DIAGNOSIS OF CROP INFECTION USING ARTIFICIAL INTELLIGENCE AND INTERNET OF THINGS

[1]ADITI P. PATIL [2]MAHADEV S. PATIL

Rajarambapu Institute of Technology, Islampur, Maharashtra 415409, India

Abstract: *The economic growth of developing country India mainly depends upon agriculture sector. Also, agriculture provides food security to world's second most populous country. So, the agriculture sector ensures both economic growth as well as food security. To increase crop yield, monitoring the health of crop is important as health of crop directly affects production quality and quantity. Health of the crop is damaged due to presence of crop infection; hence to avoid spread of such diseases it is important to identify the infection at early stage. In India, near about 30% farm production is lost due to late diagnosis of crop infection. Thus, early identification of crop diseases is very important. We can recognize the crop diseases by observing various part of the plant like leaf, stem, flower and fruit. However, plant leaves are commonly used for disease diagnosis. Various aspects used for disease diagnosis are discussed in this paper with their merits and demerits. This paper highlights the various classification, segmentation and feature extraction techniques used for crop infection identification.*

Keywords: ***AI, Image processing, Infection identification, IOT, Plant pathology.***

1. INTRODUCTION

Agriculture is the science, art and practice of growing crops and livestock. Since Independence, agriculture sector plays the major role in India's economic development and national food security. Presently it contributes 18% to country's Gross Domestic Product and around 60 % of total working population is directly or indirectly engaged in agriculture. Along with this, growth of other allied sector and overall Indian economy depends upon agriculture sector. But considering the total workforce involved in agriculture sector, India's average crop yield is still lower than those of major world economies like Europe, USA and China. One of the main reasons of this failure is the traditional way of farming. To ensure future sustainable growth of the agriculture sector and to increase overall farm production quality and its quantity use of IOT is inevitable. IOT is an interconnected system that can collect and transmit data over a wireless network without human intervention.

By the use of modern IOT technology, Indian farmers can certainly be benefited, as they can remotely monitor and regulate their farm in real time.

Plant diseases affects growth and health of the crop which ultimately affects the final produce of the farmer, so plant diseases put food security at risk and can cause great damage to the farmer final income as well. To avoid such severe economic loss at the end, early detection and control of crop infection is important.

2. PLANT PATHOLOGY

The cause of plant infection by a plant pathogen is studied in Plant pathology. The main goal of plant pathology is to study the factors which cause plant infection, the study of disease development mechanism, understand the interconnection between agent and plant disease with respect to the environmental condition and finally develop a system that can control the disease.

Disease is a structural or physiological abnormality that is injurious to the plant or its part. Any entities which can insight the disease is known as a pathogen. Fig 1 shows the classification of plant pathogens.

2.1. Animate Causes

This type of infection causes due to animate or living or cellular organisums. It consists of Eukaryotes like Fungi, Protozoa, Algae, Nematodes, Parasitic flowering plants.

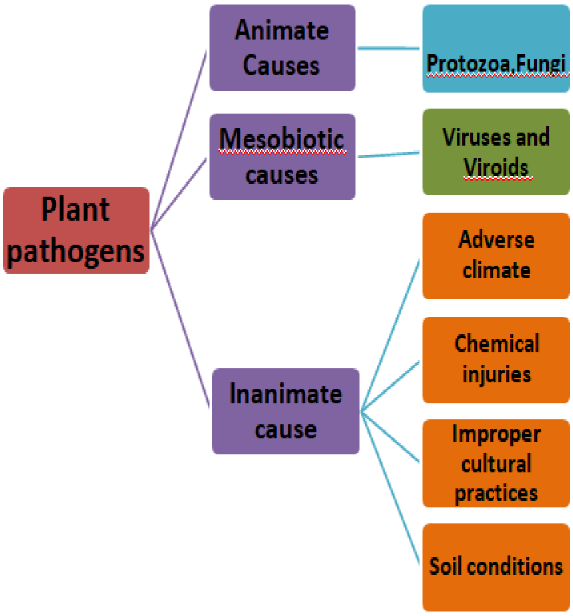

Figure 1. Classification of plant pathogens

2.2. Mesobiotic causes

This type of infection caused by living or non-living organism. It includes Viruses and Viroids. Animate and Mesobiotic diseases are inflectional diseases they spread from one crop to another crop, so damage occurs due to these types of diseases are much more as compared to the inanimate diseases. If we fail to identify inflectional diseases at early stage it can destroy the entire field, so to prevent losses identification of crop infection at early stage is necessary

