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An Empirical Survey of Machine Learning-Based Plant Disease Prediction Models

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Abstract: ***The occurrence of diseases in plants badly impacts the agricultural production, which increases the food insecurity when the diseases are left undetected. Particularly important for ensuring the availability of production of agricultural and food are the major crops, such as maize, rice, and others. Effective control and prevention of diseases in plants are based on disease forecasting and early warning, which is essential for managing and making decisions regarding agricultural productivity. In rural parts of developing nations, observations by knowledgeable providers remain the main method for plant disease identification as of yet. This draws researchers in for ongoing experienced monitoring, which may be cost-prohibitive on large farms. Besides, in some remote areas, farmers require the assistance of the agricultural experts, which is the expensive and time-consuming process. Hence, automatic disease identification for plants is important to promote the monitoring of large crop fields, which encourages the contribution of the accurate, less-expensive, automatic, and fast technique to perform the detection of diseases in plants. In this survey, the automatic detection methods used for the plant disease detection based on the deep learning methods are discussed. The importance of the deep learning methods for the detection of disease is demonstrated through the schematic sketch on the other basic machine learning techniques in agricultural applications.***

Keywords: Automatic Detection, Plant Diseases, Deep Learning, Agricultural Production, Plant Disease Detection.

I. INTRODUCTION

In the agricultural field, the eruption of diseases in crops has a huge impact on the yield. Massive loses can takes place during the massive outbreak similarly, small-scale outbreak can also cause a serious impact on the crop yields by affecting the quality of the crops. To protect plants from numerous diseases and increase agricultural production, recognition and classification of various diseases are performed [1][2][3]. Estimation made in United States reveals that the population increases rapidlyby next 30 years [4]. Report from the Food and agricultural organization shows that to tackle the amount of food for entire population, 70-90% of food is yet required, which imposes the pressure on the food production.

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Even though, the promotion of the food production has been done, 16% of the plants are affected by the bacteria and fungi diseases, which should be minimized by forecasting the diseases. To ensure the productivity of the crop, there is a need for the advanced methods to predict and classify the diseases and the significant thing to be noted is the prevention of crop damages [5]. The main reason for the loss of income in agriculture is due to the improper or late recognition of diseases that occurs due to the weeds and pests [6]. The proportion of the green house gases is controlled to enhance the gain of the crops but it increases the spread of viral, bacterial and fungal diseases. The yield of the crop with full potential can be obtained by continuously monitoring and repetitive detection of diseases [7][8][9]. The economic loss due to the crop can be greatly reduced, when the disease detection is performed in-advance. The detection can be made based on the appearance because petioles and leaves contains the majority of the symptoms [10][11][12][13]. In the traditional perspective, the diseases are identified manually by the experts, which consumes more time and the accuracy is reduced. Due to the manual intervention, there is a probability of error occurrence [14]. To overcome the disadvantages in the traditional method, numerous spectroscopic as well as imaging techniques are employed to detect the diseases, but there is a necessity for precise instruments and a large number of bulky sensors [15][16]. The cost of these methods is increased due to the components, but the efficiency achieved is low. Latterly, the advancement in the technology and the availability of the camera and other electronic gadgets allows the individuals to automatically detect the disease through deep learning and machine learning methods. The automatic detection using image processing techniques are an widely used and satisfactory methods for the detection of diseases [17][18][19][20][21][22][23][24][25].The deep learning techniques make the availability of various architectures, like convolutional neural network (CNN), and under CNN Alexnet, Google net and so on. The disease detection methods utilize the preprocessing techniques for the recognition of species and the accuracy of detection are also improved using these techniques [26][27]. In this research, the review of the existing detection methods for plant diseases is discussed with the detailed summary of the benefits and drawbacks. Moreover, the article carries the analysis of the feature extraction-based approaches, segmentation methods and the classification models and the motivation for the disease detection is portrayed in detail. Finally, the future direction of the research is presented. The organization of the article: section 2 covers a summary of the current techniques, and the analysis is discussed in section 3.

Finally, Section 4 lists the gaps and finally, section 5 concludes the paper.

