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A Study on Various Methodologies for Plant Leaf Disease Detection and Classification

Arpan Singh Rajput*[1]
Research Scholar
Jabalpur Engineering College, Jabalpur
arpansinghrajput@gmail.com

Dr. Shailja Shukla[2]
Professor
Jabalpur Engineering College, Jabalpur
Shailja270@gmail.com

Dr. S. S. Thakur[3]
Former Principal
Jabalpur Engineering College, Jabalpur
samajh_singh@rediffmail.com

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Abstract: Disease detection is basically a principal aspect in ameliorating agricultural production. The presented research concentrates on devising Plant Leaf Disease (PLD) detection together with an identification process intended for larger fields of crop production. Here, an inclusive study on disease recognition together with the classification of plant leaves utilizing Image Processing (IP) methods is performed. Since this technique is unpredictable and inconsistent, the customary manual visual quality examination can't be systematically stated. Furthermore, an extraordinary quantity of expertise is involved in plant disease diagnostics as well as the inconsistent processing times. Therefore, IP is implemented for plant disease recognition. Next, an imperative role is played by the Deep Learning (DL) together with Machine Learning (ML) classifiers in leaf disease classification. Centered upon an assessment of the formerly recommended top-notch techniques, a comprehensive discussion on disease detection together with classification performance is given. Lastly, the challenges and also some prospects for future ameliorations are discussed as well as classified.

Key words: Plant leaf disease identification and classification, Segmentation methods, Feature extraction, Classification methods, deep learning, Machine learning.

1. INTRODUCTION

An imperative role is played by the plants in working as well as maintaining the equilibrium on this earth [1]. Agriculture stands for the art of cultivating plants. It is the major donor to the Indian economy [2]. An atypical state of the plant that bothers the plant's normal growth is Plant disease [3]. Plant diseases lead to major production together with economic losses in the agriculture industry [4]. The developing countries' economy mostly relies upon agricultural productivity [5]. In most instances, diseases are detected on the plant's leaves or stems [6]. Regular monitoring together with a timely response by the farmer is vital for reducing yield losses of crops caused by disparate diseases [7]. The diseases are manually recognized by means of the Farmers with preceding symptoms of plants as well as using experts. Nevertheless, it is time-consuming in detecting the actual diseases with naked eyes [8].

The whole crop can well be saved from the disease if the disease is detected at an early stage [9]. Thus, automatic disease detection is vital. It helps in the precise Early Diagnosis (ED) of PLD [10]. Some utmost effectual techniques for disparate categories of applications are the IP together with Computer Vision (CV). For instance, detecting, quantifying, as well as classifying plant diseases [11]. Lately, , as well as ML, has been ML is employed for detection. By utilizing semantic features, classification tasks were performed previous to the DL trend [12]. Features say boundary, color, shape, along with texture are extracted by the Feature Extraction (FE) techniques to distinguish the leaf disease [13]. Therefore, scientists and farmers should study the traits of the crop along with the reaction to disparate stress factors [14]. Over the past '25' years, to ameliorate the precision, reliability, and also accuracy of image analysis aimed at detecting along with classifying plant diseases, Major advancements were performed [15]. The general structure for classification together with recognition of PLD is depicted in Figure 1. This paper signifies the survey of the newest growths and enhancements of the computer and IP techniques in PLD detection and identification, in addition to classification with stress on IP in a significant way.

