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Classification Models for Plant Diseases Diagnosis: A Review

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Abstract:

Plants are important source of our life. Crop production in a good figure and good quality is important to us. The diagnosis of a disease in a plant can be manual or automatic. But manual detection of disease in a plant is not always correct as sometimes it can be not be seen by naked eyes so an automatic method of detection of plant diseases should be there. It can make use of various artificial intelligence based or machine learning based methods. It is a tedious task as it needs to be identified in earlier stage so that it will not affect the entire crop. Disease affects all species of plant, both cultivated and wild. Plant disease occurrence and infection severity vary seasonally, regarding the environmental circumstances, the kinds of crops cultivated, and the existence of the pathogen. This review attempts to provide an exhaustive review of various plant diseases and its types, various methods to diagnose plant diseases and various classification models used so as to help researchers to identify the areas of scope where plant pathology can be improved.

1. Introduction

Plants are regarded as an essential source of life on the Earth. Among the almost 1.7 million varieties of living organisms, that included human beings, animals, algae, and plants, the plant is the most crucial to all remaining living organism. Human existence is dependent on plants because if plants remain, humans remain as well. Plants fulfill various requirements, including food, medicine, cloth and house. Plants serve as the foundation of the food chain in the environment. Plants also provide the basis for the majority of drugs, including Ayurvedic remedies.

A good harvest not only benefits the farmers, but it also contributes significantly to the nation's economic development. However, obtaining desired production levels is difficult due to a variety of factors such as diseases, pests, climate and many more. Keeping the utilization of the plants in mind, the identification of plant diseases becomes the most important, since right identification leads to better crops production.

Plant Illnesses are a natural element of the environment and one of the several ecological variables that serve to maintain the millions of living organisms in equilibrium with each other. Plant diseases have been recognized since the time of the first literature. Plants were harmed by illness 250 million years ago, according to fossil records. Diseases like blights, mildews and rusts, caused starvation and other significant shifts in the economies of countries since the beginning of the civilization. A plant becomes unhealthy when it is repeatedly disrupted by certain causative factor including biological and environmental, resulting in an unusual life processes that disturbs the plant's normal development, structure, and function. Disease affects all species of plant, both cultivated and wild. Plant disease occurrence and infection severity vary seasonally, regarding the environmental circumstances, the kinds of crops cultivated, and the existence of the pathogen. Certain plant species are especially vulnerable to disease outbreaks, but many others are less susceptible to them.

For thousands of years, people have thoughtfully picked and grown plants for clothing, food, shelter, beauty, fiber, and medicine. Disease is one of the deadliest hazards among several risks that must be addressed when plants are removed from their native habitat and cultivated in the fields under sometimes unfavorable conditions. Many important ornamental and crop plants are highly vulnerable toinfection and would struggle to survive in the nature without humans' involvement. Planted crops are frequently more prone to infections than their wild counterparts. This is due to the fact that enormous plants of the same breed, with a similar genetic profile, are grown in close proximity, often spanning hundreds of Kilo-metre square.

1.1 Problem

Plant diseases are a worldwide hazard to feed a growing population, it may also be devastating for small-scale farmers whose lives are dependent on crops production. Small-scale farmers produce greater than 80 percent of crops yields in developing countries(UNEP, 2013), and more than

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50% yield reduction is observed due to plant diseases and pests (Harvey, C. A., Rakotobe, Z. L., Rao, N. S., Dave, R., Razafimahatratra, H., Rabarijohn, R. H., et al., 2014). Moreover, small farming families belong to the class of the majority of starving people (Fifty percent) Sanchez, P. A., and Swaminathan, M. S. , 2005) , these small-scale farmers are always sensitive to pathogen-related food supply disruptions.