2.3. Inanimate cause

Inanimate disease are not associated with any animate or viral pathogen so they are not transmitted from one crop to another crop that's why these diseases are less harmful as compared to the animate and mesobiotic diseases. These types of infection causes due to adverse climatic conditions like light, temperature, humidity, rain, forest, storm; adverse soil conditions like soil moisture, texture, structure, pH, nutrition; Chemical injuries like pollution and pesticide; Improper cultural practices includes depth of sowing, improper irrigation, improper fertilization, improper harvesting. By using various types of sensors like soil moisture sensor, ph meter, temperature sensor connected to the processor, we can control this parameter by using internet of things techniques. There are several agricultural application having different platform, architecture of IOT, wireless agriculture sensors,cloud computing and communication technologies (Muhammad Ayaz et.al.2019). (Wen-Liang Chen et.al.2019) presented a micro weather station consist of various sensor for monitoring of field; it uses AI and IoT technology. It develops AgriTalk architecture which uses non image IoT devices for detection of rice blast disease. (Mohammad Samunul Islam et.al.2019) presents water irrigation system by using IoT technology; it uses salinity, soil moisture, water level, temperature and humidity sensors, all these sensors are connected to the Arduino Nano, it uses Raspberry Pi B3 model to take appropriate decision depending upon the reference value and corresponding measured value.

3. ELEMENT OF CROP INFECTION IDENTIFICATION SYSTEM

For identification of crop infection digital image processing technique can be used. Crop infection identification system consists of following modules: image acquisition, image pre-processing, image segmentation, feature extraction and classification. Fig.2 shows crop infection identification system. It has two periods, the training period and the testing period. In training period first crop image is captured, the captured image may or may not be pre processed. By means of segmentation, we can get only interested region out of the whole crop image. The training of classifier is done by using feature vectors related to the interested region which are extracted from captured image. In the testing period, a captured image is passed through various modules of crop infection identification system. The trained classifier classifies the captured test image as a healthy image or a diseased image. This section describes the various techniques used for infection identification of crop.

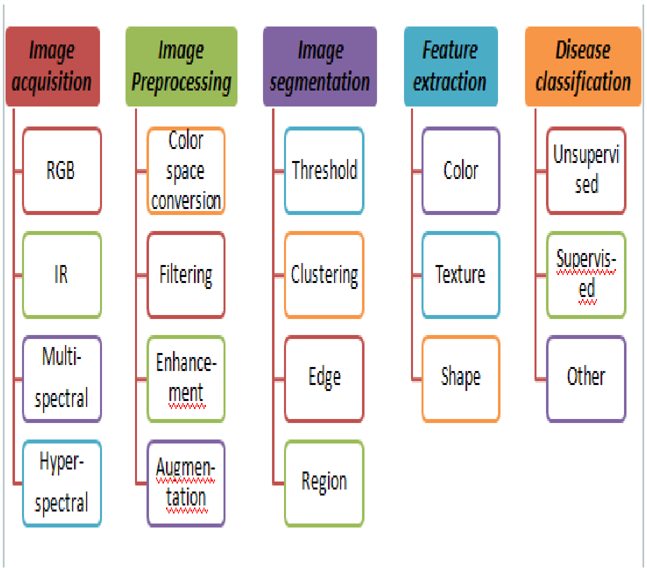

Figure 2. Crop infection identification system

3.1. Image acquisition

It is first step of the system, to train the classifier, the dataset is used which consist of many images of healthy as well as diseased crop. Many researchers use open accessible dataset like APS dataset (Bashir et al 2019), Plant Village dataset (Kusumo et al 2019), and some researcher use self captured dataset which is captured either in real time or laboratory condition.(Arnal Barbedo 2019). Fig.3 shows analysis of image acquisition technology used in article.

