Journal of Network and Innovative Computing
ISSN 2160-2174 Volume 11 (2023) pp. 036-046

Computer-Aided Plant Diseases Prediction Systems using Image Processing: Challenges and Methodologies

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***Abstract*: This paper outlines the important, motivating, and inspiring problems in agriculture, the problem of plant diseases prediction systems using hyperspectral images. An computer-aided diagnosis (CAD) system for plant diseases prediction is designed to improve the survival of plant. The numerous researches have been investigated in recent times. A typical plant diseases prediction system is composed of five main processing steps: plant image acquisition, to improve the quality of the plant image using pre-processing, selection of more informative bands from preprocessed images by band selection process, then various features to discriminate different types of plant diseases is extracted using the feature extraction technique, and finally the extracted features of the plant disease trained for classification. This paper summarizes the recent findings proposed to design the plant diseases prediction system by the researchers. Also, the paper lists out various challenges that are faced by researchers in designing the plant diseases prediction system and outline the advantage and disadvantage of the existing system.**

***Keywords*:** plant diseases prediction, machine learning, artificial intelligence, image processing, deep learning, precision agriculture **.**

I. Introduction

The stability of society and the economy, sustainable production of the crop is playing the major role. However, the plants are very frequently affected by various diseases due to environment changing and different management procedures [1]. Now a day, formers started using various measures such as use of disease-resistant seeds and spraying pesticides in order to control various disease that affect the plants. This type of solution not satisfactory because of its side effects namely, produces an environmental pollution and increases the production cost [2]. As a result, it creates significant impacts in crop production [3].

Artificial intelligence and image processing plays the major role in enhancing the agriculture from small scales to large scale smart and precision farming. There are solutions available for various plant and soil related issues using AI and image processing techniques [4]. However, the availability and collection of image based datasets is not only limited but also a challenging in particular for large scale farming [5]. Early detection of plant nutrient deficiency, diseases, crop yield, etc. is essential for efficient management of crops in large scale farming. But, early detection plays a vital role in large scale farming. The current image processing and AI based techniques are heavily dependent on RGB color images. Further, these images are collected in the farms manually which is not scalable for large scale farming [6]. In addition, RGB images suffer poor classification accuracy due to non-availability of physical characteristics of the plants beyond visual characteristics. Hence, they are not suitable for early detection tasks such as disease detection. In many common diseases of the plants, symptoms occur under the leaves, RGB images cannot acquire such symptoms for further analysis. Early detection of plant diseases improve the survival of the plant, hence hyperspectral image based plant diseases prediction system suitable to detect plant diseases at the early stage.

The rest of the paper provides detailed information and is organized as follows: a schematic diagram of designing the plant diseases prediction system is drawn in Section 2 The various ways in which plant disease image acquisition methods such as RGB, multispectral and hyperspectral camera acquire the plant disease images, popular datasets for plant disease detection used by the most of the researchers and its pros and cons is given in Section 3. In Section 4, various pre-processing techniques proposed is discussed. Section 5 deals with band selection techniques used to reduce the number of bands in an hyperspectral images of plant. In Section 6, various feature extraction techniques suggested by the researchers for plant disease prediction is discussed. Section 7 summary of the machine learning and deep learning based plant diseases prediction system is given. In Section 8, deals with various metrics used to evaluate the performance of the plant diseases prediction system. The Challenges in machine learning and deep Learning approaches is given in Section 9. Finally conclusion is drawn in Section 10.

II. General Architecture

The observations of many researchers from their finding helped us to model the generic flow of the plant diseases prediction system. A schematic diagram of a typical in designing the plant diseases prediction system is shown in Fig 1. The procedure for plant diseases prediction system includes image acquisition, pre-processing, band selection techniques, feature extraction techniques, and classification or prediction techniques.

