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Classification of Image-Based Wheat Leaf Diseases using Deep Learning Approach: A Survey

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Abstract

This paper focuses on detecting leaf diseases in wheat plants from the beginning to the end of the plant's life cycle. It highlights the best techniques for detecting various types of wheat leaf diseases and emphasizes the use of computer vision, image processing, and machine learning. The main focus is on classifying these diseases through deep convolutional neural networks, a popular image recognition and classification approach. The paper reviews various techniques for classifying image-based wheat leaf diseases, including spot blotch, stripe rust, brown rust, and powdery mildew. The paper aims to summarize the state-of-the-art techniques for detecting wheat leaf diseases.

Keywords: Computer vision; Agriculture, Deep learning; Convolutional neural networks; Image processing; Machine learning.

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1. Introduction

Agriculture is the main source of income for a majority of the inhabitants of India. Farmers choose the appropriate crops for their farms based on various factors such as soil quality, climate, market demand, and personal preference. This helps them to achieve high yields and better-quality produce [1,2]. The cultivation of crops requires advanced techniques and proper management to ensure successful results. Plant diseases can significantly impact crop yield and quality, leading to financial losses for farmers and environmental consequences [4,5]. Detecting these diseases early on is crucial for effective management, and sophisticated analysis and high-powered microscopes are often required for this purpose [6,7]. Some plant diseases can only be identified through the use of the electromagnetic spectrum, which is not visible to the human eye [8]. Remote sensing techniques can also be used to detect plant diseases, making timely recognition essential for successful crop cultivation and high yields [9].

Image processing is also having a wide variety of applications in the agriculture domain that improves the visual appearance of images and prepare images for

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measurement by applying suitable techniques. Image processing in agricultural applications serves subsequent purposes:

- To recognize diseased leaf, fruit, and stem.
- To check the disease-prone area.
- To find the shape of the disease-affected area.
- To find the color of the disease-affected area.
- To find the texture of the disease-affected area.

Diversified digital image processing tools are being used to meet these challenges [10]. However, image processing has made significant developments in the field of agricultural research [11]. Earlier, in order to identify disease severity, usually, the naked eye method was used, but it was not possible to measure the amount of disease precisely since the results attained were particular. The disease may exist on various crops' leaves, stems, or fruits. These maladies arise naturally, having varied symptoms [12,13]. Damage done by insects on various crops is also one of the major concerns. Plant scientists and experts should continuously monitor the damage incurred on the plant for timely remedial measures to be taken. The presence of these plant diseases deteriorates the quality of agricultural products. Various maladies in plants lead to deep yield losses and sometimes enforce food security [14,15]. Detection of disease at the initial state leads to proper plant growth. Recognition of diseases at proper intervals of time is also beneficial for disease control. Agricultural experts require high professional knowledge to visualize diseases to take remedial actions [16,17]. Various image processing and computer vision techniques were employed for plant leaf disease diagnosis problems [18,19]. Many computer algorithms are also employed for the processing of digital images [20,21]. However, in this survey paper, we limit our study to classifying wheat leaf diseases: spot blotch, brown rust, yellow rust, and powdery mildew. Beginning with a conversation to categorize various wheat leaf diseases in plants (Sect. 2) along with the deep learning concept for image recognition (Sect. 3). A common architecture of the wheat leaf disease detection system is presented in this section (Sect. 4). Although the efficiency of these systems mostly relies on classification techniques being employed, therefore efforts were applied to study existing literature surveys based on various state of the art techniques in conventional machine learning along with deep convolutional neural networks. Likewise, the significance of different classification models to differentiate diseased leaves in various cultures is also considered (Sect. 5). Even though satisfactory results are achieved through various techniques; still some issues and challenges are also uncovered (Sect. 6) along with inferences and future directions (Sect. 7). The reviews have a great impact on researchers, experts, and plant pathologists for timely recognition of plant leaf diseases.

2. Background

The maladies of leaves on plants are broadly classified into fungal, bacterial, and viral diseases, as depicted in Table 1. The predictability of fungal diseases is performed through their morphology and reproductive structures. Fungal diseases consist of molds, rust, mildew, rots, cankers, etc. Bacterial diseases are considered to be more primitive than fungal diseases as they have simpler life cycles in comparison to fungal diseases. The origin of bacterial diseases is through a single cell that increases in number through a division of cells. Bacterial diseases consist of a soft spot, spot, wilt, etc. Finally, viral diseases are made up of particles comprising of protein and genetic material having no allied protein like mottling, distortion, etc. [19].

Table 1. Classes of plant leaf diseases.