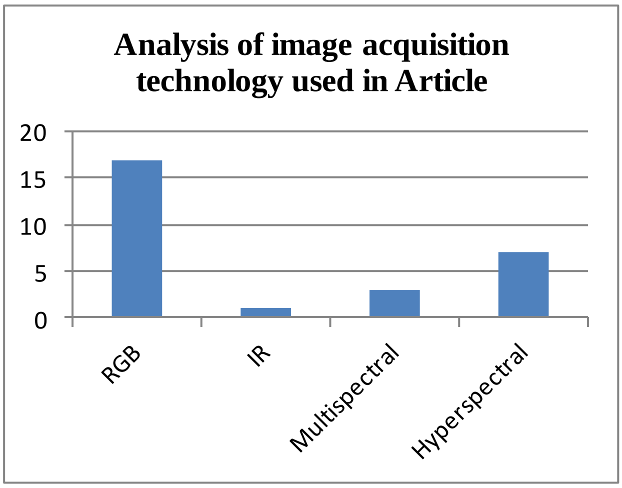

Figure 3. Analysis of image acquisition technology

3.2. Image Preprocessing

Preprocessing technique includes color space conversion, image filtering, image enhancement, cropping, and data augmentation. Input as well as output of this step is image. In preprocessing step color space conversion take place which translate the color representation from one basic to another, in (Anupama S. Deshapande et.al.2018) RGB image is converted into L*A*B color space. (N. Hanuman Reddy et.al.2019) uses HSI. Different color spaces are L*u*v, Y'CrCb, L*a*b, HSV,(Siddharth Singh Chouhan et.al.2019).color space conversion is followed by filtering and enhancement; for filtering and smoothing of image various filters like average filter, smoothing filter, median filter is used which removes the noise, illumination and lighting effect (Tanmoy Bera et.al, 2018). Augmentation also take place in preprocessing step, augmentation is nothing but the technique which increase the data image without capturing new field image (Juliana Mariana et.al.2019).

3.3. Image segmentation

Image segmentation is nothing but dividing the image into meaningful regions depending upon the particular application, so that the complexity of image is reduced, and it can be easily analyzed. Edge segmentation, region segmentation, threshold segmentation and clustering based segmentation are the segmentation techniques used in image processing. In the simple threshold based segmentation, threshold value is constant if the pixel value is above the constant value then that pixel is restore with white and if pixel value is less than the constant value then that pixel is restore with black (Namita Sengar et.al,2018). (Sivasubramaniam Janarthan et.al.2020) uses edge based segmentation, by considering various parameters like color, gray level, contrast, saturation edges of image is determined. In region based segmentation the image is split into various groups which are having similar characteristics (Shanwen Zhang et.al. 2020). In (Yuxia Yuan et.al.2021) the infected area of leaf is segmented using encoder-decoder structure based on region segmentation network (RSEDNET). (Shanwen Zhang et.al.2019) uses k means clustering algorithm for image segmentation, which is unsupervised algorithm, it classifies image through clusters having fixed apriority.

3.4. Feature extraction

Feature presents information related with objects which differentiates one object from another, features are important to detect and label objects which is useful when classification of object takes place. In literature for identification of crop infection various parameters like color, texture and shape are observed; the performance of entire set-up is based on the feature extraction technique. Features like hue, saturation, luminance, and histogram moments are colors features, whereas the texture feature extraction techniques are entropy, variance and contrast. Eccentricity, roundness and area are some features related to the shape.(S.Devi Mahalakshmi et.al.2020). Selection of inappropriate features causes over-fitting of classifier and it also increase the computational cost. Principal Component Analysis (PCA) can be used to avoid over-fitting of the classifier. (Siddharth Singh Chouhan et.al.2020). In (Juliana Mariana Macedo Araujo et.al.2020) color moments technique extracts color feature whereas texture feature and local features are extracted by using Local Binary Patterns (LBP) and Speeded up Robust Features (SURF), Bag of Visual Words (BoVW) algorithms respectively. In (Gayatri Kuricheti et.al.2019) leaf images textural analysis was carried out using GLCM, it extracts numeric features corresponding to image texture. In (Ch. Usha Kumari et.al.2019) details like Correlation, Contrast, Homogeneity, Energy, Standard Deviation, Mean and Variance are extracted. Histogram of oriented gradients (HOG) gives better result with machine learning algorithm, for detecting leaf image based crop diseases SVM classifier with HOG features can be used (Haridas D. Gadade et.al.2020). Wavelet transform uses mathematical framework for extraction of texture features, in some literature Haar wavelet transform is used (Duo Long et.al.2019).