The disease in plants is detected and after detection, the classification is done based on the disease. Farmers visually see the symptoms of diseases on plants. By that time, most of the crops are affected by the disease. Here early detection is missed. So farmers use fertilizers to control the disease. This leads to soil pollution and thereby affects the healthy crops. When these crops are consumed by humans, their health will also get affected.

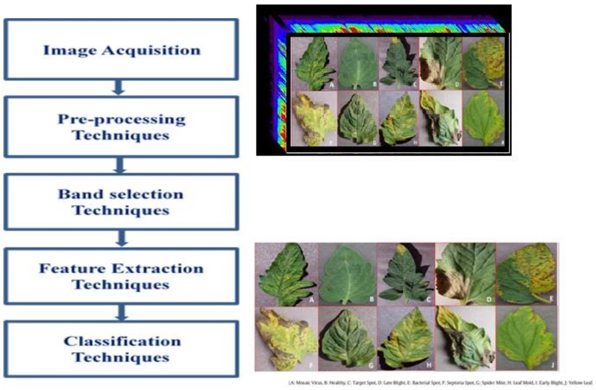

Figure 1. General flow of plant disease detection

III. Image Acquisition

The acquisition of plant disease image can be acquired by means of various sensors such as charge coupled devices (CCD), multispectral, hyperspectral and thermal sensors. Among these, the hyperspectral sensor based camera is widely used for early detection of plant disease. From the study, we understand the researchers are using push -broom, whisk-broom and snapshot hyperspectral camera. In order to capture the whole image of the plant at one time, snap shot hyperspectral camera used. Push-broom hyper spectral camera is to capture one line of the plant image whereas the whisk-broom hyper spectral camera is used to capture the one point of the plant image at a time.

Image Capturing for Plant disease detection can be performed in RGB Camera, multispectral camera and hyperspectral camera. RGB camera is using CCD sensors to capture the colored image of plant in the visible range of wavelength from 400 to 700nm. So the captured RGB images are used to extract the visible symptoms of various types of plant diseases. This is achieved by extracting the features based on the color, shape and texture. So these visible features are used to train the classification model in order to differentiate various types of plant diseases. Some of the notable advantages in RGB camera based system are easy to implement and less expensive. The following challenges are need to address while designing RGB based system ,RGB based plant disease prediction system performance often affected by the various factors such as lighting conditions, rotation,scaling,translation(RST variant). RGB images are useful when the symptoms are visible. When an RGB camera is used to take an image of the affected crop, it will not identify earlier detection.

Multispectral images contain more band information compared with RGB images. Satellite imagery and images obtained from the combined use of a UAV with a multispectral camera are two common ways to obtain the multispectral image.

Advantages: accurate mapping of large area plant disease mapping, it is useful

Challenges: It failed to capture the early detection of visible symptoms of plant disease.

It order to overcome the drawback of RGB and multispectral camera such as early detection of plant diseases, hyperspectral cameras are used. Hyperspectral camera based systems facilitate the efficient design of plant disease prediction system in non-destructive way. It is used widely to identify different types of plant diseases, nutrition deficiency, plant stress monitoring.

Advantages: Only Hyperspectral camera will be able to do earlier detection which was not visible to the human eye. So the information will be available even beyond the visible spectrum.

Challenges: The information will be available in wider band. So proper band selection has to be done without any loss of information. This will improve the speed of processing. Redundant information will be present in many bands. So redundancy needs to be reduced.

The classifiers are trained to classify plant disease from acquired images. The benchmark datasets available to design plant disease prediction system are given below in Table.1.