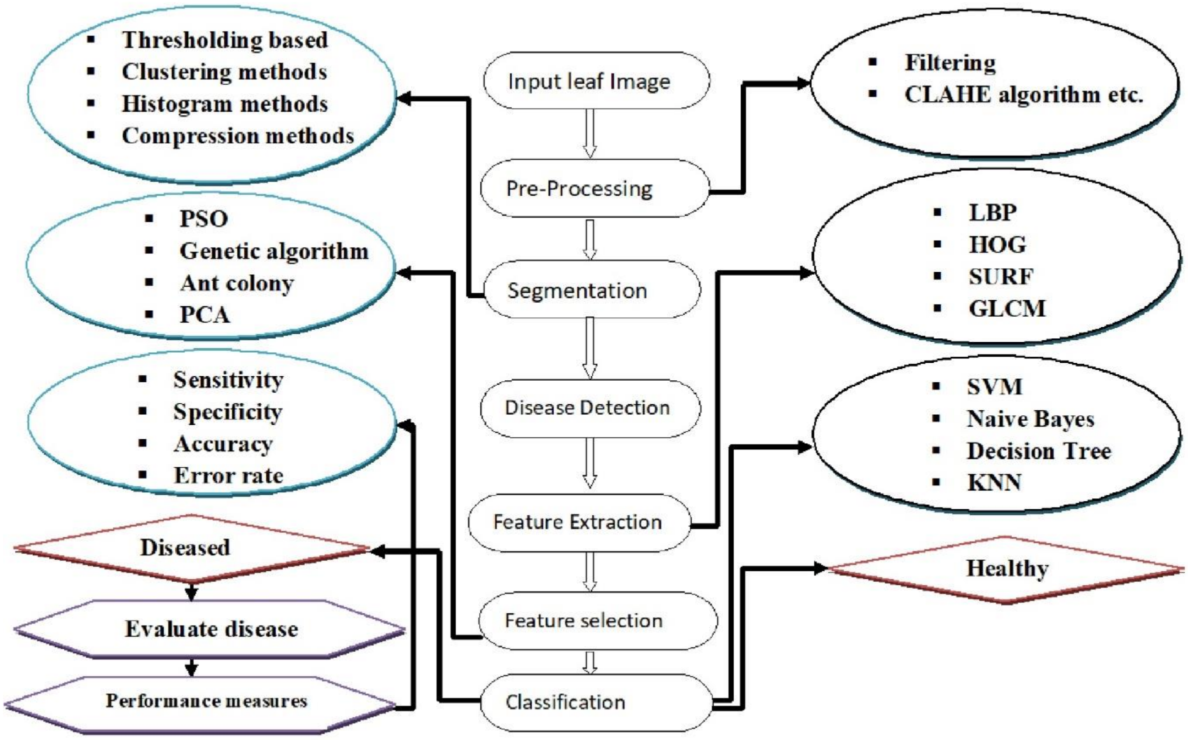

Figure 1: General structure for classification and identification of PLDs

2. LITERATURE REVIEW

For recognizing and classifying PLD, CV technology was studied and extensively utilized in agriculture applications. The presented study emphasized the latest studies that reflected IP methods' contribution in the PLD detection together with their classification under an assortment of field conditions. Section 2.1 discusses the preprocessing techniques. Section 2.2 describes the segmentation methods aimed at leaf disease images. Section 2.3 describes the FE methods. Section 2.4 elaborates the classification grounded on DL techniques. Section 2.5 discussed the leaf diseases classification using ML techniques. Section 2.6 describes the disease classification techniques.

2.1. Preprocessing Techniques

To ameliorate the image quality of gathered images, preprocessing is done for eradicating the noise via the technique. The inputted images are preprocessed, which is then inputted into the FE techniques. The preprocessing of leaf disease images is elaborated here.

N. R. Deepa and N. Nagarajan [16] commenced a Kuan filter aimed at pre-processing the inputted leaf images. Kuans filtered Hough transformation-centered reweighted linear programs boost classifications was introduced for enhancing the disease Detection Accuracy (DA) with minimal time. Pre-processing, FE, together with classification was the ‘3’ processes that were involved. As of the plant dataset, some leaf images were amassed. The boosting classifier joined the weak learner outcomes and made a strong ‘1’ to attain top disease DA with minimal error. However, the system had merely focused on similar parameters aimed at classification.

S. Kalaivani et al. [17] rendered a median filter aimed at preprocessing the affected leaf images. Every pixel on the image was examined by the image preprocessing technique. It successfully eliminated affected regions as of '3' disparate diseases that affected leaf disease. As per the maximal histogram values, the affected area was segmented by means of computing each pixel as of the preprocessed image. In addition, dice similarity metrics examined the similarity of the affected region. The indices-centered histogram intensity segmentation achieved 98.79% accuracy when weighed against the existent method. However, the system wasn’t suitable for intricate features.

Ramar Ahila Priyadharshini et al. [18] posited Principal Components Analysis (PCA) aimed at preprocessing the maize leaf disease. Aimed at maize leaf disease classifications, Deep Convolutional Neural Networks (DCNN) were generated.

As of the PlantVillage dataset, the experimentation was performed. For identifying '4' disparate classes, the Convolutional Neural Networks (CNN) were trained. The learned model attained 97.89% accuracy. The possible effectiveness of the technique was found. However, it was hard to foresee plant diseases in the early stage.

Jinzhu Lu et al. [19] formed a spectral preprocessing aimed at yellow leaf curl disease on tomato leaves. Grey Level Co-occurrences Matrix (GLCM) extracted the '24' texture features. The receiver operators characteristic curve analysis assessed the performance of every feature. Utilizing Yonden's index, the best threshold values of every feature were computed. The mean value of correlation extracted as of the band ratio image encompassed the best performance and the AUC was 1.0. However, it was trained with merely similar spectral images.

Siddharth Singh Chouhan et al. [20] recommended scale-invariant features transform technique for preprocessing along with FE. The Neural Network (NN) training was optimized with a bacterial foraging optimization utilizing the utmost disparate features. Lastly, the radial basis functions NN was utilized for the diseased area extraction as of the mango leave images. The experimentation's outcomes authenticated the higher-level accuracy of the system aimed at the anthracnose diseases segmentation attaining an average specificity along with sensitivity. However, the system was affected via over-segmentation.

2.2. Segmentation Methods for Leaf Disease Images

This section elucidates the segmentation aimed at dividing the images into disparate segments. Segmentation simplifies the image depiction into something, which is comprehensible and simple to assess.

R.Suganya and R.Shanthi [21] instigated a piecewise Fuzzy C-Means (piFCM) clustering in favor of the segmentation of plant leaf images. To remove the noise together with artifacts, the inputted images went through pre-processing. Next, the pre-processed image was inputted to the segmentation stage for attaining the segments. The Deep Belief Networks (DBN) took care of the classification phase. The Rider Optimizations Algorithm (ROA) was integrated with the Cuckoo Searches (CS) to generate Rider-CSA. The Rider-CSA-DBN trounced the prevailing techniques with maximal accuracy, sensitivity, together with specificity, correspondingly. Nevertheless, this system was sensitive to noise.