II. A SURVEY OF THE RELEVANT LITERATURE ON DETECTION AND SEGMENTATION TECHNIQUES

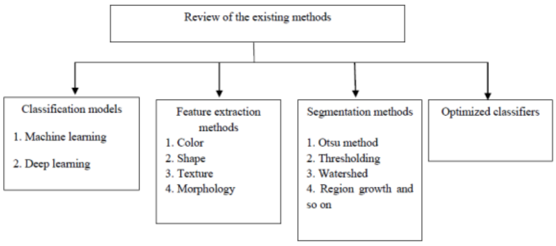

Figure 1. Categorization of the section

The existing works carried by the researchers to detect the disease in plants along with its advantages and disadvantages are enumerated in this section. Figure 1 shows the categorization of the section in demonstrating the significance of classification, segmentation, and feature extraction methods. In the plant disease detection model, the segmentation is the significant step, which is followed by the feature extraction from which the significant information of the segmented output is extracted. By using obtained features, classification is performed and the various classification models explained in the existing articles are detailed in this section.

A. Based on Training Models

In this section, it is shown with advantages and disadvantages how trained models are used for plant disease detection. Manish Kumar *et al.* [5] created a multilayer perceptron model-based expert system, in which the disease is classified using machine learning. The model highlighted the decreased in the overall cost by the deployment of sensors, but the disadvantage is that the classifier parameters are measured only for the independent binary classifiers'. S. Mustafa *et al.* [27] invented a hybrid intelligent system for the detection of diseases utilizing the Support Vector Machine (SVM), probabilistic neural network and Naive Bayes that helped the individuals to identify the plant species, and disease in earlier time, but the stumbling block is that there is an increase in the computational time. Kshyanaprava Panda Panigrahi*et al.*[28] disease is detected in maize plants using the techniques of machine learning like Random forest, K-nearest neighbor, Naïve Bayes, decision tree that effectively detect the disease with higher accuracy rate, but it lacks the capability of dealing with high dimensional data. Pengjiang*et al.* [25] introduced an INAR-SSD model based on the incorporation of the Rainbow concatenation and Inception module with single shot multibox detector that effectively extract the discriminative features with good accuracy, but the pitfall is that the detection of small objects is limited. Xihaizhang*et al.* [29] incorporated the deep learning methods googlenet and Cifar10 for the detection of diseases in maize leaves, which exhibited strong robustness and the higher diversity of the pooling regions with less number of iterations. However, smaller datasets create a barrier to the classifier's accuracy, seeking the need for the huge data for the classifier training. Murk Chohan*et al.* [30] using a convolutional neural network the disease in plant is detected automatically, which can be interconnected with drone for the live detection of diseases. The major drawback of the convolutional classifier is that the classifier suffered from the computation complexity. Guofeng yang *et al.* [3] used LFC-Net, which is the combination of the location network, feedback network as well as classification network that extracts the highly informative region in minimal iterations. The invented model is a multi-network collaborative model that makes the availability of self-supervised mechanism for the classification. Furthermore, the huge efforts are needed to identify the different stages of disease. Junde Chen *et al.* [31] inception module and image net are used to pretrain VGG net based on deep convolutional neural networks of transfer learning. Even at very complex situations, the classifier acquires good accuracy rate, but the computational complexity of the classifier is high.

B. Based on feature extraction methods and classifier

In this context, the review of the various feature extraction modules developed in the existing literature is discussed. In [32], the texture-based feature extraction methods are demonstrated, which highlights that the spatial features, shape, texture, and color are significant in the detection of sick plants. It is suggested that the lesions demonstrate the significant information about the plant diseases. Among the features, color is a stable feature, insensitive to the image augmentation methods. However, color characteristics failed to capture the local features from the image and image clarity is often a challenge. Furthermore, texture features play a prominent role in detection of disease for which the statistical features, Gray-Level Co-occurrence Matrix (GLCM) features, linear binary pattern, and so on are employed. Even though the texture features impact the classification performance, the resolution of the image is a challenge, and the minor deviations in the images need to be extracted that is impossible using the existing texture descriptors. Moreover, the shape-based features focusing the geometry, area, and plant invariants are significant for the plant disease classification. Even though the stable shape features are compared with the features of color, the required recognition rate is not acquired [33]. In [34] [35], the authors demonstrated the need for the morphological features in the disease classification, which yields the necessary information of the plants. However, the accuracy is affected when the minor deviations in the plant morphology is ignored. In the following articles, the deep learning method for feature extraction is performed. Rudresh Dwivedi*et al.* [36] developed the network for the detection of disease in grape leaf that avails dual mechanism for the evaluation of features. The network works based on the faster RCNN that greatly reduces the human intervention with higher recognition rate. There is a necessity of high level features to differentiate healthy and unhealthy leaves. Xuannie*et al.* [13] initiated a disease detection model based on faster RCNN network, where the features are extracted using the attention mechanism. The usage of multilevel features improved the detection performance without affecting the other process,

