availability of diverse cameras in the market. The resolution of the camera, pricing, frame rate, and image transfer rate are the crucial elements that need to be evaluated before selecting the appropriate camera. As optical sensors for disease detection, RGB imaging, thermal sensors, multi- and hyperspectral reflectance sensors, and fluorescence imaging are employed. RGB (red, green, and blue) camera is the simplest source of images for disease recognition and quantification,[29] yield prediction,[30] ripeness detection,[31] weed detection,[32] and insect detection.[33] RGB sensors are widely used to monitor plants throughout their growing season. RGB-color pictures are useful for the detection of biotic stress in plants. Along with RGB LAB (L - lightness and A and B- colour-opponent dimensions), YCBCR (Y for color compression scheme and CB for blue-difference chroma components and CR for red-difference chroma components), HSV color space, the spatial context helps in detecting plant diseases.[34] Both spectral and spatial features of captured objects are evaluated by multispectral sensors in a broad wavelength even in near-infrared wavelength also. Hyperspectral 3D images taken by airborne sensors can be employed precisely for the detection of soil-borne diseases or later stage of plant diseases.[35] Infrared thermography (IRT) uses thermal sensors to detect temperature of plants and correlate that with water status of plant, and the microclimate around the plant and detect the change in rate of transpiration due to early infection by a plant pathogen.[36,37] Fluorescence imaging with an LED or laser light is used to detect photosynthetic electron transfer to calculate variations in plants' photosynthetic activity due to biotic and abiotic stresses.[38,39] Stereo cameras, 3 dimensional laser scanners, ultrasound, or densitometry can be used to get information about plant architecture or plant biomass to detect the presence of plant pathogenic diseases.[40]

Neural network (NN) for Plant Disease Detection-

NNs are mathematical abstractions that can be used as a promising artificial intelligence tool for data mining and feature extraction from spectral data.[1] Single-Layer Perceptron (SLP), SOM networks, MLP, RBF-networks, PNN, DNN and CNN are major types of neural network.[1] In past few years deep learning in NNs has become a promising tool for stress phenotyping. CNN is an extensively used DL architecture that integrates biological vision and neural systems. CNN is an effective approach for identifying and categorising hyperspectral pictures because of its higher accuracy rate and resolution. In most cases, multiple NNs were used for the analysis of the hyperspectral dataset. NN models are a combination of neural architectures and learning algorithms. FFNNs, BPNNs and GRNNs are the most widely used NN models for nonlinear and hyperspectral data analysis for disease prediction and diagnosis.[1] In recent years rapid and accurate detection of plant disease at an early stage becomes an important factor in controlling disease progression and avoiding yield loss. NN models along with hyperspectral data make the path easy towards the identification of plant pathogenic diseases at the early stage. During pathogenesis changes in reflectance, and pattern has been observed due to the induction of pathogen-specific toxins or enzymes. Hyperspectral sensors detect the change in reflectance from the leaf structure and chemical composition.[14] Hyperspectral data are used to design an NN model to evaluate with a trained and representative NN. Hyperspectral non-imaging data requires spectral processing with NN algorithm for disease detection.

CONCLUSION

Plant biotic stressors are the main causal organism behind huge yield loss in crops. Disease detection at the early stage makes it possible to avoid yield loss. Through conventional methods, it is not possible to detect plant pathogenic diseases at the early stage. Machine learning is a promising approach for image-based disease phenotyping with higher accuracy and reliability. NNs along with hyperspectral data make the path easy for disease detection. Deep learning, a sub-part of machine learning, is widely used for data acquisition, data pre-processing and data analysis for the quantification and prediction of disease severity.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ABBREVIATIONS

DNN: Deep Neural Networks; **CNN:** Convolutional Neural Networks; **ELISA:** Enzyme-linked immunosorbent assay; **IF:** Immune Fluorescence; **IPT:** Image Processing Techniques; **MLA:** Machine Learning Algorithms; **DL:** Deep Learning; **ML:** Machine Learning; **PCA:** Principal Component Analysis; **SVM:** Support Vector Machine; **CA:** Cluster Analysis; **PLS:** Partial Least- Square (PLS); **NNs:** Neural Networks; **ELISA:** Enzyme-Linked Immuno- Sorbent Assay; **RT-PCR:** Reverse Transcription Polymerase Chain Reaction; **Co-PCR-** Cooperative PCR; **M-PCR:** Multiplex PCR; **NASA:** Nucleic acid Sequence-based Amplification; **RPA:** Ribonuclease Protection Assay; **RT-LAMP:** Reverse Transcription Loop-mediated Isothermal Amplification; **FISH:** Fluorescence *in-situ* Hybridization; **CCF:** Comprehensive colour feature; **LBP:** Local Binary Pattern; **HSV:** Hue, Saturation and Intensity Value; **DT:** Decision Trees; **RF:** Random Forest; **ANN:** Artificial Neural Networks; **SVM:** Support Vector Machines; **PCA:** Principle Component Analysis; **MLC:** Maximum Likelihood Classification; **KNN:** K-Nearest-Neighbours; **NB:** Naı¨ve Bayes; **SOM:** Kohonen's Self-Organising Map; **MLP:** Multi-Layer Perceptron; **RBF:** Radial-Basis Function; **PNN:** Probabilistic Neural Network; **FFNN:** Feed-Forward Neural Networks; **BPNN:** Back-Propagation Neural Networks; **GRNN:** Generalized Regression Neural Networks.

SUMMARY

Plant diseases restrict agricultural and industrial output. They lower productivity and have a negative impact on fruit and crop quality, resulting in a scarcity of food. The worldwide farming economy declines harmed from a

decline in production. The amount and quality of today's agricultural output, as well as the value and financial returns, have all decreased as a result of pathogen-related food losses. As a result, in plant pathology, "early detection" in conjunction with "rapid, precise, reliable, and cost-effective" diagnostics has also become the new maxim, particularly for new diseases or tricky pathogens difficult to characterize and challenging to face. To manage, contain, and prevent diseases, however, early recognition and disease severity assessment are crucial. The first stage in determining the severity of a disease, which is essential for the efficient application of preventive measures, is damage localization. The next horizon for diagnostic laboratories is the development of novel field-applicable technologies that will ensure that the tools and methods employed are appropriate for operational situations. The painstaking task of maintaining large farms is eliminated by automatic plant disease detection, which also identifies the disease early enough to prevent plant destruction. Portable systems and the Internet of Things (IoT) are vital components of this platform. Technological advancement has opened up a number of opportunities in the diagnosis of plant diseases. However, enormous difficulties are there in the path of new methods accessible on a broad scale for automated disease detection.

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