Xiao Chen et al. [22] instituted Binary Wavelet Transform joined with Retinex (BWTR). The image was denoised together with ameliorated in preprocessing phase. Next, the KSW separated the tomato leaves as of the background, which was optimized via the Artificial Bee Colony (ABCK). Lastly, to recognize the pictures, the Both-channel Residual Attention Network models (B-ARNet) were utilized. The DA was around 89%. Centered upon the amalgamation of ABCK-BWTR with B-ARNet, the tomato leaf diseases recognition was effectual. However, this system encompassed less convergence.

Muhammad Attique Khan et al. [23] generated a Sharif saliency for segmentation. Image amelioration was done as a pre-processing step. It effectively ameliorated the local contrast. This step was much vital for the FE. The refined aspects were inputted to a multiple-class Support Vectors Machines (SVM) aimed at disease identification. '5' cucumber leaf diseases were regarded and classified to attain a 98.08% Classification Accuracy (CA) in 10.52 seconds for proving this algorithm's authenticity. Nevertheless, when the inputted images encompassed lower contrast, the SHSB failed.

Somnath Mukhopadhyay et al. [24] posited a Non-dominated Sorting Genetics Algorithm (NSGA-II) centered image clustering to detect the diseased part in tea leaves. Aimed at feature reduction together with identifying the diseases on the tea leaves, PCA together with multiple-class SVM was utilized, correspondingly. '5' disparate diseases could well be detected in tea leaves. For validating this algorithm, K-Fold validation, under-fit or over-fit validation, Tick or Cross comparisons, Correlation matrix, along with comparisons of accuracy with K-Means, were performed. The outcome exhibited that this algorithm could detect the disease's type persisting on tea leaves. However, this system encompassed an indistinct fitness function. It reduced the segmentation outcomes.

M. Shantkumari and S. V. Uma [25] generated Adaptive Snake Models (ASA) for segmentation together with region recognition. Common segmentation together with absolute segmentation was the two-phase segmentation model of ASA. Quick segmentation was attained via common segmentation, and better accuracy was achieved via absolute segmentation. The ASA was better contrasted with the prevailing method. Precision, Manhattan, Recall, Jaccard along with Dice Score were utilized to assess ASA. Nevertheless, similar sort of datasets was utilized for segmentation.

Vijai Singh [26] produced a Particle swarms optimization aimed at segmentation together with the classification of Sunflowers leaf images. For getting the enhanced image, the median filtering technique was performed. It retained the actual lesion helpful information. Clipping of the leaf image was carried out for getting the interesting image region. Satisfactory outcomes were provided via the experimenting leaf images. The average CA was 98.0 %. However, this system encompassed higher searching time aimed at segmentation.

Siddharth Singh Chouhan et al. [27] posited a Hybridized NN integrated with Super-pixel clustering aimed at disease area segmentation. Scale-Invariant Features Transform for shape together with Local Binary Patterns (LBP) was utilized for texture FE. Segmentation outcomes with 0.9534 Specificity, 0.9637 Sensitivity, and also average CA (0.9656) when estimated separately proved this work's supremacy. However, this system encompassed a higher learning rate.

Liwen Gaoa and Xiaohua Lin [28] suggested a Fully Convolutional Networks (FCN) aimed at the segmentation of medicinal plant leaf images. The OTSU was utilized for obtaining a binary image considering the veins as the forefront centered upon this image, and also the major veins were detected as of it. Fine veins were detected as well as joined to the major veins in other fields past the major veins on the vein amelioration map. The experimental tests centered upon a self-constructed database together with another extensively utilized database exhibited that this technique was better compared to numerous completely automatic image segmentation encompassing DL-FCN. However, this technique ignored smaller-size datasets.

J. G. A. Barbedo et al. [29] commenced a color space transformation aimed at the segmentation of PLD symptoms. The histograms of the H as well as a color channels were manipulated by the simple algorithm. Every step was automatic with the exemption of the last step wherein the user would decide that channel rendered the better differentiation. It was helpful for an extensive assortment of plant diseases together with conditions. Nevertheless, the lower contrasted image diminished the segmentation outcomes.

Aditya Karlekara and Ayan Seal [30] generated a DL-CNN, SoyNet, aimed at soybean plant disease recognition utilizing segmented leaf images. This work encompassed '2' modules. The 1st module, by means of subtracting the intricate background, extracted the leaf part as of the complete image. The 2nd module comprised the images segmentation. An Identification Accuracy (IA) of 98.14% was attained with better precision, recall, along with f1-score. Via augmenting the assortment of pooling operations, it was probable to attain good accuracy. Nevertheless, a specific sort of soybean leaf disease was recognized.