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but there is an imbalance in the dataset used for the detection of disease.
Karthik R *et al.* [37] contrived the disease detection based on dual architectures as well as employed the attention mechanism in the residual network. The model detected the diseases by learning around 600k parameters. The architecture of the residual network is complex in structure, which is the pitfall of the method. Chen Jun-De *et al.*[38] created an automatic detection and classification system for the identification of plant diseases availing the texture feature extraction technique. It performs well even in complex background, but the disadvantage is that small deviations in the extracted features impact the classification performance. Alexander Johannes *et al.*[39] designed an hot spot based detection algorithm that incorporated with statistical inference methods that tackles the disease identification even in wild conditions as well as the naïve bayes is utilized for the filtration purposes. The method has the capability to eliminate the region with redundant visual information. In comparison to the overall number of pixels in the image, the quantity of pixels considered is extremely small.

C. Based on Segmentation Methods

In this context, the discussion on the segmentation methods is demonstrated. The segmentation methods, Otsu' method [40], k-means clustering [40] [41], thresholding [42], region growth [42], watershed [42] approaches, and so on. The defined segmentation approaches from [42] demonstrates that these approaches require manual intervention, ignore any important information required for classification, and diversity was affected. S. Aasha Nandhini*et al.*[43] established a disease detection system that is web-enabled relying on the compressing technique that reduces the complexity in the storage. The segmentation of the sick leaves is also made possible by the availability of statistically based threshold strategies. The entire information about the crop is not analyzed in a detailed manner. Shanwen Zhang *et al.* [44] segmented the leaf of plant using the hybrid clustering of superpixel clustering and expectation maximization algorithm. The complexity of the pixels is greatly reduced, that is around 1000 pixels present in the image are converted into 100 number of super pixels. The drawback is that the robustness is not explored. Aravindhan Venkataramanan [45] examined the leaf using deep learning approach that performs the classification in multiple stages and detected the objects using YOLOv3 object detector. It attains good results in less number of epochs and the model has a prior knowledge that fits many applications. The drawback is that it is not implemented in real-time environments. Amreen Abbas *et al.*[26] generated synthetic images of the tomato plants using the augmentation method Conditional Generative Adversarial Network (C-GAN) and the images are trained with densenet121, which reduces the over-fitting problems, but the methodsuffers from high computational time.

D. Based on Optimized Classifiers for Disease Detection

This section details the optimized classifiers for disease detection. R. Cristin*et al.*[9] established a deep belief network for the disease detection in leaves usin g fuzzy C-means clustering. The network is optimized using the Rider-CSA algorithm that choses the weights optimally. There is a problem of slow convergence while using this optimization. Eisha Akanksha*et al.*[46] introduced an efficient system for diagnosing the disease in maize plants named Optimistic probabilistic neural network classifier that utilized artificial jellyfish optimization. The Fuzzy-C means algorithm is used for segmentation. The usage of PNN has the capability to improve the accuracy at higher speed. The pitfall is it requires higher memory for the storage purpose. Hiteshwari Sabrol*et al.* [47] presented adisease classification based on adaptive neuro-fuzzy inference system. The features are computed using the GLCM matrix and this method reduce the misclassification rate but the experiment is carried only for grey scale images and the color images are not considered. Geetharamani G *et al.* [7] utilized six augmentation models for the detection of disease in plants using deep CNN that resolves the problems effectively. The augmentation method increases the amount of training data where the accuracy gets improved. Artificial images are created using the augmentation but real time images are not considered.R. Sowmyalakshmi*et al.* [48] initiated a convolutional neural network for the detection of rice plant disease in smart agriculture using Optimal Weighted Extreme Learning Machine (CNNIR-OWELM) and Res Nset v2 model. The incorporation of flower pollination algorithm helps to resolve multiobjective optimization problems, but the convergence is poor that affected the classification accuracy. Dhruvil Shah *et al.* [49] designed an Res TS (Residual Teacher/Student) architecture, which effectively detects the disease using the residual network and degrades the exploding gradients or vanishing issue. The residual network heavily depends upon the batch normalization is the deprivation of the method. Vempaty Prashanthi*et al.* [50] examined the graphical detectable pattern and identified the infection in plants using convolutional neural networks. The invented model detected around 13 unique ailments, but there is a need for the further enhancement in the precision. Qiaokang Liang *et al.* [51] innovated a system based on the computer assisted approach named Severity Estimation Network (PD2 SE-Net) and Diagnosis of plant disease which detects the disease as well as the severity of the disease also estimated. The usage of adam algorithm reduces the storage space. Although it performs well in terms of accuracy, there is a problem of over fitting which diminish the effectiveness of the classifier.