IV. Image Preprocessing

Pre-processing of images is done mainly to remove unwanted noises present in the image and also to avoid redundancy. This will reduce the computational time and complexity of processing. The following are the various preprocessing techniques used by the researchers , Dark, bright band removal ,Saitzky Golay Smoothing, Calibration, Savitzky–Golay filtering method for denoising, Multiplicative Scatter correlation to remove additive and multiplicative scattering effects, Tree crown Segmentation , alignment and radiometric, correction, image calibration, Savitzky-Golay algorithm for denoising , min/max normalization, simple linear iterative clustering (SLIC) super pixel algorithm, calibration, ROI selection, threshold segmentation, mean std variation calculation, PCA for severity class separation, Step wise wavelength selection /Sequential wavelength selection(combination of forward and backward strategies, salt & pepper noise removal, Gaussian blur, saturation, hue, and contrast, Preprocessing: Radiation calibration, Otsu thresholding, Morphological opening & Closing, Contour extraction., Gaussian filtering.

Table 1. Popular benchmark datasets for plant disease prediction system

Dataset	Sample Images	Description
Plant Village Dataset [32]		14 crops & 38 diseases of 54,309 images.
PlantDoc Dataset[33]		13 crops & 17 diseases of 2598 images
NLB Dataset [34]		1 crops & 1 diseases of 18,222 field images
RoCoLe: coffee disease dataset[35]	 Healthy ,Leaf miner, Rust ,Brown Leaf Spot,Cercospora Leaf Spot	390 coffee plants, total of 1560 images, 5 diseases
Cassava disease dataset [36]		Total of 5656 images for 5 disease classes: healthy(316 images), cassava bacterial blight(466 images), cassava brown streak disease(1443 images), cassava green mite(773 images), and cassava mosaic disease (2658 images)
Corn disease & severity dataset [37]		4455 images of 3 corn diseases
Rice plant diseases [38]		Rice crop, 3 diseases, rice blast(400 Images), brown spot((400 Images), hispa(400 Images), healthy(400 images), and a total of 1600 images

sample Apple Leaf datasets 1 [39]	 Healthy, Apple rust, Apple scab,Apple rust &Apple scab	Apple rust(622 images), Apple scab(592 images),both Apple rust and Apple scab(91 images) ,healthy (516 Images) types images , Marssonia blotch(120 images),Alternaria leaf spot (166 images),Healthy(118 images).
Digipathos Dataset [40]		46,513 images across 171 diseases affecting 21 different crops

V. Band Selection

The image information is available in a wider band spectrum. Only there will be minor differences in information in many bands. So band selection is done without loss of major information. This will make the processing faster with accurate image information. Principal component analysis (PCA) and genetic algorithm (GA), back-propagation (BP) neural network are used by various researchers to reduce the number of band and redundancy band for better feature extraction.

VI. Feature Extraction

Feature extraction is performed to identify the color and the texture of affected plants from healthier plants. The various method proposed by the authors for feature extraction is given below, adaptive Reweighted Sampling (CARS) and Successive Projection Algorithm(SPA), CARS-RF, continuous wavelet analysis (CWA), Successive Projection Algorithm, Modified Red Deer optimization algorithm (MRDOA), Background removal, Band screening.

VII. Classification/ Prediction

Finally, the model is trained to identify the extracted features and the classifier will do the classification based on the metrics used. The Deep learning technique gives accurate results when compared with the Machine learning technique [41, 42]. Based on the index values, the accuracy may also be calculated. Existing prediction system used following classification algorithm: Parsimonious machine learning (ML) algorithms based Ensemble model ,Random Forest, Gradient Boost, X- gradient Boost, Support Vector Machine (SVM), random forest (RF), and classification and regression tress (CART), and logistic regression (LR), extreme learning machine (ELM), a deep learning convolutional neural network (DLCNN), DDMA-YOLO network, The summary of various recent machine leaning and deep learning based approaches is given in Table 2 & Table 3 respectively.

VIII. Quantitative Evaluation

In this section the detail description of the quantitative evaluation of the plant disease detection system such as quality metrics and quality indices is given.