2.3. Feature Extraction Methods

A vital role is played by the FE in the CV and ML field for the object's description in the inputted image. Each object encompasses its shape, size, motion, color, together with texture; thus, the extracted object is categorized into its relevance class via FE. This section discussed the disparate FE techniques,

Feng Jiang et al. [31] recommended CNN for extracting the rice leaf disease image aspects. Next, for classifying and predicting the particular disease, the SVM was implemented. Via the 10-fold cross-validations technique, the optimum parameters of the SVM were attained. Grounded upon DL along with SVM, the average correct identification rate of the rice disease recognition was 96.8%. This accuracy was higher contrasted with the customary back-propagation NN. Numerous higher-quality rice diseases image samples ought to be rendered for improving rice disease IA.

Karthik R et al. [32] rendered a 2D convolutional layer intended for FE. It was addressed via learning the features automatically utilizing CNN. '2' disparate deep architectures were presented for detecting the infection sort in tomato leaves. For learning important features aimed at classification, the 1st architecture implemented residual learning. The 2nd architecture implemented an attention mechanism over the residual deep network. 98% accuracy was achieved. However, it wasn't appropriate for real-time applications.

Xuebing Bai et al. [33] recommended a Fuzzy C-Means (FCM) for the extraction of cucumber leaves spot disease. Centered upon HSI space, '3' runs of the marked-water-shed algorithm were implemented for isolating the targetted leaf. The pixel's neighborhood means the gray value was computed as a sample point, instead of an FCM grayscale. It rendered an effectual together with robust segmentation means aimed at sorting as well as grading apples on cucumber disease diagnosis. It was effortlessly adapted aimed at other imaging-centered agricultural applications. Nevertheless, the system encompassed computational intricacies.

Aakrati Nigam et al. [34] suggested a PCA aimed at FE of paddy leaf images. Utilizing digital pictures, disparate paddy leaves were attained. Next, the RGB was transmuted into the HSV to re-size the picture utilizing k mean clustering with image segmentation. Aimed at the paddy leaf diseases classification, the FE together with BFO-DNN was executed. For ameliorating the detection rate together with reduced entropy loss, this classification technique was employed. This system's performance of accuracy was 98%. However, this method needed more time for diagnosing the leaf infection.

J. Praveen Kumar and S. Domnic [35] generated Circular Hough Transforms (CHT) intended for FE of the rosette plant leaf. A statistical-centered technique was utilized for image amelioration. The extraction of leaf area in plant image utilizing a graph-centered technique was performed. Via applying CHT, the total leaves in the plant image were counted. 95.4% segmentation accuracy was achieved. But, more plant phenotyping wasn't employed for segmentation.

2.4. Classification based on deep learning techniques

This section elucidates the DL techniques aimed at PLD classification. Concerning accuracy together with effectiveness on larger datasets, DL show enhanced performance in agriculture. In DL, the features are extracted automatically as of data as well as learned more effectually contrary to handcrafted features. Additionally, DL resolves intricate issues more effectively and lessens the error rate. This section renders a concise discussion of the DL classifiers with disparate datasets aimed at PLD classification.

Miaomiao Ji et al. [36] formed a CNN to differentiate leaves with common grape diseases as of leaves (healthy). For extracting complementary discriminative aspects, the amalgamation of manifold CNN enabled the UnitedModel. Therefore, the representative capability of UnitedModel was ameliorated. The experimentation's outcomes exhibited that it attained the best performance on disparate assessment metrics. It got an average corroboration accuracy of 99.17% as well as a test accuracy of 98.57%. Nevertheless, this couldn't be executed for instantaneous diagnosis of grape leaf diseases on the intricate background.

Mohit Agarwal et al. [37] posited a CNN aimed at disease detection on tomato leaves. There were '3' conventional, '3' max-pooling layers, along with '2' fully connected layers. This model was better contrasted with the pre-trained model. Concerning classes, the CA varied as of 76% - 100%, together with the average accuracy was 91.2%. Nevertheless, this method utilized the same dataset and attained less testing accuracy.

Hu Gensheng et al. [38] instigated a DCNN for tea leaf disease recognition. For ameliorating the capability of extracting image features automatically of disparate tea leaf diseases, a multiple-scale FE module was included in the ameliorated DCNN of a CIFAR10-quick model. For lessening the total model parameters as well as accelerating the mode computation, the depth-wise separable convolution was utilized. The average IA was 92.5%. It was higher contrasted with the conventional ML as well as DL. However, this technique needed loads of data intended for better performance.

Siddharth Singh Chouhan et al. [39] formed Bacterial foraging optimizations (BFO) centered Radial Basis Functions NN (RBFNN) for PLD's identification together with classification. BFO was utilized to assign an optimal weight for RBFNN. It augmented the speed in addition to accuracy in identifying and also classifying the areas infected of disparate diseases on the plant leaves. The network's efficiency was increased via searching as well as grouping seed points encompassing common attributes for the FE. Higher accuracy was attained by the technique in the diseases' recognition together with classification. Nevertheless, accurate segmentation of the disease area was an intricate task.

Hu Gensheng et al. [40] generated conditional deep convolutionals Generatives Adversarial Networks (GAN) for tea leaf's disease classification. SVM segmented the disease spots on images via extracting the color together with texture features. It had formed training samples in favor of data augmentation by considering the segmented disease spot images as an input. This DL trained with increased disease spot images identified the diseases precisely. The average IA reached 90%. However, this technique needed a wide-ranging training period.