3.5. Disease classification

This module identifies specific infection of crop. Accomplishment of this module is based on all previous modules like data acquisitions, preprocessing, segmentation and feature extraction. In this step depending upon the symptoms present on the plant captured image it diagnose the particular diseases. For classification of crop infection, machine learning classifier model is trained with dataset of crop images. Classifier classifies leaf image as an inflected or healthy leaf.

Artificial Intelligence (AI) system has an ability to take decisions without being explicitly programmed. Classifying objects using Machine Learning (ML) uses two types of techniques. The supervised classifier techniques uses labeled data set and unlabeled data set was used by the unsupervised classifier. K-means clustering, Fuzzy c-means and LDA are unsupervised classifier where as Naive-Bayes, ANN, Decision tree, Ada-Boost, SVM and K-NN are supervised classifier. Rice crop infection identification is done with combination of K-means clustering; SVM and CNN based classification techniques. (Gaurav Verma et.al.2019). (Pushkara Sharma et.al.2020) presented a model that compares varies classification techniques namely logistic regression, KNN, CNN, SVM, the dataset used consists of more than 20,000 images with 19 total classes. From result the CNN has highest accuracy. From references, it has been seen that SVM is a commonly used machine learning algorithm used for crop infection detection.

Deep Learning is an application of AI used for identification of crop infection. (Qiaokang Liang et.al.2019) presents a PD2SE-Net50 model that can be estimated infection severity, recognize species and classify the plant infection by using deep learning method. A Global Pooling Dilated Convolution Neural Network (GPDCNN) is used for crop infection identification, it combines dilated convolution with global pooling (Shanwen Zhang et.al.2019). By comparing LeNet, StridedNet, and VGGNet models it observed that VGGNet model has highest accuracy (Sammy V. Militante et.al.2019). To predict the occurrence of diseases environmental information obtained from weather stations is analyzed through Long Short-Term Memory (LSTM), and deep learning YOLOv3 model is used for image recognition (Ching-Ju Chen et.al,2020). SoyNet is compared with three hand-crafted features based methods and six popular CNN models namely, VGG19, GoogleLeNet, Dense121, XceptionNet, LeNet, and ResNet50. All the experiments are performed on PDDB database (Aditya Karlekar et.al.2020).

4. Analysis and discussion

Table 1. Comparative evaluation of existing research work

Authors& Year	Crop	Diseases	Techniques	Accuracy
Anupama S. Deshapande et.al.2018	Maize	Northern leaf blight Common rust	Details of infections are extracted with Haar wavelet GLCM and infection identification is done with KNN and SVM.	KNN-85% , SVM-88%
Konstantinos P.et.al.2018	Soyabean	Downy	Classification of infection is done with VGG CNN model and K-means clustering is used for segmentation.	99%
Xuan Nie et.al.2019	Strawberry	Verticillium wilt	Details of infections are extracted with Faster R-CNN and multi-task learning and infection identification is done with SVM.	99%
Juliana Mariana et.al.2019	Soybean	Rust, Bacterial damage, Brown color of Septoria, Powdery mildew, Mosaic and Copper phytotoxicity	Feature extraction by color moments technique, LBP, SURF BoVW. And infection identification is done with SVM.	75.8%.
Jayme Garcia Arnal Barbedo et.al.2019	Common Bean, Cassava, Citrus Coconut, Corn, Coffee, Cotton Cashew		Deep learning technique	Common Bean 95% Cassava 83% Citrus 62 % Coconut 97 % Corn 66 % Coffee 77 % Cotton 100 % Cashew 83 %
Qiaokang Liang et.al.2019	Apple,Grape, Cherry, Peach,Pepper	General diseases	Deep learning and PD2SE-Net	98%
Shanwen Zhang et.al.2019	Cucumber	Anthracnose,Downy mildew, Powdery mildew, Leaf spot, Gray mold.	A global pooling dilated convolutional neural network (GPDCNN)	94.65%