A. *Quality Metrics*

From the exiting paper, we came to know that the quality metrics such as accuracy, precision, recall, sensitivity, specificity, F1 score and Kappa coefficients are used by the most of the researchers in order to evaluate the performance of the plant disease detection system. The description of the widely used quality metrics for quantitative evaluation is given in Table.4

Table 2. Machine Learning Approaches

Year	Disease and Crops	Indices	Sensitive bands	Metrics
2021[1]	**Disease:**Powdery mildew **Crop:** Wheat	NDTI**,**VI,PMI.MSR, PRI, PhRI, MCARI, ARI, SIPI, NPCI, RVSI, NBNDVI, NRI, TVI, TCARI, PSRI ,AI	437.2 nm to 976.2 nm	OA=82.35%Kappa Coefficient=0.56
2022[2]	**Disease:** Powdery mildew**Crop:** wheat	**mDI**	580- 720nm	SVR-PLSR R^2 = 0.733-0.836,RFR,R^2 =0.742-0.852,MC-RFR, R^2 =0.849-0.859,RMSE= 2.084-2.177,MAE=1.684-1.77
2021[3]	**Crop:** cucumber **Disease:** Powdery mildew	RWP,REP,SR	660–780 nm	Overall Accuracy= 95%
2021[5]	**Crop:** Strawberries **Disease:** Anthracnose, gray mold	-	780 -900 nm	**OA**=100%
2020 [6]	**Crop:** tobacco **Disease:**tomato spotted wilt virus infection	-	400 to 1000 nm with 128 bands	OA=95.8% (6–8days post-inoculation DPI)
2020[7]	**Crop:** Peanut **Disease:** Bacterial wilt (BW) caused by Ralstonia solanacearum diseases	15 vegetation indices and spectral indices (NDSI and RSI)	730 nm and 790 nm	**RMSE ,**BWI1 =0.2 BWI3 =0.20 BWI4 =0.27 BWI6 =0.28
2022[8]	**Crop:** tea plants **Disease:Plant stress**	-	780 -1000 nm	OA (94.12%-94.28%)
2022[9]	**Crop:** Grapevine **Disease:** Esca disease	-	1596–1687 nm	82.77-97.17%
2022[10]	**Crop:**Wheat **Disease:** fusarium head blight	Normalized difference vegetation index (NDVI))	400-1000nm	SVM accuracy (CA) of 95.6 % ANN 82.9
2022[11]	**Crop: Sweet potato Disease:** sweet potato disease	-	400-1000nm	Accuracy=99.52%
2020[12]	**Crop:** Rubber **Disease:** Leaf blight	Six vegetation index	700–1000 nm	Spectral Angle Distance (SAD)
2020[13]	**Crop: tea Disease:** star disease and anthrax	-	400-900 nm	ELM Accuracy=95.77%

2022[14]	**Crop:** Rubber Tree **Disease:**Leaf Blight	-	400-700 nm	Accuracies of 98.0 to 99.8%.R2=0.97 to 0.99
2022[15]	**Crop:** wild rocket salad crop **Disease:** soil-borne disease	NDVI	550 -700 nm	Accuracy=0.656 Kappa=0.5470

Table 3. Deep Learning Approaches

Year	Disease and Crops	Indices	Sensitive bands	Metrics
2022 [16]	**Plant leaf Disease** Detection	-	400-900 nm	Accuracy=99.73% F1-score=99.78% in Plant Village dataset and Accuracy=99.68%, and F1-Score=99.71% in Rice Plant dataset.
2023[17]	**Crop: tea Disease:** Tea leaf blight (TLB)	-	400-1000 nm	Accuracy 95%
2022[18]	**Crop: Apple Disease:** apple valsa canker	-	400-900 nm	accuracy =98%
2023[19]	**Crop:** potato **Disease:** potato late blight (PLB)	-	680 - 750 nm	Full band Accuracy=73.9% Specific band Accuracy=79%
2023[20]	**Crop:** Pepper seed **Disease:** Pepper seed viability	-	278–1723 nm	Accuracy= 88.99%
2020[21]	**Crop:** wheat **Disease:** Fusarium head blight (FHB) presence in	-	400–750 Nm	Accuracy and F1 score= 100 %
2020[22]	**Crop:** cabbage **Disease:** Plasmodiophora brassicae (clubroot)	VI- (ARI) and (PhRI)	380–1030 nm.	Accuracy =85%
2023[23]	**Crop:** potato & tomato **Disease**: potato (Solanum tuberosum) and tomato (Solanum lycopersicum)	-	400-750 nm.	Accuracy = 99.25%, Precision=99.67% , Recall=99.33% and F1-score=99.33%
2023[24]	**Crop:** General **Disease:** Plant root disease	-	400-900 nm	Accuracy=0.941, sensitivity=0.960, and specificity=0.921