In the age of environmental changes around the world plant diseases have become a problem because they can reduce the amount of production and quality of agricultural goods significantly. Automatic-detection of crop illnesses is a key research domain because it might help in monitoring the huge fields of crops and, as a result, recognize disease signs as-soon-as they occur on plant leaves. Precise recognition and diagnosis of crop diseases is essential for food security and the control of the spread of exotic pathogens/pests This allows image-based automated evaluation, control systems, and robot-guiding using machine-vision. Visual recognition, on the other hand, is time-consuming, inaccurate, and limited to narrow crop fields. Though improvements have been achieved in all dimensions of plant disease detection; boosting accuracy, specificity, sensitivity and efficiency have remained a crucial issue that should be addressed. The suggested system is an effective solution for detecting and classifying plant leaf diseases automatically and accurately. We proposed an approach to capture the diseases at initial stage.

1.2 Motivation

Visual investigation by naked eyes is still the primary technique of disease diagnosis in villages of developing countries (Chen, J. et.al 2020). These traditional methods require skilled monitoring on a regular basis. Many of the farmers detect the plant diseases manually on self-experience basis. Generally, this self-investigation does not capture initial symptoms of the infection at early stage of diseases which gives chance to the

pathogens to spread out in the whole crop fields. Many times, this visual inspection fails to recognize the diseases accurately. Some aware farmers feel it appropriate to take expert advice to identify the disease. Therefore, farmers in remote areas need to plan a long journey to see a plant pathologist, that is both expensive and time- taking (Bai, X.et.al, 2018; Ramcharan, A.,2017). Certainly, laboratory-based illness detection is more precise. But it leads to diagnosis delays. Late diagnosis causes a reduction in crop yields. Hence, automated and accurate disease identification in plants is very important to ensure better quantity and quality of crops.

1.3 Plant Diseases and its types

Plant diseases are broadly classified into 2 types: pathogenic and non- pathogenic.

1.3.1 Pathogenic Disease

Pathogenic diseases are also known as parasitic or infectious diseases. Pathogenic illnesses are caused by infectious microorganisms. This type of diseases spread very fast due to pathogen’s ability of being multiply at fast rate. Major causing organisms of this sort of illnesses are Bacteria, fungus, and virus. Figure 1.1 depicts the types of pathogenic diseases.

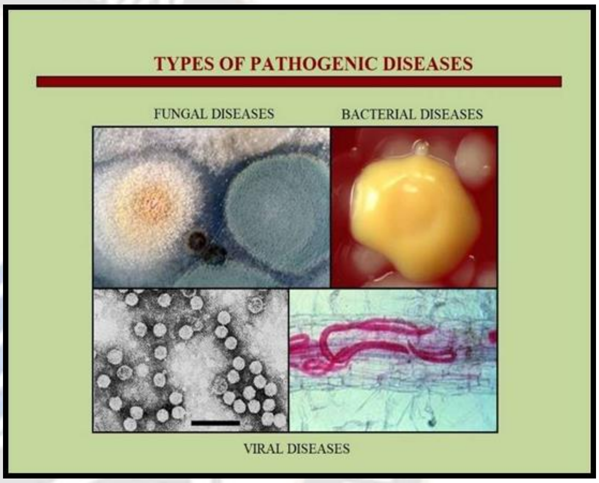

Figure 1.1 Types of Pathogenic Diseases

1) Bacterial Diseases

Bacterial leaf spot is a common name for a bacterial illness. In order for the bacteria to cause an illness in a plant, the bacteria first penetrate and multiply in the tissue of plant. Most bacteria cause only one significant symptom, while some cause a variety or mix of symptoms. In general, determining if a plant is infected with a bacterial infection is not hard; however, identifying the pathogenic organism at the initial level necessitates separation and identification of the microorganism using a variety of laboratory procedures. Moisture and temperature have a big impact on bacterial illnesses. Usually, a small temperature difference decides whether or not a bacterial illness will emerge. In several situations, moisture in the form of a water layer on leaves and stems surfaces is one of the main reasons for developing an infection. It begins as tiny, yellow-green spots on new leaves that are distorted and curled, or as greasy-looking lesions with water-soaked and dark appearance on older leaves and stems. The majority of foliage parasites travel from one infected plant to other by dust, rain, and wind. Following are some commons symptoms caused by bacteria:

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a) Necrosis
b) Vascular wilt
c) Tumours
d) Soft rot