Jun Sun et.al.2020	Maize	Leaf blight	multiscale feature fusion detection method	91.83%
Yang Zhang et.al.2020	Tomato	Powdery mildew, Mildew, Mildew fungus and ToMV	k-means used for segmentation, Faster RCNN , ResNet101	97.71%
Shanwen Zhang et.al.2020	Cucumber	Gray mould,Powdery mildew, Scab, Bacterial angular and Anthracnose	IoT, K-mean clustering, SADH	Powdery mildew=100% Bacterial angular=88% Scab=90%
Linyi Liu et.al.2020	Wheat	Fusarium head blight	Red-edge head blight index (REHBI)	78.6%
Sivasubramaniam Janarthan et.al.2020	Citrus	Leaf Blight,Red Scab,Red Leaf Spot	Neutral Network Classifier	95.04%
Ching-Ju et.al.2020	All	Tessaratoma papillosa.	YOLO V3 model is used for object detection, CNN with feed forward neutral network is used for the classification	90%
Babar Manzoor Atta et.al.2020	Wheat	Stripe rust	Fluorescence emission spectroscopy	
Aaditya Karlekar et.al.2020	Soybean	Bacterial blight, Copper phytotoxicity, Leaf cercospora, Mela,Mildio, Phytophora rot, Rust, Southern blight	Neutral Network Classifier	98.14%.
Weihui Zeng et.al.2020	Rice, Cucumber	Rice sheath blight, Rice blast, Rice flax spot, powdery mildew, Cucumber downy mildew, Cucumber target spot	Self- Attention Convolutional Neutral Network	95.33%
Yuxia Yuan et.al.2021	Corn, Wheat, Cucumber	Corn leaf blight, Corn round spot, Wheat strip rust, wheat anthrax, cucumber target disease	Neutral Network	90%

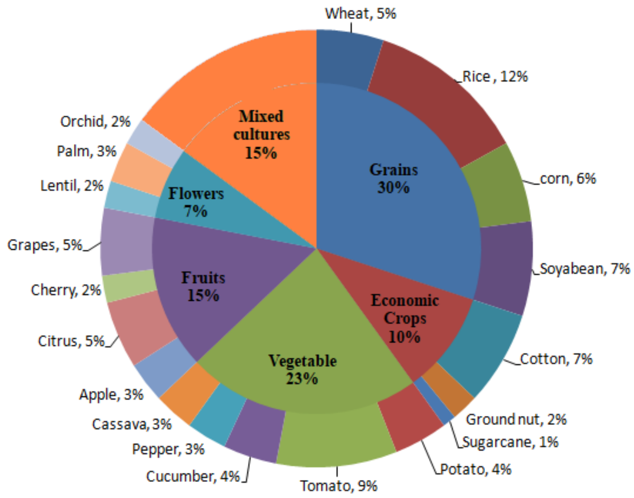

Figure 2. Research in various crops

Heterogeneity in leaf photography significantly affects the performance of infection identification module to identify and differentiate infected leaves. Many articles examine leaf infection of one crop (or culture) and some focus on infection by ignoring the crop. Fig.4 represents percentage of research papers on infection identification. Obviously, grain crops are widely studied and very few studies focus on floriculture plants. There are some plants which are not studied because they are unknown or their data images are not available. Though sugarcane is most cultured crop in India, the research on sugarcane is only one percent. It is tough to get a leaf image dataset for a specific infection. This actuality is seen by limited size of dataset used in literature, less than 10% literature uses large dataset. The images used at training phase are larger than that of testing phase. From the table 1, the accuracy of disease prediction highly depends on captured image quality, data set of captured images and information extracted from image. The experimental result is greatly affected by the type of dataset used in research, that is real-time or laboratory. The real-time dataset increases the complexity of the system, but it is most acceptable in agricultural research. Depending upon the captured images and requirements, the image processing techniques can be selected from a range of techniques. The second point of concern is different stages of leaf infection, which complicate the image acquisition task. For specific identification of infection in early stage the concept of leaf back can be considered in sensor based system. Beside of considering an infection in a particular culture, if we consider common infection in set of culture it will solve the problem of limited dataset size. Depending upon the nature of database images, a preprocessing and segmentation technique can be selected from variety of techniques. Various techniques for feature extraction are texture feature extraction, GLCM, SIFT, LBPS, Gabor filter transform, wavelet transform, and histogram of oriented gradients. Various Segmentation techniques are edge base segmentation, threshold based segmentation K- means clustering based segmentation and various classification techniques are K-means clustering, fuzzy logic, SVM, ANN, k-NN, among the above SVM is commonly used classification techniques where as ANN has highest accuracy.