Peng Jiang et al. [41] created DCNN intended for the instantaneous detection of apple leaf diseases. The GoogLeNet inception structure along with rainbow concatenation was introduced. The INAR-SSD realized detection's performance of 78.80% mAP in ALDD, with 23.13 FPS detection speed. The INAR-SSD rendered a higher-performance solution aimed at the ED of apple leaf diseases that performed instantaneous detection of these diseases with high accuracy as well as fast detection speed compared to preceding methods. Nevertheless, data requirements led to overfitting in tandem with underfitting.

Qingmao Zeng et al. [42] suggested DCGAN aimed at the categorization of Citrus leaf Disease. This was centered upon the Huanglongbing (HLB)-infected leaf images attained as of PlantVillage together with crowdAI. A dataset of 5,406 citrus leaf images that were infected via HLB was generated. Next, '6' disparate sorts of well-known models were trained to do the severity detection of citrus HLB for finding which models' types were more appropriate in detecting HLB severity with the same training situation. This technique achieved 92.60% accuracy. Nonetheless, the instantaneous environmental datasets were not tested.

Mehmet Metin Ozguven a and Kemal Adem [43] posited Region-centered CNN (quicker R-CNN) aimed at automatic detection of Leaf Spot (LS) disease that occurs on sugar beet. 155 images were taken to train as well as test the disease severity detection via imaging-centered expert systems. The overall right classification rate was 95.48% as stated by the test outcomes. Additionally, this approach exhibited that changes on CNN parameters as per the image as well as areas to be detected could augment the quicker R-CNN success. However, the system encompassed poor-quality images that lessened the accuracy level. A review of DL algorithms is exhibited in table 1.

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Table 1: Classification based on DL techniques

Author	Classifier	Dataset	Results achieved	Limitations
Y. A. Nanehkaran et al. [44]	CNN	PlantVillage database	Accuracy - 91.33% Recall- 90%	Low efficiency due to errors.
S. Hernández and **Juan L. López** [45]	Bayesian DL	Plant-Village dataset	Accuracy- 96% Precision- 94% F1-score- 96%	This generated less confident outcomes intended for the correctly as well as incorrectly classified samples.
L. Selvam and **P. Kavitha** [46]	CNN	Dataset captured from Velananthal and Thandarai villages.	Accuracy- 96% Precision- 98% F1-score- 97% Recall- 96%	However, this method needs large datasets to provide precise results.
Jose G.M. Esgario et al. [47]	CNN	Plant-Village	Accuracy- 97.07% Precision- 96.85% Recall- 96.69%	The images utilized were captured under restricted conditions. It could well be deemed as a con for the realistic application of this system.
Abdul Waheed et al. [48]	DenseNet	Healthy crop (3720 images), Common rust (3816 images), Cercospora LS Gray LS (1644 images), and Northern leaf blight (3152 images).	Accuracy- 98.06% Precision- 92% Recall- 94% F1-score- 93%	This technique identified the particular corn leaf diseases.
Geetharamani G. and **Arun Pandian** [49]	DCNN	Diseased as well as healthy plant leaf images as of the Plant-Village dataset.	Accuracy - 96.46% Recall- 99.8% F1-score – 98.15%	A small size of datasets was utilized for the training process, which degrades the classifier's performance.
Bin Liu et al. [50]	GAN	Plant-Village dataset.	Accuracy- 98.70%	This was unstable, which causes the gradient vanishing issue.
Umit Atila et al. [51]	EfficientNet	Plant-Village	Accuracy- 99.91% Precision-98.42%	Similar kinds of plants were utilized for classification.
P. Lohith Kumar et al. [52]	Multilayer Perceptron NN (MPNN)	Plant-Village	Accuracy- 98.11% Specificity- 97.38% Sensitivity- 97.79%	Difficult of showing the problem to the network.
Uday Pratap Singh et al. [53]	Multilayer-CNN (MCNN)	Dataset was taken at the Shri Mata Vaishno Devi University, Katra, J&K, which comprised 1070 Mango tree leaves images.	Accuracy- 97.13%	This technique had some inconsistencies with real-time datasets.

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Shanwen Zhang et al. [54]	Global pooling dilated-CNN (GPDCNN)	Real-world cucumber diseased leaf image dataset	Accuracy- 94.65%	But it slowly recognized the diseases.

2.5. Leaf Diseases classification using Machine learning techniques

This section elaborates on the ML classifiers that are utilized for PLD detection.

Christoph Romer et al. [55] examined an SVM aimed at pre-symptomatic wheat leaf rust detection. Few robust features were desired for pre-symptomatic pathogen identification. It encompassed most information pertinent to the provided classification task. The co-efficient of polynomials fitting the spectra were employed for classification rather than selecting merely the most pertinent wavelengths. The global curve characteristics were specified. High CA (93%) utilizing piecewise fitting via polynomials of 4^{th}-order CA was attained. Nevertheless, when the dataset had more noise, this didn't perform very well.