2) Fungal Diseases

Fungi are responsible for the bulk of contagious plant infections, accounts for nearly two-thirds. All economically significant crops appear to be affected by fungus; in many cases, many fungi may spread infection in a single species of plants. Usually, widespread or local necrosis is caused by a fungal disease. It can either slow down the usual development or cause extreme aberrant development in a part or the whole plant. Fungi propagate mostly by spores, which are abundant. Dust, water, wind

streams, birds, insects, and the remnants of diseased plants can all carry and spread the infection. Following are some commons symptoms caused by fungi:

a) The majority of flower, fruit, and leaf spots
b) All true and white rusts, sooty moulds, mildew, smuts, anthracnoses, leaf curls, andneedle casts
c) blightsd)cankers
d) e) Shoot, bud and leaf galls
e) wilts
f) Scabs, wood, fruit, root, and stem rots and many more

3) Virus Diseases

They can only grow or reproduce within a live cell of a specific host. A single species of plants can be infected by multiple distinct viruses. Virus infection causes major illness in essential food plants like palm, sugarcane, rice, corn, oats, wheat, tomato, potato, sugar beet, orange, and peach. Infections are often more severe in crops cultivated asexually—that is, through sprouts, cut divisions, and cuttings, in comparison of crops cultivated sexually by using seeds. Following are some commons symptoms caused by viruses:

a) Dwarfing of whole plants or stems, leaves
b) Necrosis (internal death, drooping or wilting, streaks, circular spots, andleaf spots)
c) Malformations (proliferation, rosetting, deformation of flowers and leaves)
d) Variation in color (vein clearing, yellow mottling, yellowing)

1.3.2 Non-pathogenic Disease

Non-pathogenic diseases are also known as non-parasitic or non- infectious diseases. These types of illnesses, which might appear abruptly, are created by a lack ofavailability, a deficiency, an inappropriate balance, or an excess of climatic and soil parameters. Non-pathogenic illnesses in plants can emerge as a result of;

a) Mechanical injuries caused by animals or human being,
b) Genetic defects in seeds
c) Air pollution in environment
d) Toxic chemicals
e) Variations in climatic factors (temperature, moisture, humidity, rain etc.)
f) changes in soil parameters (organic matter, texture, soil humidity, soil pH, etc.), andso on.

2. LITERATURE REVIEW

The relevant studies related to plant disease diagnosis and classification is included in this section to identify unexplored areas that could be further explored.

2.1 Review of Existing Methods

During the 1990s, researchers and agricultural scientists started to focus their attention on computer-based solutions for disease detection and classification in plants. We have included such computer-based solutions from several peer reviewed academic journals and academic conferences in literature review.

2.1.1 Related to Plant Disease recognition using DIP techniques

In a variety of applications and domains, image-processing has shown to be an efficient-method for examining and solving related problems. From the farmers' perspective, factors such as yield, disease, and product quality were essential criteria in the agriculture industry. For a long period of time, farmers seek expert advice for solutions to agricultural problems.

Expert counsel is not always feasible, and maximum times the expert’s availability and services take time. When compared to previous manual approaches, the image processing analysis for agricultural challenges (plant identification, yields prediction, fruit sorting, crop disease recognition, etc.) has proven to be more accurate and more efficient.

In this subsection, we have discussed a literature survey on various methods and approaches, which are suggested by different researchers in different years for plant leaf disease detection using image processing techniques.

N. N. Kurniawatti et al., 2019 introduced a DIP-based technique for rice disease identification and categorization. The primary goal of the present study was to create a prototype model for detecting rice illnesses such as “narrow brown- spot disease (NBSD), brown-spot disease (BSD), and blast disease (BD)”. The focus of this work was to obtain rice characteristics from offline picture samples. In

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proposed approach, image capture was followed by automated thresholding based on the Otsu technique and local entropy threshold to transform RGB pictures into binary images. The noise was removed using a morphological algorithm namely the region filling approach. Then, from rice leaves pictures, image attributes such as damaged rice leave color, spot color, border color, and kind of lesion were retrieved. As a result of using the production rule approach, rice illnesses may be identified with an accuracy rate of 94.7 percent. This strategy has a lot of potentials to be useful. In this procedure, the Otsu threshold is utilized to detect illness spots, and the median filter was applied to eliminate any unneeded lesions.