From past study it was observed that the accuracy of diseases prediction highly depend on captured image quality, Data set of captured images and information extracted from image. There is no any reliable data analysis system which will deal with Image annotation & pre labeling of plant for early stage detection. Present systems having predefined sets of dataset which fulfill the requirement but if any disease left unconsidered then it leads inaccurate prediction. It is observed that some machine learning techniques like NN, deep NN, and SVM has overfitting issue, which should be solved without affecting the accuracy. Most of the literature uses controlled condition images for their system, uncontrolled condition images increases complexity of the system. To deal with overfitting issue various techniques like Data Augmentation, Regularization, Dropouts can be used.

Plant diagnosis by image analysis will perform better than visual inspection & rating of severity of diseases. To avoid inaccurate prediction a versatile system with flexible requirement has to be developed. Most of the researchers focus on the detection and classification of infection but the infection itself has a several stages. Thus a system which identifies the type and stage of infection and accordingly suggest suitable measures will be of great interest. Currently pesticides are spread periodically throughout the entire field, if system designed has ability to detect infected portion of the field then it will reduce the use of pesticides by applying it in particular portion only. Some web portal and mobile application identifies particular disease in specific culture, so another research objective is to develop an online system for identification and classification of infection. In future this system will replace the need of specialist suggestion at early stage of infection. Nutrition deficiency is also detected as an infection, so the system which differentiates deficiency and infection can be developed.

5. Conclusion

Every year a huge amount of crops are damaged due to infection, in many cases it is too late to identify the type of infection and its precautionary action. To deal with this, the use of IOT-based sensors and communication technologies is necessary. This paper delivers a review of different techniques used by researchers in agriculture; it also shows the types of crop infections and its causes. A comparative study of research papers based on crops, diseases, techniques and accuracy of the system has been done. The accuracy of the hybrid network models such as PD2SE-Net is relatively higher than the conventional models, and it can be effectively applied to crop infection identification. A summarized study of the various techniques used for image acquisition, preprocessing, segmentation, feature extraction, and classification has been done

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REFERENCES

[1] *Aditya Karlekar, Ayan Seal. 2020. SoyNet: Soybean leaf diseases classification. Computers and Electronics in Agriculture. 172 : 105042-105050.*

[2] *Albert Cruz, Yiannis Ampatzidis, Roberto Pierro, Alberto Materazzi, Alessandra Panattoni, Luigi De Bellis, Andrea Luvis. 2019. Detection of grapevine yellows symptoms in Vitis vinifera L. with artificial intelligence. Computers and Electronics in Agriculture 157 : 63-76.*

[3] *Anupama S. Deshapande, Shantala G. Giraddi, K. G. Karibasappa, Shrinivas D. Desai. 2018. Fungal Disease Detection in Maize Leaves Using Haar Wavelet Features. Information and Communication Technology for Intelligent Systems 1: 275-286.*

[4] *Babar Manzoor Atta, Muhammad Saleem, Hina Ali, Muhammad Bilal, Muhammad Fayyaz. 2020. Application of fluorescence spectroscopy in wheat crop: early disease detection and associated molecular changes. Journal of Fluorescence. 30 : 801-810.*

[5] *Ching-Ju Chen, Ya-Yu Huang, Yuan-Shuo, Chuan-Yu Chang ,Yueh-Min Huang. 2020. An AIoT based smart agricultural system for pests detection. IEEE Access. 8 : 180750-180761.*

[6] *Chuan Lin, Guangjie Han, Xingyue Qi, Jiaxin Du, Tiantian Xu,Miguel Martłnez-Garcła. 2021. Energy-Optimal Data Collection for UAV-aided Industrial WSN-based Agricultural Monitoring System: A Clustering Compressed Sampling Approach. IEEE Transactions on Industrial Informatics. 17 : 4411-4420.*

[7] *Dmitrii Shadrin, Alexander Menshchikov, Andrey Somov, Gerhild Bornemann, Jens Hauslage, Maxim Fedorov. 2019. Enabling Precision Agriculture through Embedded Sensing with Artificial Intelligence. IEEE Transactions on Instrumentation and Measurement. 69.*