Jagadeesh Basavaiah and **Audre Arlene Anthony** [56] posited a Random Forest (RF) for tomato leaf disease classification. Developing a method intended for identifying leaf disease on tomatoes by enhancing the CA and lessening computational time was the main objective. The utilization of a fusion of manifold features enhanced the CA. For training together with testing purposes, Hu Moments, Color histograms, Haralick as well as Local Binary Pattern features were utilized. The CA was 90% aimed at the RF classifier. Nevertheless, this system was infective with instantaneous prediction.

Muhammad Attique Khan et al. [57] generated a Multiple SVM for the apple leaf diseases classification. The hybrid method ameliorated the apple LS. It was the amalgamation of de-correlation, 3D-Gaussian filter, 3D box filtering, together with the 3D-Median filter. Next, the strong correlation-based method segmented the lesion spots. Their outcomes were optimized via the amalgamation of Expectation-Maximization (EM) segmentation. Lastly, a comparison-centered parallel fusion fused the color histogram, color, and LBP features. The Genetic Algorithm (GA) optimized the extracted features along with the One-vs-All M-SVM classified them. 92.9% CA was attained by the M-SVM. However, it was computationally pricey.

K. Suganya Devi et al. [58] recommended a combination of Histogram on Oriented Gradient (HOG), Harris corner detector, as well as KNN (H2K) for precise detection in addition to the classification of diseases in groundnut leaf. Image acquisition, image preprocessing via implementing the binary mask, HSV for segmenting the diseased part, features detection as well as extraction utilizing H2K centered classification was performed. For improving crop production as well as maximizing the yield, the H2K helped. It was employed to classify the diseases with enhanced 97.67% accuracy. However, this system encompassed lower DA.

Tian et al. [59] suggested a K-means algorithm centered upon the adaptive clustering aimed at the tomato leaf images segmentation. For devising the algorithm, the white paper back-ground images were utilized. In addition, natural back-ground images were employed for validating the algorithm. Via a sequence of pretreatment experimentations, the clustering number was ascertained automatically by means of computing the DaviesBouldin index. The preliminary clustering center was provided to avert the clustering computation as of falling into a local optimal. It segmented the tomato leaf images more accurately as well as effectively. The key drawback was that it needed more calculation to gauge the validity index.

2.6. Leaf Disease Classification Techniques

Classifiers-centered techniques are employed to identify the images relying upon their FE. Numerous classification techniques are discussed. Table 2 elucidates the disparate classification techniques, their benefits, and their cons.

Table 2: Classification and FE methods for different leaf diseases

Author	**Classifier used**	**Feature extraction method**	**Diseases identified**	**Disadvantage**
Md. Rasel Mia et al. [60]	SVM	GLCM	Dag disease, Golmachi, Moricha disease, and Shutimold.	Texture-based features were not considered.

Chiranjeevi Muppala and **Velmathi Guruviah** [61]	A deep NN with search and rescue optimization (DNN-SAR)	SSD algorithm	Yellow Stem Borer	It was expensive for complex data models.
Kanthan Muthukannan and **Pitchai Latha** [62]	GA-centered feed-forward NN (GA_FFNN)	GLCM	Bitter gourd (Brown LS), beans (Pest leaf minor), Cotton (Mineral Deficiency), chilly (Pest), pigeon pea (Blight Leaf minor), together with tomato (LS).	Outcomes exhibited that Higher fitness was not attained by this technique.
Xuan nie et al. [63]	Region-Based-CNN (faster R-CNN)	HOG as well as GLCM	Strawberry verticillium wilt is basically a soil-borne, multiple-symptomatic disease.	To amass the feature map of the area proposal, hordes of Disk space were needed.
S. K. Pravin Kumar et al. [64]	Artificial bee colony-centered FCM (ABC-FCM).	Polar Fourier transforms (PFT).	Disease Cedar_apple_rust, crop diseases	Low CA.
Prabira Kumar Sethy et al. [65]	Deep NN with Jaya Optimization Algorithm (DNN_JOA).	GLCM	Sheath rot, Bacterial blight, brown spot, together with blast disease.	High error rate due to misclassification.
Balasubramanian VijayaLakshmi and **Vasudev Mohan** [66]	Fuzzy Relevance Vector Machine (FRVM)	GLCM and LBP	Leaves are affected by means of shadow or any disease	The leaves with complicated backgrounds were hard to identify.
Yunyun Sun et al. [67]	Simple Linear Iterative Clusters with SVM (SLIC-SVM).	GLCM	Tea anthracnose, Tea netted blister blight, Tea brown blight, Exobasidium vexans Massee, together with Pestalotiopsis theae.	But this technique provided some irrelevant features.

3. RESULT AND DISCUSSION

The outcomes of disparate DL as well as ML classification techniques were analyzed here. Aimed at the prediction, disparate sizes of datasets were used. Training along with testing was done on the inputted dataset. The algorithms' performance is compared and examined to exhibit their efficiency in leaf disease detection. Centered upon some performance metrics, say accuracy, precision, together with recall, the performances are estimated.