Fungal diseases	Bacterial diseases	Viral diseases
Molds	Soft spot	Mottling
Rust	Spot	Distortion
Mildews Rots	Wilt	Dwarfing
Cankers		

2.1. *Wheat leaf diseases*

Wheat is one of the utmost significant sustenance yields in the world. It is one of the chief foods of North Indians. Wheat is primarily a rabi/winter crop, which contributes 67 % of the entire production that is extremely distributed towards northern parts of Uttar Pradesh, Punjab, and Haryana [20]. Wheat is the second largest significant staple food next to rice, consumed by 65 % of the Indian population. Wheat is developed throughout the world with a yearly creation of over 600 million tones. Wheat production must keep on expanding every year by 2 % to accomplish the future requirements of the growing inhabitants. Various wheat leaf diseases are also found in India, like rust, powdery mildew, loose smut, leaf blight, and Karnal bunt. Viruses on leaf diseases may adversely influence a wheat crop and lessen yields due to the mismanagement of crops. During the spring season, wheat leaf disease conditions worsen, especially in wheat-growing areas. Thus, cultivators should plan to oversee wheat leaf diseases sufficiently to recover yields and benefits [21]. Major wheat leaf diseases are described as follows:

2.1.1. *Spot Blotch/Helminthosporium leaf blotch*

2.1.1.1. *Symptoms*

Fig.1A depicts lesions produced through this disease getting longer to oval in shape and usually showing a dark brown color. During the maturity period, the centers of lesions are surrounded by an irregular dark brown ring, and a light brown color gets converted to a tan color.

2.1.1.2. *Development*

The beginning of key infections starts with chlorotic flecks or spots, mainly on the lower leaves. These infection areas expand, turn dark brown, and frequently combine. During disease severity, affected leaves or leaf sheaths may decrease too early [22].

2.1.1.3. *Distribution*

It is found worldwide but particularly widespread in humid and high rainfall-prone areas [26].

2.1.2. *Yellow rust/stripe rust*

2.1.2.1. *Symptoms*

The pustules of stripe rust generally made thin and fine stripes on the leaves, which comprise yellow to orange-yellow urediospores shown in Fig 1.B. Spots can also be found on leaf sheaths, necks, and glumes.

2.1.2.2. *Development*

Major infections occurred through wind-borne urediospores traveling large distances. The infection increases quickly during free moisture prevalence, and temperatures range between 10-20 °C. When the temperature rises above 25 °C, the reduction of urediospores is observed and produces black teliospores.

2.1.2.3. *Host/distribution*

Stripe rust can be found in wheat, barley, and triticale, along with numerous other associated types of grass. It commonly originated in cereal-grown areas [22].

2.1.3. *Leaf rust/brown rust*

2.1.3.1. Symptoms

The size of postulates is smaller than stem rust, roundabout, or somewhat curved, more often don't combine, and contains masses of orange to orange-dark colored urediospores. Fig. 1C illustrates mostly the uppersides of leaves containing disease-prone areas. The symptoms are also visible on the leaf sheaths.

2.1.3.2. *Development*

This disease category is ordinarily light and prevails through wind-borne urediospores that might cover large distances. Disease growth rapidly increases under moisture conditions along with temperatures close to 20 °C.

2.1.3.3. *Host/distribution*

Leaf rust can influence wheat, triticale, and numerous correlated types of grass. This infection is discovered at any place where cereals are grown [23].

2.1.4. *Powdery mildew*

2.1.4.1. *Symptoms*

Fig.1D represents obvious primary indications of this malady where the upper portion of leaves and leaf sheaths contains white to pale gray, fuzzy, or fine states of mycelia and conidia. The color of matured tissues is yellowish-gray. This light fungal material can be scoured off well with the help of fingers. During expiration, cleistothecia can be seen in mycelia.

2.1.4.2. *Development*

This fungal infection develops under cool, hazy, and moist conditions.

2.1.4.3. *Host/distribution*

The host specificity is high in this fungal infection. This fungus is prevalent in the northern hilly areas as well as in some parts of Rajasthan [23].

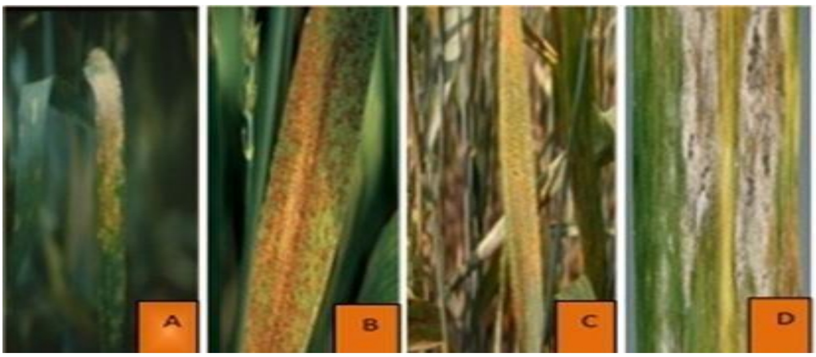

Fig. 1. Sample images of different wheat leaf diseases (A) spot blotch, (B) stripe rust, (C) leaf rust, and (D) powdery mildew.

2.2. *Importance of the review article*

The classification of image-based wheat leaf diseases using a deep learning approach is important because it provides a more accurate and efficient method for detecting and identifying plant diseases. Deep learning algorithms can automatically learn complex features and patterns in the images, enabling them to classify different diseases accurately. This can help farmers to quickly and effectively address the issue, leading to improved crop yields and reduced financial losses. Additionally, this approach can also reduce the need for manual labor and time-consuming analysis, making disease identification more accessible and cost-effective.