In 2008, the approach of image pre-processing for identifying the illness lesions was presented by Ying et al., 2008. They have taken image samples of cucumber downy mildew, powdery mildew, and speckle to conduct the experiments. The impact of 2 filters, a median filter and a simple filter was studied in the suggested work. Authors ultimately picked the median filter to effectively remove noise disturbances. The median filter was utilized in this article to smooth the digital pictures and to get quality image. Interested leaf section was separated from complex background using 2-apex technique. Snake model and edge detection technique were experimented to locate lesions in diseased leaves. Snake model has given better result. The thresholding approach was applied to turn the filtered picture into a black and white image, and the infected lesions were then discovered employing the edge detection method.

In 2010, Zhang et al. (2010) presented the results of establishing image processing algorithms to identify rust severity from multi-spectral pictures in their work. They have applied 2 methods namely threshold setting and centroid locating to recognize rust severity. In first experiment, "sick regions were separated from leaf image by developing a rapid manual threshold-setting approach based on the Hue Saturation Intensity color space". They have determined the ratio of diseased region and the rust color index and used them as disease detection parameters to estimate the rust severity. In second experiment, centroid locating approach was developed. In centroid locating approach, firstly leaf color distribution map was determined then centroid of this distribution was analyzed to identify rust. Authors have experimented their method on 32 leaf image samples of soybean plant and it was observed that the threshold-setting-method was capable to identify rust-severity in controlled environment, while the centroid locating approach was capable to identify rest severity in real crop field environment.

Patil et al. (2011) introduced an illness recognition technique based on disease severity calculation for sugar plants. They have applied thresholding segmentation techniques on plant leaves to get infected portions. These segmentations were done in 2-phases. In the first-phase, the leaf region was identified in the input image using simple thresholding. In the second phase, infected regions were identified using triangle thresholding. Finally, "diseases severity was determined by calculating the ratio of lesion area and leaf area". The algorithm's accuracy is determined by calculating the percentage difference of standard and experimented lesion area. The standard area of lesions was determined using standard shape like rectangle, square, circle and triangle using a paintbrush tool. Accuracy in percentage was computed by subtracting percentage difference of standard and experimented lesion area from 100. The average accuracy of suggested strategy was recorded as 98.60%.

In 2012, Piyush Chaudhary et al. (2012) developed an automatic technique to detect infected lesion on the leaves of crop using DIP techniques. They have analysed and compared the cons and pros of different color space (HSI, YCbCr, CIELAB) used in disease detection. Authors have illustrated that CIELAB color space was very effective to remove the noises that was induced in leaf images due to leaf vein and camera flash. Median filter was applied on leaf images to smooth the images. Finally, Otsu's-thresholding approach was used to segment the infected spot from leaf images.

Naikwad, S. and Amoda, N. (2013) proposed a histogram matching technique to recognize plant disease. Color features and edge-detection techniques was used to match the histogram of the diseased portion in the leaf. Features were extracted using "Color Co-occurrence Method (CCM) and texture analysis". "Spatial Gray-level Dependence Matrices" were used to develop CCM. The suggested method can achieve better results with advanced color features and large datasets.

Dhaygude et al. (2013) [25] presented a plant disease detection technique consisting of four steps. This technique is based on image-segmentation and the color co-occurrence Method. In the first step, the input RGB image was converted into HSV color format. Here HSV image was utilized for a color descriptor. In the next step, green color pixels were removed and masked using a threshold value. In this step, diseased portions were achieved by removing green pixels from the leaf. In the third step, equal-sized patches were segmented from the diseased regions. Then useful patches were chosen which contains more than 50% information. Finally, in the last step, texture analysis was performed on useful segments using color co-occurance matrix to recognize the plant diseases.