Figure 2 (a) depicts the leaf disease classification utilizing DL techniques. DCNN [70] renders 99.5% accuracy and 94.67% precision. CNN [75] and RPN [69] attain 96.76% and 91.5% accuracy. Next, 98.8% accuracy and 96.7% precision are attained by the GoogleNet [73]. Next, MLP-CNN [74] and DenseNet [48] provides 99.2% and 92% of accuracy, which is higher than CNN [75]. 99.91% of accuracy and 98.42% precision is attained by the EffiecientNet, which is higher than other techniques. The effective recall of classifiers used in leaf images is exhibited in Figure 2 (b). CNN [44] provides the 90% recall. 94% recall is attained by the DenseNet [48]. After that, DCNN [49] achieves 99.8%, which is higher compared to other techniques. Next, R_CNN [43] provides 97% of recall.

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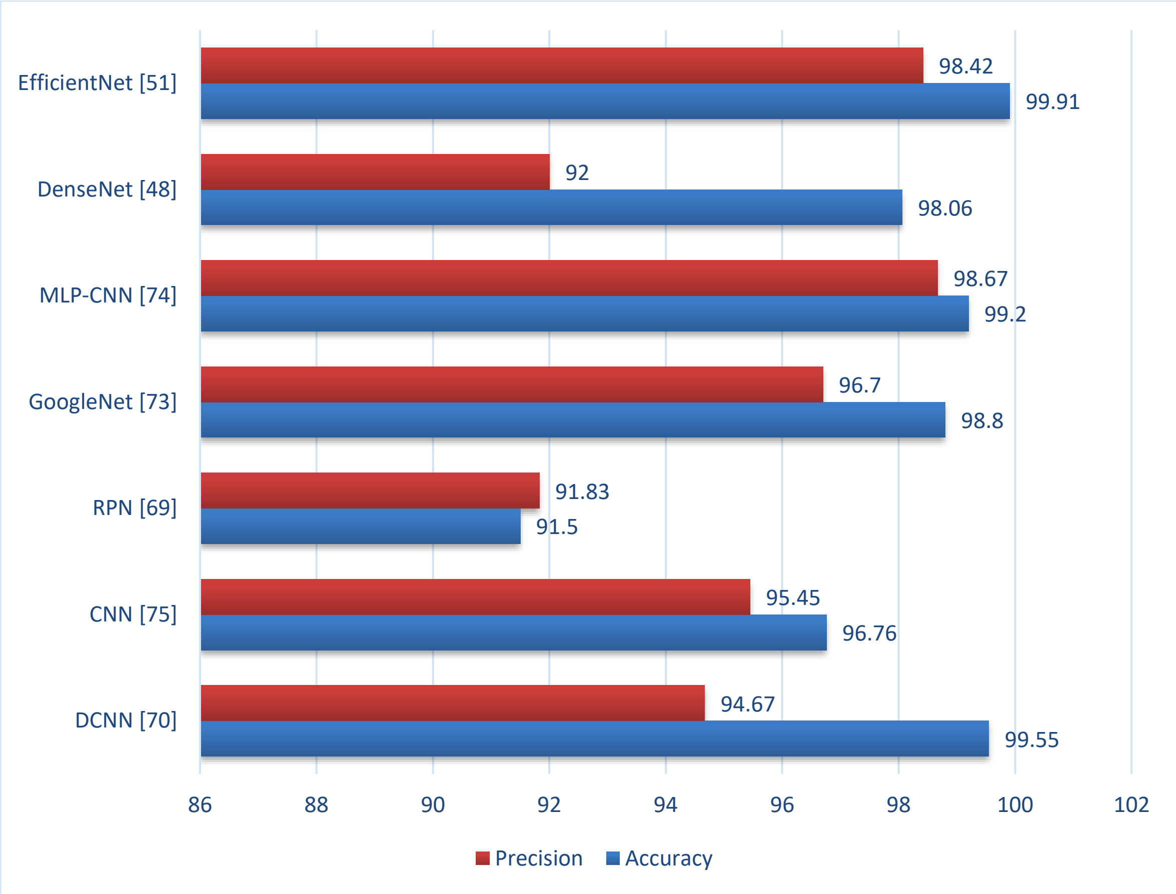
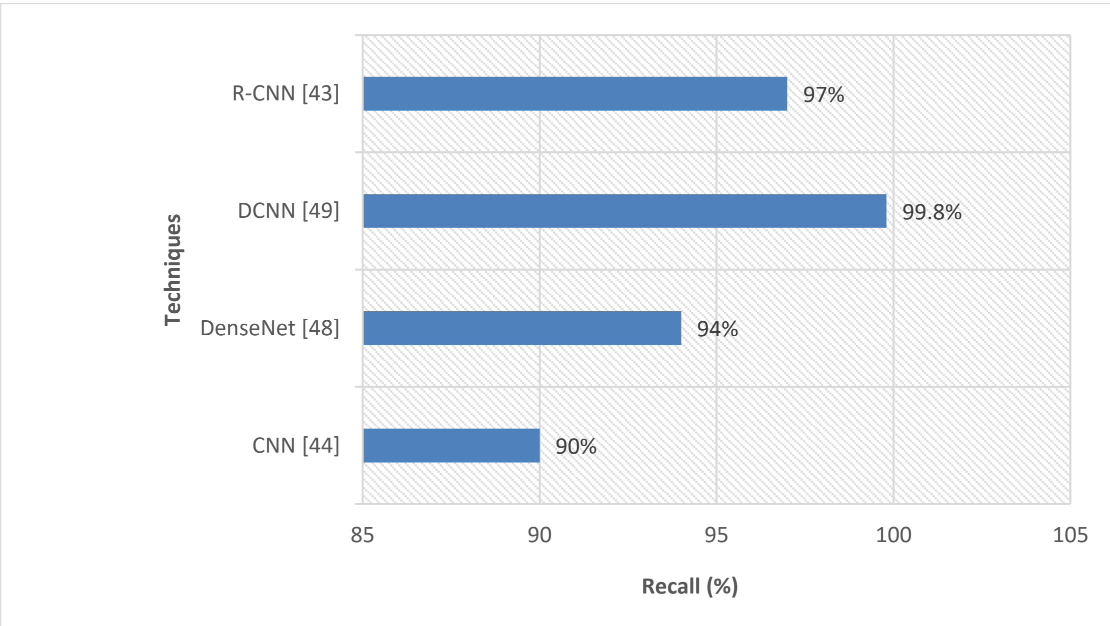