[8] *Dongyan Zhang, Xingen Zhou, Jian Zhang, Yubin Lan, Chao Xu, Dong Liang. 2018. Detection of rice sheath blight using an unmanned aerial system with high-resolution color and multispectral imaging. Plos One.*

[9] *Geetharamani G, Arun Pandian J. 2019. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Computers and Electrical Engineering. 76 : 323-338.*

[10] *Jaafar Abdulridha, Reza Ehsani, Amr Abd-Elrahman, Yiannis Ampatzidis. 2019. A remote sensing technique for detecting laurel wilt disease in avocado in presence of other biotic and abiotic stresses. Computers and Electronics in Agriculture 156 : 549-557.*

[11] *Jayme Garcia, Arnal Barbedo, "Plant disease identification from individual lesions and spots using deep learning", Biosystems Engineering, vol.180, pp.96-107, 2019.*

[12] *Juliana Mariana, Macedo Araujo, Zelia Myriam Assis Peixoto. 2019. A new proposal for automatic identification of multiple soybean diseases. Computers and Electronics in Agriculture. 167 : 105060-105069.*

[13] *Jun Sun, Yu Yang, Xiaofei He, Xiaohong Wu. 2020. Northern maize leaf blight detection under complex field environment based on deep learning. IEEE Access. 8 : 33679-33688.*

[14] *Kerim Karada, Mehmet Emin Tenekeci, Ramazan Tasaltın Aysin Bilgili. 2018. Detection of pepper fusarium disease using machine learningalgorithms based on spectral reflectance. Sustainable Computing: Informatics and Systems*

[15] *Konstantinos P. Ferentinos. 2018. Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture 145: 311-318.*

[16] *Li He, Shuang-Li Qi, Jian-Zhao Duan, Tian-Cai Guo, Wei Feng, De-Xian He. 2021. Monitoring of Wheat Powdery Mildew Disease Severity Using Multiangle Hyperspectral Remote Sensing. IEEE Transactions On Geoscience And Remote Sensing. 59 : 979-990.*

[17] *Linyi Liu, Yingying Dong , Wenjiang Huang1, Xiaoping Du, Binyuan Ren, Linsheng Huang, Qiong Zheng, Huiqin Ma1. 2020. A Disease index for efficiently detecting wheat fusarium headblight using sentinel-2 multispectral imagery. IEEE Access. 8 : 52181-52191.*

[18] *M. T. Kuska, A.K. Mahlein. 2018. Aiming at decision making in plant disease protection and phenotyping by the use of optical sensors. European Journal of Plant Pathology 152 : 987-992.*

[19] *Mohammad Samunul Islam, Golap Kanti Dey. 2019. Precision Agriculture: Renewable Energy Based Smart Crop Field Monitoring and Management System Using WSN via IoT. International Conference on Sustainable Technologies for Industry 4.0.*

[20] *Muhammad Ayaz, Zubair Sharif, Ali Mansour. 2019. Internet-of-Things (IoT)-based smart agriculture: toward making the fields talk. IEEE Access. 7: 129551-129583.*

[21] *Muhammad Sharif, Muhammad Attique Khan, Zahid Iqbal, Muhammad Faisal Azam, M. Ikram Ullah Lalib, Muhammad Younus Javed. 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.*

[22] *N. Hanuman Reddy, E. Ravi Kumar, M. Vinay Reddy, K. L. Raghavender Reddy and G. Susmitha Valli. 2019. Bioinformatics and Image Processing-Detection of Plant Diseases. International Conference on Artificial Intelligence and Cognitive Computing. :149-154.*

[23]

[24] *Namita Sengar, Malay Kishore Dutta, Carlos M. Travieso. 2018. Computer vision based technique for identification and quantification of powdery mildew disease in cherry Leaves. Computing 100 : 1189-1201.*

[25] *Qiaokang Liang, Shao Xiang, Yucheng Hu, Gianmarc Coppola, Dan Zhang, Wei Sun. 2019. PD2SE-Net: Computer-assisted plant disease diagnosis and severity estimation network. Computers and Electronics in Agriculture. 157 :518-529.*