3. Deep Learning in Image Recognition

In recent years, tremendous progress has been observed in the deep learning domain. Deep learning comes from machine learning [24,25]. Deep learning has entered the domain of agriculture. The most important advantage of deep learning is feature learning. It implies extracting the features automatically from raw data through various levels of abstraction [26]. This technique deals with the study of deep neural networks, which consist of numerous layers [27,28]. With the advancements in machine learning, deep learning also becomes popular due to increased chip processing capabilities, enlarged datasets, etc. [29,30]. The reasons for popularity also include many software disciplines like computer vision, natural language processing, speech and audio recognition, search engines, robotics, video games, bioinformatics and chemistry, online advertising, and finance [31,32]. As far as deep learning is concerned, convolutional neural networks are the utmost prominent approach for the classification stage, as shown in Fig. 2. CNN is often accustomed to processing image data [33,34]. This paper highlights the classification of wheat leaf diseases utilizing a deep learning approach. LeCun first introduced CNN for the classification of handwritten digits [35]. CNN holds dual core structures: a convolutional layer and a pooling layer [36,37]. A convolutional layer consists of various units having feature maps. Each unit is related to the previous layer by local patches in the feature maps over a set of weights identified by a filter bank [38-40]. This result consisted of the locally weighted sum delivered through a non-linear ReLU. The pooling layer combines all the semantically similar features [41,42]. Reduction in the data rate is achieved through various layers, namely pooling and convolutional layers. Most of the top rankers rely on the CNN-based method used in the largest object recognition contest (ILSVRC). Outstanding results are attained in image recognition [43]. CNN architectures employed for classification purpose includes AlexNet, VGG, GoogleNet, ResNet, etc. In addition, the open-source deep learning frameworks required for implementation are Tensorflow, Keras, Caffe, Theano, etc.

4. Wheat Leaf Disease Detection System

Advancements in computer vision and object recognition allow the classifying of multiple diseases in plants [44-46]. Due to the scarcity of resources and expertise on leaf disease detection nationwide, the necessity of a method to recognize leaf diseases automatically is crucial [47]. Also, smartphones' high computing power, better resolution display, and inbuilt sets of accessories help identify diseases [48]. Computer vision along with machine learning-based methods, are employed to detect various diseases like apples, rice, tomatoes, potatoes, etc. [49,50]. To meet the challenges of wheat leaf disease detection systems, this survey introduces a deep convolutional neural network algorithm for recognizing and classifying wheat leaf diseases [51]. The given system learns visual characteristics directly from images through training and would be able to recognize various maladies in plants utilizing a deep learning approach through convolutional neural networks [52,53]. The basic architecture for diagnosing wheat leaf diseases can be described in Fig. 3. The phases for the wheat leaf disease detection system include dataset preparation [54], neural network training, testing, and validating data, followed by classification through deep CNN.

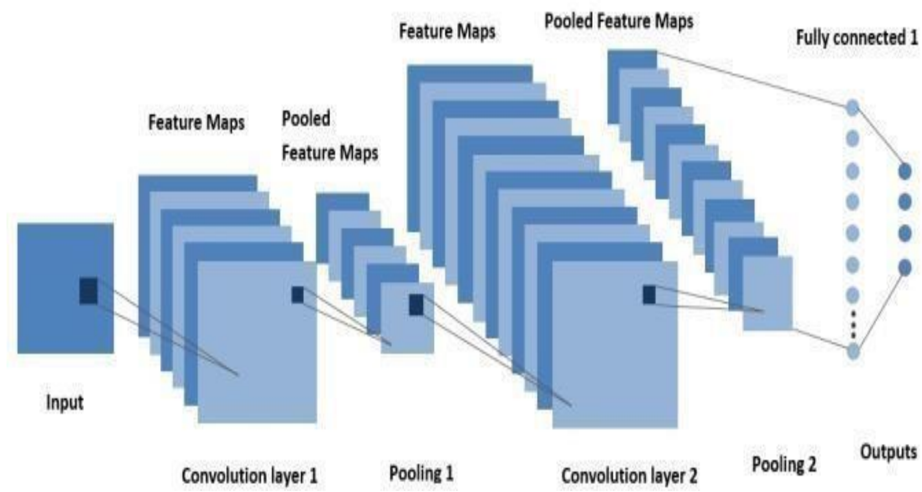

Fig. 2. Convolutional neural network [60].

4.1. *Dataset preparation*

The dataset of the wheat leaf disease detection system can be acquired through various internet sources like IPM, APS database, etc. [55,56]. The image dataset can also be collected from various research institutes as well as from the fields. To obtain higher accuracy, good-quality images are required. CCD color cameras and Android mobiles can be used to solve this purpose. Once the images are captured, each image is annotated with the appropriate label to achieve 100 % accuracy during the testing of data. Since the images of the dataset acquired are in different formats and resolutions, therefore they need to be preprocessed to get better feature extraction and consistency. To do preprocessing, the images in the dataset will be resized and cropped along with noise removal [57]. Data normalization is done by deducting the mean from each pixel and dividing the result obtained through standard deviation. Data normalization increases the convergence rate during the training of data. Finally, data augmentation [58] was applied for the network to gain more appropriate features for expanding the dataset and to reduce overfitting [59,60].