(a)



(b)

Figure 2: Classification based on DL techniques

The ML-centered CA of leaf disease detection is exhibited in Figure 3. RF [63] renders 82.5% accuracy. AdaBoost [67] and SVM [71] give 94% and 90.67% accuracy. Next, 92.9% accuracy is attainted by the MSVM [57], which is higher compared to SVM [71]. 97.67% is attained by the H2K [58], which is higher than all other techniques. SLIC-SVM [67] renders 95.78% accuracy.

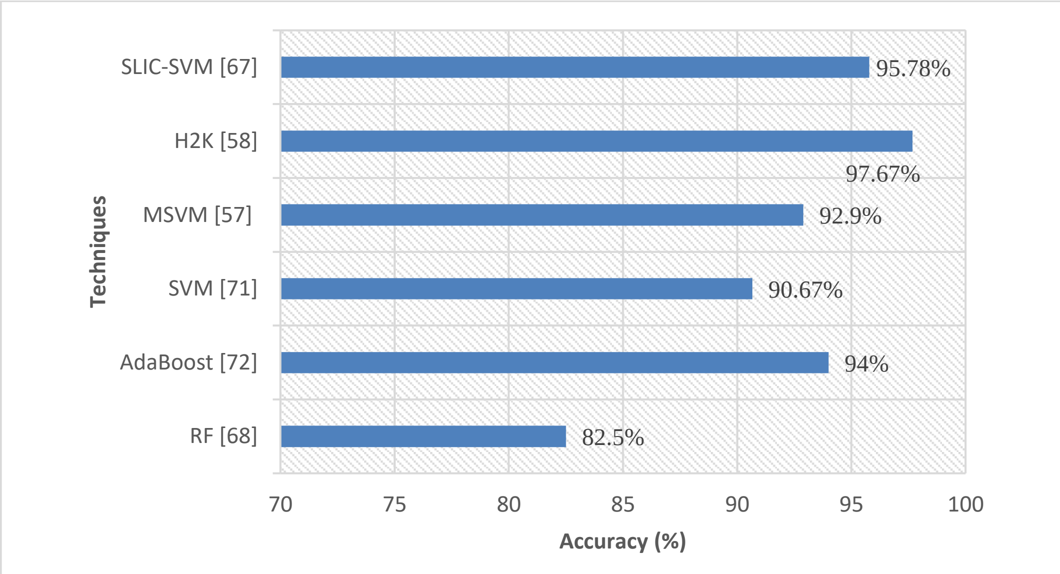


Figure 3: Classification based on ML techniques

4. CONCLUSION

The concepts together with techniques that are utilized by disparate researchers to identify as well as classify diseases, challenging issues, and issues are highlighted. Limiting the effect of plant diseases on agricultural production utilizing IP techniques is the eventual objective. In addition, it is imperative to comprehend the correlation betwixt the disease's symptoms and its effects on yield. It is hard for an individual to assess all imperative concepts present in the literature on account of the large quantity of agriculture as well as horticulture applications centered upon the PLD's detection together with classification. This is a cause for missing potential solutions intended for problematic issues. More novel algorithms should be implemented as well as more concepts concerning tools ought to be comprehended to achieve better outcomes. More reliable outcomes should be rendered by means regarding the accuracy as well as quality parameters that are required in this extremely competitive as well as changing industry. A concise discussion of well-known detection as well as classification techniques together with possibilities of extensions is rendered. Centered upon the key findings as of the preceding studies, the subsequent future aspects can well be regarded for additional research: i) an unexplored amalgamation of FE, selection, as well as learning techniques can well be employed to augment the detection together with classification techniques' effectiveness. ii) By means of developing advanced algorithms, prevailing work can well be extended to attain higher speed together with accuracy. iii) To attain better accuracy, the total data for training as well as testing purposes can well be augmented.

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