Particle Swarm Optimization (PSO) is a new image segmentation technique proposed by Muthukannan and

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Latha (2015). PSO is a self-regulating, efficientunsupervised technique for better segmentation and feature extraction. HFE method was used to extract the relevant features. There were 3 components in this method in which one was analyzing the texture features and the other 2 components were analyzing shape and color features, respectively. The co-occurrence grey level matrices of several leaves were then used to calculate the hybrid characteristic coefficients. The suggested approach was validated on several photos of infected leaves, and the results were promising. According to the findings, the HFE strategy helped in disease classification by improving the accuracy of the classification and reducing false classification. Finally, the suggested HFE technique might be useful for improved classification of a variety of diseases found in plant leaves.

Rishi and Gill (2015) discussed image processing algorithms for identifying and classifying crop diseases. They talked about how important picture compression is for disease detection. The authors investigated and examined the importance of Otsu's thresholding method for segmentation, the K-means clustering for noise removal, and image cropping in the recognition of diseases.

Zhang et al. (2017) proposed a new illness recognition approach for cucumber plants that comprises three cascaded processes: K-means segmentation to segment infected leaf pictures, collecting “shape and color” characteristics from infected regions, and sparse representation (SR) for categorizing infected leaf images. The classification in the SR space may significantly cut computational costs and increase detection rate, which is a great benefit of this technique. This method is able to detect 7 most frequent leaf diseases found in cucumber plants with an overall detection accuracy of 85.7%.

Singh and Misra (2017) applied soft computing to segment the diseased region in plant leaf. This study proposed a method for picture segmentation, which was used to recognize and categorize the diseases found in plant leaves automatically. It also included an overview of several disease categorization systems that may be utilized to detect leaf diseases. The genetic algorithm is used to do “image segmentation”, which is an important part of “disease detection” in plant leaf disease.

As per the above discussion, we have seen that DIP techniques for identifying crop diseases and determining the severity of crop diseases are efficient, accurate, and convenient. It will assist farmers in determining the precise amount of insecticide needed to apply, lowering the disease management costs and reducing theenvironmental pollution. Traditional approach’s human-induced mistakes and subjectivity are no longer an issue. But image processing alone is not able to build a smart system for disease detection and classification, which can learn characterizing features from the input data. An automatic\intelligent\smart disease recognition and classification model can be built by combining DIP operations with ML and/or DL techniques. In the next subsection, we have surveyed various techniques that used DIPoperations in combination with ML techniques to diagnose leaf illness found invarious plants.

2.1.2 Related to Plant Disease Recognition and Classification using ML along with DIP Techniques

In this subsection, we have discussed a “literature review” on various techniques and approaches, which were suggested by different researchers in different years for plant leaf disease diagnosis and categorization using various DIP techniques in combination with ML approaches. In these systems, lesions identification was done by DIP techniques and disease classification was performed by ML models. Here image processing techniques are utilized in following order:

1. To enhance visual characteristics of images
2. To segment the interested region from input image
3. To retrieve the significant visual features (Texture, morphological, and color features) from segmented regions.

While ML techniques are utilized to perform classification task.

In 1999, Sasakoi et al. (1999) determined shape and spectral reflection features by using genetic algorithms to diagnose the infections in the plant. In this paper, automated identification method for cucumber anthracnose was suggested by theauthors. The impact of optical filtering on illness identification is based on distinct spectral reflection properties. To diagnose disorders, they employed a genetic algorithm to build identification factors based on 2 angles of spectral reflection and attributes of the shapes of sample images. Conventional computer vision approaches need labor-intensive and time-consuming preprocessing and feature creation. Thecorrectness of the learning method and features creation decides the success of proposed method. The identification impact, however, was not as good as planned due to a lack of use of disease texture and color features.

Helly et al. (2003) introduced a new technique in which the input picture is first converted to a Hue Saturation Intensity (HSI) color format, further, the Fuzzy C- mean technique was applied to separate the infected part from the image. The “shape, size, and color” characteristics of infected lesions were obtained and finally, these extracted features were fed into ANN for disease identification and

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classification. Authors claimed that the proposed system was 97 percent accurate.