2019[25]	**Crop:** General **Disease:** Plant leaf disease	-	400-700 nm	Accuracy =96.6% F1-score=0.982 Recall=0.99 Precision=0.965
2019[26]	**Crop:** Pearl millet **Disease:Mildew** disease	-	400-700 nm	Accuracy = 95.00%, Precision = 90.50%, Recall = 94.50% F1-score = 91.75%.
2017[27]	**Crop:**Wheat **Disease: wheat**	-	400-700 nm	Accuracy = 98.00%
2018[28]	**Crop:** Apple **Disease:** Marssonina blotch	-	356-1180 nm	Accuracy = 86.10% F1 Score=0.85
2020[29]	**Crop:** Rice & Maize **Disease:** Rice stacknurn & leaf scald.Maize eyespot & Gray leaf spot	-	400-700 nm	Rice Accuracy=92%, sensitivity=80%, and specificity=95% Maize: Accuracy=80.38%, sensitivity=60.76%, and specificity=86.92%
2021[30]	**Crop:** Tomato **Disease**: Tomato leaf disease	-	400-700 nm	Accuracy = 99.51%(Class 5), Accuracy = 98.65%(Class 7), and Accuracy = 97.11%(Class 10)
2022[31]	**Crop:** Apple & Coffee **Disease**: leaf disease	-	400-700 nm	Accuracy= 99.79%(Apple Leaf datasets), Accuracy=97.12%(Coffee Leaf dataset)
2022[14]	**Crop:** Rubber Tree **Disease:**Leaf Blight	-	400-700 nm	Accuracies of 98.0 to 99.8%.R2=0.97 to 0.99
2022[15]	**Crop:** wild rocket salad crop **Disease:** soil-borne disease	NDVI	550 -700 nm	Accuracy=0.656 Kappa=0.5470

Table. 4 Widely used quality metrics for performance evaluation

S.No	Quality metric	Description
1	$Accuracy = \frac{(TN + TP)}{(TN+TP+FN+FP)}$	It is ratio between the number of correct assesments and total number of assesments
2	$Sensitivity = \frac{TP}{(TP+FN)}$	It is ratio between the number of true positive assessment and the total number of positive assessment.

3	$Specificity = \frac{TN}{(TN+FP)}$	It is ratio between the number of true negative assessment and the total number of negative assessment.
4	$Precision = \frac{TP}{(TP+FP)}$	The ability of a prediction model to return only the data points in a class
5	$Recall = \frac{TP}{(TP+FN)}$	The ability of a prediction model to identify all data points in a relevant class.
6	$F1\ Score = \frac{2 * Precision\ x\ recall}{(Precision + Recall)}$	The harmonic mean of recall and precision .
7	$Kappa\ Coefficient = \frac{2 * (TP * TN - FN * FP)}{(TP+FP)(FP+TN)+(TP+FN)(FN+TN)}$	It indicates the amount of agreement between frequencies of two sets of data collected on two different experiments.