[26] *Shanwen Zhang, Subing Zhang, Chuanlei Zhang, Xianfeng Wang, Yun Shi. 2019. Cucumber leaf disease identification with global pooling dilated convolutional neural network. Computers and Electronics in Agriculture. 162 : 422-430.*

[27] *Shanwen Zhang,Wenzhun Huang, Haoxiang Wang. 2020. Crop disease monitoring and recognizing system by soft computing and image processing models. Multimedia Tools and Applications. 79 (2) :30111-30133.*

[28] *Siddharth Singh Chouhan, Uday Pratap Singh, Sanjeev Jain. 2020. Applications of Computer Vision in Plant Pathology: A Survey. Archives of Computational Methods in Engineering. 27 : 611-632,*

[29] *Sivasubramaniam Janarthan , Selvarajah Thuseethan ,Sutharshan Rajasegarar ,Qiang Lyu, Yongqiang Zheng, John Yearwood. 2020. Deep metric learning based citrus disease classification with sparse data. IEEE Access. 8 : 162588-162600.*

[30] *Sukhvir Kaur, Shreelekha Pandey, Shivani Goel. 2019. Plants Disease Identification and Classification Through Leaf Images: A Survey. Archives of Computational Methods in Engineering .26 : 507-530.*

[31] *Sukhvir Kaur, Shreelekha Pandey, Shivani Goel. 2018. Semi-automatic leaf disease detection and classification system for soybean culture IET Image Processing 12 : 1038-1048.*

[32] *Syeda Iqra Hassan, Muhammad Mansoor Alam, Usman Illahi, Mohammed A, Al Ghamdi, Sultan H. Almotiri, Mazliham Mohd Su'ud. 2021. A Systematic Review on Monitoring and Advanced Control Strategies in Smart Agriculture. IEEE Access. 9 : 32517-32548.*

[33] *Tanmoy Bera, Ankur Das, Jaya Sil, Asit K. Das. 2018. A Survey on Rice Plant Disease Identification Using Image Processing and Data Mining Techniques. Emerging Technologies in Data Mining and Information Security 3: 365-376.*

[34] *Vibhor Kumar Vishnoi, Krishan Kumar, Brajesh Kumar. 2021. Plant disease detection using computational intelligence and image processing. Journal of Plant Diseases and Protection. 128 : 19-53*

[35] *Weihui Zeng, Miao Li. 2020. Crop leaf disease recognition based on Self-Attention convolutional neural network. Computers and Electronics in Agriculture. 172 : 105341-105347.*

[36] *Wen-Liang Chen, Yi-Bing Lin, Fung-Ling Ng, Chun-You Liu, Yun-Wei Lin. 2019. RiceTalk: Rice Blast Detection using Internet of Things and Artificial Intelligence Technologies. IEEE Internet of Things Journal .7.*

[37] *X.E. Pantazi, D. Moshou, A.A. Tamouridou. 2019. Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers. Computers and Electronics in Agriculture. 156 : 96-104.*

[38] *Xuan Nie, Luyao Wang, Haoxuan Ding, Min Xu. 2019. Strawberry verticillium wilt detection network based on multi-task learning and attention. IEEE Access. 7: 170003-170011.*

[39] *Yang Zhang , Chenglong Song , Dongwen Zhang. 2020. Deep learning-based object detection improvement for tomato disease. IEEE Access. 8 : 56607-56614.*

[40] *Yingying Dong, Fang Xu, Linyi Liu, Xiaoping Du, Binyuan Ren, Anting Guo, Yun Geng, Chao Ruan, Huichun Ye, Wenjing Huang, Yining Zhu. 2020. Automatic System for Crop Pest and Disease Dynamic Monitoring and Early Forecasting. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 13 : 4410-4418.*

[41] *Yong Ai1, Chong Sun, Jun Tie1, Xiantao Cai. 2020. Research on recognition model of crop diseases and insect pests based on deep learning in harsh environments. IEEE Access. 8 : 171686-171693.*

[42] *Yuxia Yuan, Zengyong Xu, Ganu Lu. 2021. SPEDCCNN: spatial pyramid-oriented encoder-decoder cascade convolution neural network for crop disease leaf segmentation. IEEE Access. 9 : 14849-14866.*

11.2. Book