In 2004, Moshou et al. (2004) used Multilayer perceptron and Self-organisation map to detect yellow rust disease in wheat. wheat infection is recognized by using reflectance measurements. At an initial phase of yellow rust infection, spectral reflectance of infected and healthy plants was examined. Next, the variation in spectral reflectance of infected and healthy plant was explored. between healthy and sick wheat plants was explored in this study. A spectrograph placed at spray boom level was used to capture in-field spectral pictures. The researchers devised a normalisation approach based on light intensity adjustments and reflectance. Based on SOM, a unique approach for explaining interrelationships between variables and visualising data characteristics is described. On the basis of neural networks, disease identification technique has been built. An accuracy of 99% was achieved in the result analysis.

Sammany and Medhat (2007) introduced a plant disease detection system based on a roughset approach to minimize the dimensions of extracted color and morphological features. In this paper, An ANN-based classifier was utilized to detect plant illnesses. The plant symptoms were classified using a neural network based on the leaf spot classes. Discolored (D), red-spotted (RS), white-spotted (WS), and Yellow-spotted (YS) are the four main classes. A set of discriminating factors are retrieved from a segmented leaf picture and afterward utilized for classification in order to identify the leaf spot class. These discriminating factors correspond to the spots' color and morphological properties. First, they improved the parameters using roughset approach and the design of neural networks using genetic algorithms. Then optimized neural networks along with SVM were employed to recognize the diseases of the plants. As seen in the result analysis, all of the situations resulting from the rough sets technique had greater accuracy (90 percent) than utilizing the entire feature set. This suggests that decreasing the number of features enhanced MLP's generalization ability while having no effect on the classification accuracy.

Meunkaewjinda et al. (2008) proposed a technique for diagnosing grape plant illnesses. This method is based on image classification and detection techniques. The suggested method was divided into three sections: In the first step, the color of the leaf was retrieved from the complicated surrounding of leaf picture, in second step, the infected region's color was extracted, In the last step, the disease was classified.

In this study, a BPNN was combined with a SOFM to distinguish grape leaf colors. MSOFM and GA were also used to segment the leaf infection. Finally, Gabor Wavelet was used to filter the segmented picture, and SVM is used to categorize the leaf infection of the grape plant. Three classes of grape leaf were used to conduct the experiment. These classes are; healthy, rust disease, and scab disease. Despite the fact that there are several limits to retrieving color pixels from the image's background. For any farm products evaluation, the technique has shown to be quite promising.

In 2009, Li et al. (2009) used Probabilistic Neural Network (PNN) to identify 2types of diseases namely rice leaf roller and Aphelenchoides besseyi Christie found in rice plants. PNNs are a type of feedforward neural network that uses Parzen windows as its foundation. The activities of a PNN are grouped into a 4-layer feedforward network. Two types of spectral bands (visible and Shortwave Infrared) information were processed using PNN to detect the diseases. PCA approach was applied to form principal component spectrum by using the visible and Shortwave Infrared bands. Result analysis illustrated that the proposed system had a 95.65% accuracy rate inpredicting illness and insect infection. Large memory requirement is drawback ofPNN model.

Liu et al. (2009) suggested a technique for distinguishing the healthy and sick parts of rice leaves using a BPNN as a classifier. Brown spot disease was chosen to investigate the proposed technique in this study. The input values to the BP neural network were color properties of healthy and diseased regions. The findings suggest that this technique may be used to diagnose other illnesses as well.

Al-Hiary et al. (2011) presented an ANN-based crop disease recognition and categorization approach. The underlying principle that serves as the foundation in every computer vision classification system is nearly identical. First, a digital camera was utilized to collect digital photos from the interested farms. The obtained pictures are then subjected to image processing techniques in order to identify valuable information for next study. The photos are then classified using a variety of classification approaches based on the particular application. Here, Tiny whiteness, Late scorch, Ashen mould, Cottony mould, and Early scorch are the five illnesses considered for the study. The RGB pictures of leaves were transformed into the CIE Lab format. To locate the sick section of the leaf, the K-means approach was utilized. The Green section of the leaf was masked in the original picture. For feature extraction, the diseased areas are transformed to Hue saturation intensity format. The hue and saturation component of the HSI format was used to produce spatial grey level dependence matrices. "Texture features" were obtained and fed in the ANN classification model. Finally, classification task is completed using a NN. Authors claimed that suggested technique was 94% accurate. Similar

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approach was applied by Mrunalini et al. to recognise plant diseases.