Where TP means True Positive, it indicates the presence of disease correctly classified during the classification process. TN means True Negative; it indicates the absence of disease correctly classified during the classification process. FP means False positive, It indicates wrongly classified the presence of disease but actually no such disease. FN means False negative , It indicates wrongly classified the absence of disease but actually disease presence.

B. Quality Indices

The widely used indices are:

Normalized Difference Texture Indices (NDTI)

$$NDTI = \frac{(T1 - T2)}{T1 + T2} \quad (1)$$

T1, T2 are the texture features of the selected sensitive wavelength

Vegetation Indices(VI): Powdery mildew index (PMI),Modified simple ratio (MSR), Photochemical reflectance index (PRI),Photosynthetic radiation(PhRI), Modified chlorophyll absorption ratio index (MCARI), Anthocyanin reflectance index (ARI), Structure independent pigment index (SIPI), Normalized pigment chlorophyll ration index(NPCI), Red-edge vegetation stress index(RVSI), Narrow-band normalized difference vegetation index (NBNDVI), Nitrogen reflectance index (NRI), Triangular vegetation index (TVI), Transformed chlorophyll absorption and reflectance index (TCARI), Plant senescence reflectance index (PSRI) ,Aphid index(AI).Mildew disease Index(mDI): It is calculated using average severity of leaf disease (LAI) of diseased leaf and diseased leaf rate.

$$LAI = \frac{\frac{DW1 + Dw2}{Dw1}(LA)}{S} \quad (2)$$

DW1 and DW2 are the dry weights of the leaves and the remaining leaves of 20 plants, respectively, and S is the sampling area of each plot. LAI is a dimensionless indicator to characterize the vigorous degree of vegetation. Photosynthetic capacity- maximum carboxylation rate (Vcmax), carbon-based constituents (CBC, including lignin), and leaf biochemical traits and tree-crown temperature (Tc) as an indicator of transpiration rates, Red and red-edge parameters-Red-well point (RWP) and the red-edge inflexion point (REP), Spectral ratio (SR). Vegetation Index's-anthocyanin reflectance index (ARI) and physiological reflex index (PhRI)

IX. Open Challenges and Discussions

A. Challenges in Machine Learning (ML) Approaches

1. Most of the ML based approaches described as black-box models because the way features are extracted is not known to the users.
2. Identifying correlation among the bands to extract the biological significance of the plant diseases by ML algorithm is difficult.
3. Selecting suitable features for better classification of the various plant diseases is challenging by the ML Algorithms.
4. Extracting RST invariant shape and texture information from the plant image is more challenging in ML based approaches.

5. Selecting the suitable ML algorithm for specific type of plant diseases classification.

B. Challenges in Deep Learning (DL) Approaches

1. Parameter tuning of the various deep learning architecture for plant diseases prediction system is difficult.
2. Identifying suitable deep learning architecture for specific plant diseases prediction system is difficult.
3. Complexity of the deep learning based model is high.
4. Overfitting issue
5. Getting labelled training samples for better classification of deep learning model is difficult.

X. Conclusion

Many researchers have developed successfully different plant diseases prediction system using image processing, machine learning and deep learning techniques to improve the global food production and food security. Among these techniques, deep learning approach based plant disease prediction system outperform in terms of classification accuracy .However there are some limitation in the deep learning approach needs to be addressed: Parameter tuning of the various deep learning architecture for plant diseases prediction system is difficult, Identifying suitable deep learning architecture for specific plant diseases prediction system is difficult, Complexity of the deep learning based model is high, Overfitting issue, Getting labelled training samples for better classification of deep learning model is difficult. Most of the existing system using plant village dataset to validate the performance of proposed framework. Those systems failed to predict the early detection which is essential for precision and smart agriculture. Early detection of plant disease detection requires the system need to identify plant disease before the visual symptoms appear. Hence hyperspectral image based plant prediction system suitable to predict plant disease early.

Acknowledgment

We thank the anonymous reviewers for their constructive comments and VIT, Vellore for providing space to carry out this research.

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