III. ANALYSIS AND DISCUSSION

Based on the analysis in this section the existing approaches performed in different experimentations. The segmentation methods, classifiers and the parameter metrics-based analysis are detailed in the below sections

A. Segmentation methods-based analysis

The analysis is carried based on the segmentation methods and the performance measures used are mentioned in the table 1. The various segmentation methods used here are: CNN, binary thresholding algorithm, Histogram-based segmentation, Mean based thresholding strategy, K-mean clustering method,

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label edge detection method, Fuzzy-c means, pi FCM, hybrid clustering, Semantic segmentation, and Otsu based segmentation.

The Otsu thresholding method automatically performs the image thresholding and provides the result based on the two classes, such as foreground and background. Due to its speed and uncomplicated coding, the Otsu method is more efficient. The analysis is represented by a bar chart shown in figure 1.

Table1.Evaluation using segmentation techniques

Segmentation methods	Achievements	Published papers
CNN	Accuracy, Precision, Recall, F1 measure	[50]
Binary thresholding algorithm	F1 measure	[49]
Histogram-based segmentation	Accuracy, Sensitivity, Precision, Recall, F1 measure	[48]
Otsu	Accuracy	[47]
Mean based thresholding strategy	Accuracy	[43]
K-mean clustering method	Accuracy, Precision, Recall, F1 measure	[27]
label edge detection method	Accuracy	[28]
Fuzzy-c means	Accuracy, Sensitivity	[46]
piFCM	Accuracy, Sensitivity, specificity	[52]
hybrid clustering	Time	[38]
Semantic segmentation	Accuracy	[51]

B. Analysis based on the feature extraction methods

In this section, various feature extraction methods used by the existing methods are highlighted as shown in table 2 and the graph is plotted based on the methods shown in figure 2. From the observed papers, the features are extracted based on the techniques Attention mechanism, Neural networks, Heatmaps, Statistics, CNN, ResNet-50, VGGNet, Gray-Level Spatial Dependence, orthogonal matching pursuit (OMP) algorithm, YOLOv3, DenseNet, colour thresholding, RGB feature extraction, PNN, Texture, GMDH-Logistic approach, Deep CNN. Here,CNN features are the most frequently-used feature extraction method that renders a great solution to resolve the problem of vanishing gradients.

Table 2. Analysis based on Feature Extraction in The Disease Detection

Features extraction methods	Research articles
Attention mechanism	[36] [13] [39]
Neural networks	[50]
Heatmaps	[49]
Statistics	[5]
CNN	[48] [29] [30][25][53][37]
ResNet-50	[3]
VGGNet	[31]
Gray-Level Spatial Dependence	[47]
orthogonal matching pursuit (OMP) algorithm	[43]
YOLOv3	[45]
DenseNet	[26]
colour thresholding	[27]
RGB feature extraction	[28]
PNN	[46]
Texture	[52]
GMDH-Logistic approach	[38]
Deep CNN	[51]