4.2. *Neural network training, testing, and validation*

In this phase, training and testing of datasets through Deep CNN would be performed after splitting the datasets into various train test splits, followed by validation of image data for the prediction of wheat leaf diseases. [61,62].

4.3. *Classification through Deep CNN*

After validating and testing through Deep CNN, the classification of wheat leaf diseases was performed to find the model accuracy for identification purposes [63,64].

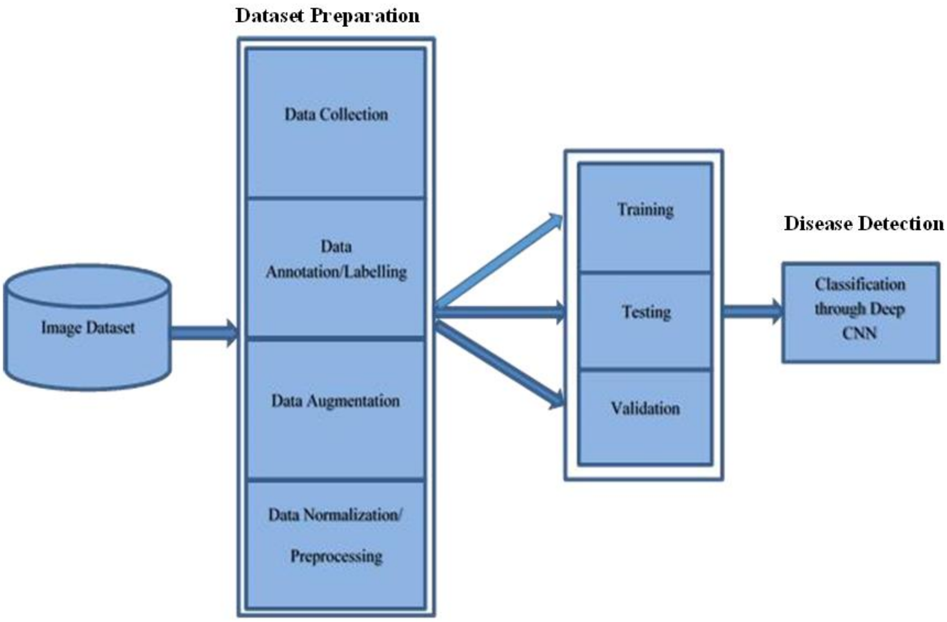

Fig. 3. Wheat leaf disease detection system [60].

5. Related Work

In this survey paper, the main emphasis of the literature survey was on the classification of leaf diseases through various conventional machine learning techniques along with deep convolutional neural networks [65-67]. The same is categorized in the below Table 2 and 3, respectively. Here literature survey categorization is performed based on various types of crops utilized and is discussed as follows:

5.1. *Survey based on wheat leaf diseases*

Tian *et al*. [65] depicted a stacked generalization structure. Here three classes of SVM extracted three diversified feature sets in low- and middle-level categories. Hence are further used for depicted stacked generalization structure. This approach demonstrates classification results by considering three classes of support vector machines. These three classes of SVM extracted three diversified feature sets that are further used for training purposes. With the knowledge of plant pathology, three diversified extracted feature sets of three classes were classified into both low and middle-level categories. Then middle-level features were extracted from mid-categories originated by lower classifiers. In the end, higher-level SVM trained and fixed errors from extracted features to improve training purposes. The proposed method gives better results in wheat leaf disease recognition.

Majumdar *et al*. [66] presented a simple, novel, fast, and efficient system using the fuzzy c-means technique to find and detect the presence of wheat leaf diseases. During the first phase, the feature set was selected according to inter and intra-class deviations, and finally, classification results reported 56% accuracy on 310 samples. In several cases, the output may be indefinite. It is one of the single disadvantages of using this kind of approach. This problem can be dealt with using an enhanced feature selection technique.

Gaikwad and Musande [67] developed a wheat leaf disease detection solution. To start with the histogram method, the author revealed that a healthy wheat histogram had a maximum peak as compared to unhealthy wheat. In the second method, the author observed that SVM provided better results as compared to neural networks for fungal disease detection.

Kumar *et al.* [68] proposed a new approach utilizing various image processing techniques. Various tools were employed for accomplishing the task of disease detection, like K-means, GLCM, and PNN. Researchers recommended that performance increases with the rise in the training data. The author also suggested fuzzy logic for better accuracy and speed.

Lin*et al.* [69] developed a unified matrix-based CNN approach using deep learning. In this system, a total of 16652 wheat leaf disease images were used. Better accuracy is achieved in fine-grained image classification as compared to AlexNet and VGG16.

Goyal *et al*. [70] proposed a classification scheme for wheat disease detection using optimal resources. The given method classifies 10 wheat diseases along with 97.88% test accuracy. Using this method, accuracy has been improved.

Aboneh *et al*. [71] suggested a method to detect early wheat leaf diseases using several deep CNN models. The advanced deep learning model chosen for giving the best accuracy was the VGG19 model, with 99.38 % accuracy.