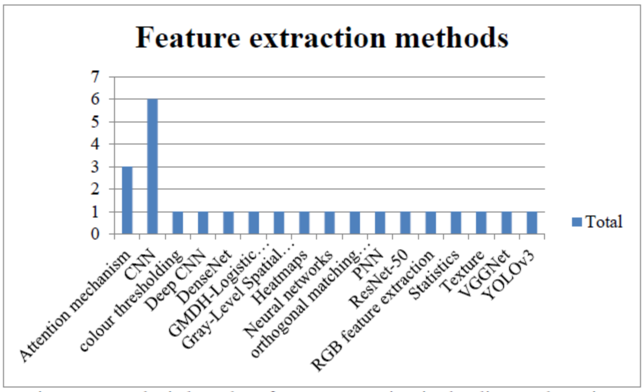

Figure 2. Analysis based On Feature Extraction in The Disease Detection

C. Detection of diseased plants based on the analysis of classifiers

In this section, the analysis is carried based on the classifiers used in the disease detection of plants and the achievements made also enumerated in the table 3. From the observation made, the conclusion can be made as that the deep learning methods are widely used compared with machine learning methods. There is no need for data labeling, the outcome can be obtained based on the user perspective by tuning their parameters and optimizing them, works well in unstructured data and automatic deduction of the parameters made the deep learning techniques to be more effective.

Table 3. Detection of Diseased Plants Based on The Analysis of Classifiers

Classifier	Achievement	Papers-used
Faster R-CNN	Accuracy-93%	[36] [13]
Deep CNN	Accuracy-97.4%	[50]
ResTS	F1 measure-90.2%	[49]
MLP	Accuracy-87%	[5] [52]
CNN	Accuracy-94.2%	[48] [39] [38] [37] [51]
Deep CNN	Accuracy-96.9%	[29] [25] [31] [53]
Neural network	Accuracy-90%	[30]
LFC-Net	Accuracy-99.7%.	[3]
Adaptive neuro-fuzzy inference system	Accuracy-90%	[47] [27]
SVM classifier	Accuracy-90%	[43]
Resnet18	Accuracy-94%	[45]
Conditional Generative Adversarial Network (C-GAN)	Accuracy- 91%	[26]
Random forest classifier	Accuracy-79.23%	[28]
PNN	Accuracy-95.55%	[46]

IV. RESEARCH GAPS AND CHALLENGES

A. Based on segmentation

- In practical applications, the technique that makes availability of segmentation or edge detection is complex and provoked by the computational time. The segmentation process is challenging due to the morphological operations as well as light conditions [29][36].

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- Commonly, the image segmentation of plants is performed through fixed threshold in order to distinguish the normal, spot and background pixel. However, the image collected will have fuzzy, unclear, uneven and uncertain which creates overlapping [44]

B. Based on feature extraction

- Layer-wise Relevance Propagation (LRP) heatmaps includes the negative and positive inputs which makes the measurement of the sensitivity difficult due to the noise present in the gradient heatmaps [10][49].
- It is an challenging task to define the small discriminative features which will be useful in fine-grained visual categorization [3].
- Interpretation of the optimal parameter values and extracted variables is a strenuous task due to the occurrence of information distortion [38].
- In machine learning techniques the performance will be purely based on the manually selected features. For the process of enhancement of the classification automatic identification of the features are necessary [37].
- While detecting the disease in plants, sometimes there is a huge variation in the properties of the disease pattern. So for the efficiency wide range of data should be analysed in an automated way without human intervention [37].

C. Based on classification

- The presence of abundant information and judgment value about the crop leaves or plants make the process of finding and locating regions difficult [3].
- To obtain better and satisfactory performance there is a need of large training samples for the deep learning network [37].
- The identification of specific patterns in the plants is performed using the soft computing model results in poor accuracy. Improving the accuracy rate of this model is a challenging task to be handled [52].
- To represent the whole image the features of multiple annotations are taken into account. These multiple annotations are dense annotations that create limitations in the scalability and usability of the applications [3].
- The number of diseases occurs on the same leaves, the occurrence of spot is small, or the environmental factors can affect the quality of classification [25].

V. CONCLUSION

The reviews for the disease detection of plants utilizing the previous work of the researchers are enumerated in the manuscript. The study is particularized based on the segmentation methods, optimizations used, classifiers used and the highlighting parameter metrics. The challenges overcome while detecting the diseases in plants are also enumerated. The achievements made by different researchers are also discussed. The manuscript provides anidea towards the enhancement of disease detection in plants for the high yield in agricultural purposes.

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