Jiang *et al*. [72] developed a wheat disease identification system for seven CNN models. After applying retuning training tactics, performance improvement has been noticed.

5.2. ***Survey based on other leaf diseases***

Anthonys and Wickramarachchi [73] presented a disease identification system for paddy crops through membership functions. The system recognized three major paddy crop diseases prevalent in Sri Lanka: brown spot, rice sheath blight, and rice blast. Images were segmented using the Sobel method. Then all three features (texture, color, and shape) were extracted for diseased spots on the leaf. It is a fast method. Better results were achieved for superior-quality images. The proposed method identifies a brown spot with higher accuracy in comparison with the other two diseases. Even though the accuracy after classification for 50 samples was 70 % on average. The proposed approach shows better accuracy with a small recognition time but still has noise effects that deteriorate performance. Likewise, with the growth in the number of images of each disease, besides proper threshold gives more accurate results.

Jian and Wei [74] proposed a method to detect angular leaf spots, downy mildew, and brown spot diseases of cucumber leaves. Tests were performed in two groups through various kernel functions. For the first time, the author took 60 leaf samples and for the second time, he took 336 spots of leaves as samples. The given approach used an SVM-based polynomial, sigmoid kernel, and radial basis function. Out of the two sets, RBF kernel-based SVM gives the best results by taking each spot as a sample in comparison to the other test set.

Yao *et al*. [75] developed a system utilizing SVM to identify rice blasts, bacterial leaf blight, and sheath blight. Herein, unhealthy spots were segmented for shape and texture feature extraction or their combination. This mixture of shape and texture features gives overall 97.2 % accuracy for 216 acquired images. Although performance degrades with only shape features. The proposed approach also provides recommendations for mixing shape and texture features to detect early diseases with more accurate results for other crops.

Kurniawati *et al*. [76] developed a prototype system to diagnose various types of maladies, namely brown spots, blasts, and narrow brown spots prevalent in paddy crops. The binary image was segmented in this system through local entropy and otsu threshold. Four features were validated for classification through the production rule, including boundary color, lesion type, spot color, and paddy leaf color. Out of the two threshold methods, the local entropy threshold achieved the best results with 94.7 % accuracy.

Ramesh, *et al*. [77] suggested a model for comparing classification results of papaya leaf diseases with healthy leaves employing a random forest classifier. In total, 160 images of papaya leaves were collected for disease classification. The features were extracted using the HOG method.70 % accuracy was achieved in the case of the random classifier as compared to other classifiers.

Mokhtar *et al*. [78] developed an efficient approach for comparing SVM performance with various kernel functions. This study focused on texture characteristics for tomato leaf disease detection using GLCM.SVM with linear kernel achieved higher classification results (99.83 %) on 400 trained images and 800 tested images using N- fold cross-validation.

Sannakki *et al.* [79] designed a system to distinguish grape leaf diseases, specifically powdery mildew and downy mildew. Grape leaves were segmented through K-means clustering along with GLCM. Finally, feed-forward BPNN was employed for classification. The given work accomplished 100 % accuracy using hue features only.

Sandika *et al*. [80] proposed a method by extracting ROIs of 900 images of grapes diseases under an uncontrolled environment using the random forest classifier. This method provides a comparison report of four classifiers, namely PNN, SVM, BPNN, and random forest, besides texture features, along with some statistical features for classification. Best classification accuracy for background separation and disease classification was achieved using GLCM features and a random forest classifier.

Islam *et al*. [81] proposed a work utilizing multiclass SVM along with image segmentation to distinguish potato leaf diseases, namely late blight and early blight, through minimized efforts. This system detects over 300 images with an accuracy of 95 % on a massive scale.

Singh and Misra [82] presented a survey utilizing an image segmentation technique termed a genetic algorithm for disease detection of various crops at an early stage. The results obtained were prominent and efficient in comparison to the earlier classification techniques.

Pooja *et al*. [83] suggested a leaf disease detection technique consisting of 250 images consuming image processing and machine learning techniques. Here the classifier utilized was the SVM classifier. Better results were achieved using images of five types of plant leaf diseases.

Krithika and Veni [84] detected various cucumber diseases, namely Alternaria leaf blight, bacterial wilt, cucumber green mottle mosaic, leaf miner, leaf spot, cucumber mosaic virus, etc., using image processing techniques through multiclass SVM. Here approaches used 1AA and 1A1 that were extended in the future for early detection of diseases in bigger farms.

Awate *et al*. [85] developed a disease detection system for recognizing fruits employing various image processing techniques. The given system detects various diseases in grapes, apples, and pomegranates. Future work suggests smart farming as well as disease severity estimation of diseases.

Sladojevic *et al*. [86] proposed the latest generation approach based on deep CNN to classify diseased leaf image datasets. The proposed system recognizes 13 types of diseases using the Caffe framework. Initially, the original images collected were 3000. With appropriate transformations, the database of images increased to more than 30,000. This study attained an overall accuracy of 96.3 %, giving more importance to augmentation than fine-tuning.

Mohanty *et al*. [87] offered a novel approach for categorizing plant leaf diseases via smartphones through deep CNN. Various researchers conducted experiments on a 54306 image dataset using 38 diseased leaf pairs. The experimental outcomes obtained an average accuracy of 99.35 % using trained models.

Oppenheim *et al*. [88] design an algorithm for the detection of four potato diseases along with healthy potatoes using deep CNN. Various images of potato diseases were acquired under uncontrolled conditions. CNN models were trained to better recognize the amount of dataset required for classification through deep learning. Results obtained on the least amount of trained data range from 83 % to 96 % containing 90 % trained data showing the correct classification of fully trained CNN models.

Wang *et al*. [89] suggested an approach to automatically determine the severity of the disease through deep CNN using discriminative features through fine-grained classification. Using apple black rot images in the Plant Village dataset, the author trained small CNN having various depths from scratch. Finetuning of four deep learning models, namely VGG16, VGG19, Inception-v3, and ResNet50, was also performed. Through the evaluation system, the performances of both types of networks were assessed. Best accuracy achieved through fine-tuned VGG16 model having 90.4 % accuracy rate.

Amara *et al*. [54] suggested a deep-learning model using LeNet architectures to recognize two banana diseases, namely banana speckle and banana Sigatoka under challenging conditions. These conditions included complex backgrounds, illumination, diverse image resolution, pose, size, and orientation. This confirmed that the proposed method detected leaf diseases accurately by miniature computational effort.

Atole *et al*. [90] suggested a system to recognize rice diseases under three classes, i.e., normal, unhealthy, and golden apple snail infection, with pre-trained weights and biases. Here transfer learning using the AlexNet deep network approach was used. The division into the training-testing set was also performed. Stochastic gradient descent was applicable for a base learning rate of 0.0001, taking a batch size of 30. The accuracy attained was 91.23 %.

Baranwal *et al*. [91] suggested a deep-learning-based CNN model for the recognition of apple leaf diseases covering Apple Black Rot, Apple Cedar, Apple Rust, Healthy Apple, and Apple Scab, showing the best accuracies as 98.71 %, 99.27 %, 98.70 %, and 97.3 % respectively. The proposed system detects 2526 images of apple leaf diseases by fine-tuning the CNN model to achieve the best accuracies through the change of parameters like a dropout.

Ma *et al*. [92] detected four cucumber diseases using balanced and unbalanced data through deep CNN. A comparison of results was also performed with conventional classifiers like SVM, Random Forest, etc., Using AlexNet architecture; better accuracy is achieved through deep CNN. The recognition is performed based on the indications of diseases. Besides that, transfer learning was also applied to get better results in comparison to disease detection from scratch by considering quality datasets.

Yang *et al*. [93] developed a deep-learning method using the CNN algorithm for image recognition of 10 rice diseases. If we compare this method with other previous methods, we know that the current methodology performs better training, converges faster, and recognizes better with 95.48 % accuracy.

Zhang *et al*. [94] presented improved deep CNN-based models named GoogLeNet and Cifar 10 to recognize and classify nine maize leaf diseases. Here, recognition accuracy achieved is 98.9 % through GoogLeNet and 98.8% through the Cifar10 model.

Yujian *et al.* [95] proposed an evaluation-based model that consists of various architectures like VGG 16, Inception V4, ResNet with 50, 101, and 152 layers, and DenseNets with 121 layers. The given approach recognizes 38 different categories of leaf diseases using deep CNN. Here DenseNets performs best compared to the other CNN architectures considering fewer parameters.

Geetharamani and Pandian [96] presented a deep CNN-based model to identify 39 different types of leaf diseases using AlexNet, VGG16, Inception-v3, and ResNet architectures. The dataset consists of 54305 images of species. The accuracy achieved in this case is 96.46 %.

Priyadharshini *et al.* [97] developed modified LeNet-based architecture to detect four classes of maize leaf diseases. The proposed method uses a deep CNN-based algorithm on 3852 leaf images of the maize dataset. The proposed method attains an efficiency of 97.89 %.

Rangarajan *et al*. [98] developed a deep CNN-based approach for the classification of tomato leaf diseases using pre-trained AlexNet and VGG16Net. This model detects seven categories of tomato leaf diseases and shows better classification accuracy using AlexNet when considering a computational load.

Arsenovic *et al.* [99] developed a two-stage architecture model that enhances the accuracy of the classification of leaf diseases under various wild conditions. A new leaf disease dataset was also introduced to enhance the classification results.

Aravind *et al.* [100] designed a transfer learning-based approach for recognizing three categories of leaf diseases utilizing AlexNet architecture. Here dataset includes 4063 images. In this type of detection system, features extracted from AlexNet were applied to MSVM to enhance classification accuracy.

Liang and Zhang [101] proposed a multiplier classifier integration approach to detect leaf diseases consisting of 38 categories from the unhealthy dataset. The given method displays better results as compared to the earlier approaches while considering efficiency.

Long *et al.* [111] presented a wheat image dataset obtained in real-life growth circumstances, encompassing individual field and glasshouse environments, and classified into five classes: healthy plants and four foliar diseases, yellow rust, brown rust, powdery mildew, and Septoria leaf blotch. A deep learning model was trained through this dataset. CerealConv, the resultant model, has a classification accuracy of 97.05 %. When evaluated in opposition to skilled pathologists on a selection of photos from the broader dataset, the model outperformed the best-performing doctor by 2 %. Image masks were utilized to demonstrate that the model was driving its classifications with the proper information.

Rani *et al*. [113] developed an operative method for in vitro micropropagation of Berginia ligulate consuming various concentrations of growth regulators. The results of this protocol can benefit commercial growers and contribute to the preservation of rare and endangered medicinal plants. The advancement of plant tissue culture has the potential to provide cost-effective production of these plants, their cells, and the substances they produce. There is a need for further research in this area in developing and undeveloped countries to conserve medicinally important plants.

Table 2. Classification techniques for wheat leaf diseases.

Ref.	Crops/ plants	Disease/ deficiency	Dataset used	Techniques/ classifiers used	Findings/results
65	Wheat	Powdery mildew, leaf blight, and leaf rust	800 images	SVM based multiple classifier system	SVM-based MCs show better performance as compared to previous SVM. Accuracy is 95.16 %.
66	Wheat	Powdery mildew, Tan spot, Septoria leaf spot and snow mold	310 images	Fuzzy-C-means clustering	Fast and efficient system. Achieved 56 % accuracy.
67	Wheat	Fungal diseases	120 images	K-means clustering, NN, and SVM	SVM (89.23 %) shows better results as compared to NN (80.21 %).
68	Wheat	Bacterial streak	Few sample images	K-means clustering, PNN	Accuracy attained was 96.7%. Recommended fuzzy logic for better results.
69	Wheat	8 diseases	16652 images	Deep CNN (matrix based)	Matrix-based CNN shows improvements having validation and testing accuracies of 96.5%, and 90.1 % respectively.
70	Wheat	10 diseases	12000 images	Deep CNN	Progression of 7.01 % and 15.92 % accuracy in comparison to VGG16 and RESNET50.
71	Wheat	Few diseases	1500 images	Advanced Deep CNN models	VGG19 model shows the highest accuracy in comparison to other advanced deep learning models.
72	Wheat	Leaf rust, stripe rust, healthy wheat	2643 images	Deep CNN (Transfer learning method)	Inception-v3 model shows high performance along with 92.5 % accuracy.

Table 3. Classification techniques for other leaf diseases.

Ref.	Crops/ plants	Disease/ deficiency	Dataset used	Techniques/ classifiers used	Findings/results
73	Paddy crops	Downy mildew, brown spot, and angular leaf spot	50 images	Membership function used for classification	Better results were achieved for the detection of brown spots in comparison to other diseases
74	Cucumber	Downy mildew, brown spot, and angular leaf spot	1st time-60 images 2nd time-336 images	SVM method based on RBF, sigmoid, and polynomial kernel functions	Higher recognition rates in SVM-based RBF in comparison to the sigmoid and polynomial functions. For improved efficiency, each spot was used as a sample.
75	Rice	Bacterial leaf blight, sheath blight, and rice blast	216 images	SVM	Overall classification accuracy of 97.2 % was attained. There were recommendations for shape and texture features usage in other crops also.
76	Paddy crops	Blast, narrow brown spot, and	94 images	Otsu, median filter, Region	Local entropy threshold performed better than the Otsu

		brown-spot		filling, Production rule with forward chaining	threshold and attained an accuracy of 94.7%.
77	Papaya	Healthy and diseased leaves	160 images	Random forest classifier	70 % accuracy was achieved in the case of a random classifier as compared to other classifiers.
78	Tomato	Healthy and unhealthy leaves	400 images, 800 images	SVM (Linear, Quadratic, RBF MLP) for both datasets	Improvement in accuracy with the increase in several training samples and attained an accuracy of 99.83 % using the SVM-based linear kernel function.
79	Grapes	Powdery Mildew and Downy Mildew.	33 images	K-means clustering, Feed-forward BPNN	100% training accuracies were attained while using hue features only.
80	Grapes	Powdery mildew, Anthracnose, and Downy Mildew,	900 images	Random forest	Achieved 86 % accuracy using random forest.
81	Potato	Late blight, Early blight	300 images	Otsu, Multiclass SVM	Attains 95 % accuracy
82	Various crops	Various leaf diseases	Few sample images	SVM, K-means clustering, Genetic algorithm	Average classification accuracy attained is 97.6 %
83	Various crops	Various leaf diseases	250 images	SVM, K-means clustering	Attains 92.4 % rate of disease recognition
84	Cucumber	Leaf Spot disease, Leaf Miner and Cucumber Mosaic Virus	Few sample images	Multiclass SVM, K-means clustering	Better results achieved
85	Apple, Grapes, Pomegranate	Various leaf diseases	Few samples image	SURF, K- means clustering, ANN techniques	Satisfactory results obtained
86	Pear, Peach, Apple, Grapevine, etc.	13 diseases	33469 images	Deep CNN	Give more importance to augmentation than a fine-tuned system. Obtained accuracy of 96.3 %.
87	Multiple crops	26 diseases	54306 images	Deep CNN	Accuracy achieved was 99.35 %.
88	Potato	Black Scurf, Silver Scurf, Common Scab, black dot	2465 images	Deep CNN	Results vary from 83 % to 96 %.
89	Apple	Healthy and black Rot	2086 images	Deep CNN	VGG16 model shows better results with an accuracy of 90.4 %
55	Banana	Healthy Banana, Banana Sigatoka,	3700 images	Deep CNN	Early and fast detection method

		Banana Speckle			
90	Rice	Normal, unhealthy, golden apple snail	857 images	Multiclass Deep CNN	The accuracy obtained was 91.23 %. Integration of wheat disease detection along with localization of diseased areas.
91	Apple	Apple Black Rot, Apple Cedar, Apple Rust, Healthy Apple, and Apple Scab	2526 images	Deep CNN	Results are best in the case of DCNN as compared to conventional classifiers under field conditions.
92	Cucumber	Anthracnose, Downy mildew, Powdery mildew, and Target leaf spots	14208 images	Deep CNN	High accuracy was achieved through ResNet50 Deep CNN architecture.
93	Rice	10 diseases	500 images each	Deep CNN	The accuracy achieved is 95.48 %, with better training, fast convergence and better image recognition
94	Maize	9 diseases	500 images	Deep CNN	The average accuracy rate is 98.9 % in the case of Google Net and 98.8 % in the case of Cifar10
95	14 plant species	38 diseases	54306 images	Deep CNN	DenseNets performs better in comparison with the other architectures
96	13 plant species	39 diseases	54305 images	Deep CNN	Performs better after applying augmentation techniques
97	Maize	4 diseases	3852 images	Deep CNN	Better accuracy attained by changing kernel size.
98	Tomato	7 diseases	13262 images	Deep CNN (Pretrained Models)	The accuracy achieved is 97.29 % using VGG16Net and 97.49 % for AlexNet
99	Multiple species	Multiple diseases	79265 images	Deep CNN	The accuracy achieved is 93.67 %
100	Grapes	3 diseases	4063 images	Deep CNN (Transfer Learning)	Classification results improved after transferring features to MSVM
101	Multiple species	38 diseases	54309 images	Deep CNN (Multiple Classifier integration)	The accuracy achieved is 99.92 %

6. Limitations of Past Works

As far as the usage of classifiers for leaf disease detection is concerned, the classification category employed has great significance in the final results. From the literature survey included in this paper, classifications are made using various supervised and unsupervised classifiers like SVM, K-means clustering, and Deep CNN-based classifiers. Although traditional classifiers provide better classification results, they still show some limitations. Classification based on supervised learning requires human intervention to create labels. It is also time intensive during the training of data. On the other hand, classification based on unsupervised learning doesn't involve human intervention, providing erroneous results in some cases. Classification through deep CNN uncovers the difficulties propagated by the usage of traditional classifiers with the growth in dataset size. In other words, traditional classifiers perform well with smaller datasets, but accuracy declines with the growth in the dataset size. Hence deep CNN-based classifiers solve the purpose by maintaining the accuracy of large datasets.

7. Issues and Challenges

Although marvelous performance is attained using deep convolutional neural networks, there exist various research challenges [102-113]. The following points illustrate various issues and challenges during leaf disease detection through CNN: -

- As CNNs might be made up of tens or several layers, each layer additionally incorporates a large number of neurons; what number of layers and what number of neurons are ideal at last?
- Very-large-scale datasets are required for learning through CNN.
- Better quality datasets are recommended for accurate disease detection
- Image acquisition and monitoring of real images of leaf diseases are very laborious and time-consuming tasks.
- How to search optimal parameters in CNN from a large number of parameters?
- Choice of the best deep learning architecture for leaf disease recognition is also one of the greatest challenges
- Most variations are found in the symptom representation of various leaf diseases.
- Image background may disturb the training process.
- Under various circumstances, images taken affect the results of classification.
- We have compelled the recognition of single leaves facing up on a homogeneous background since the disease may also be present on the other sides of the leaves.
- Conditions are different during testing compared to the conditions during the training phase, which substantially decreases accuracy.
- The above techniques in the literature survey minimize the effects of diseases through detection but can't describe the severity of the diseases automatically.
- The overfitting problem appears in the case of small-size datasets.
- Dedicated hardware or GPUs of high processing power are required to solve classification problems of leaf disease detection through deep CNN.

8. Conclusion and Future Work

The manuscript has presented a survey of several techniques for recognizing and classifying leaf diseases of crops, with a focus on wheat leaf diseases. The survey compares conventional machine learning techniques and deep convolutional neural network techniques. The authors find that a deep CNN approach provides fast and accurate disease detection when trained on large datasets using baseline training, transfer learning, and fine-tuning. The literature survey conducted in the paper shows that deep convolutional neural networks provide better results for large image datasets compared to conventional machine learning classifiers like SVM, random forest, and BPNN. We will plan to inspect the performance of CNNs with advanced deep-learning models using hybrid techniques in future studies. We also aim to build a mobile device-based classification system intended for disease diagnosis to assist farmers and to focus on automatic severity approximation of detected diseases to help farmers determine how to intervene to stop the disease effectively.

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