Mrunalini et al. (2011) proposed an ANN-based "disease detection and classification technique" to identify the diseases affecting the plant leaves. This types of automatic detection of diseases are very useful for farmers as it saves time, money, effort, and the environment. They have applied 3 image pre-processing operations (cropping, smoothing, and image enhancement) to enhance the visual appearance of input leaves images. Thresholding and binarization are used to segment and locate leaf parts from the back-ground. Diseased regions were obtained by masking the green pixels. In masking operation, first of all, green pixels were identified. Then a threshold value (which corresponds to minimum intraclass variance) was computed by applying the global thresholding method. The intensity of the pixel was cleared if the green part of the pixel is less than the calculated threshold. Further, the pixels with zero intensity are eliminated. The feature extraction procedure was applied to infected regions. Authors have used the "color co-occurrence method (CCM)" to extract the necessary attributes from leaves to classify the diseases. Texture and color features were used in the features extraction process. These "extracted features" were fed into ANN to automatically detect and classify the diseases. They have claimed that their suggested method performed well.

In 2011, Image processing methods are used by Kai et al. (2011) to study illnesses diagnosis and classification for maize plants. They have acquired leaves images of maze plants to conduct the experiments. To locate the infected lesions, "RGB" images of maze leaf were transformed into "YCbCr color format". YCbCr color space approach was used to segment infected spots from leaf images. Further, the "Co-occurrence matrix" method was applied on the infected spot to get texture features of diseased regions. A backpropagation neural network architecture was applied on extracted features to identify maze diseases. VC++ platform was utilized to conduct the experiments. Result analysis indicated that the proposed system effectively recognizes the leaf diseases. Suggested model was found 98 percent accurate.

Further, Kulkarni et al. (2012) introduced a "plant disease detection" technique by applying image processing on plant leaf images. Diseased leaves of pomegranate plants were acquired for the study. They have included 3 diseases (Bacterial blight, alterneria, and Anthractnose) in this research. 89 instances of Anthractnose , 26 instances of Bacterial blight, and 8 instances of alterneria were used as input dataset to conduct the experiments. Gabor filter was utilized to discover relevantclassification features from leaf images. These extracted attributes were used by ANN classifier for automatic disease classification. ANN with 50 hidden neurons has

given optimum results. Authors have implemented the experiments at different termination error and found that termination error of 0.00001 gave best recognition rate. Total 4500 iterations were applied during training and testing of the classifier. Gradient was set on 0.02. During validation of ANN at optimum setup, recognition rate of alterneria was recorded as 81.5%, whereas recognition rates of Bacterial blight and Anthractnose were recorded as 94% and 97.5% respectively. Thus, an overall recognition rate of 91% was achieved in the result analysis.

Wang et al. (2012) demonstrated plant disease recognition system using the dataset from 2 crops, wheat, and grape. A total of 185 digital photos were evaluated, with 85 leaf samples of grape and 100 leaf samples of wheat. The photos are downsized using the NearestNeighbour interpolation approach without affecting the image resolution.

To remove noises from the photos, the median-filter was used. For segmentation, the K-means algorithm was utilized. The RGB picture was transformed to CIE XYZ color format before performing the segmentation. Further, the XYZ color format was transformed to Lab format. Features such as "texture, shape, and color" were retrieved. The dimensionality of the feature was minimized by using principal component analysis (PCA). Reduced features set requires a smaller number of neurons in the NN and hence speed up the training and validation of the suggested model. BPNN was used as a classifier to classify the diseases.

Jaware et al. (2012) proposed an accurate and fast approach for plant disease detection and categorization. Cottony mould, early scorch, ashen mould,small whitening, and late scorch are the 5 principal plant diseases that the suggested strategy is evaluated on. The RGB picture was first captured after which the acquired RGB image was transformed by establishing a transformation structure. Following that, RGB color values were changed to the space defined in the color transformation structure.

The segmentation process is then carried out utilizing the Kmeans clustering approach. The primarily green pixels are then covered. Furthermore, the diseased cluster was identified by eliminating the green color. The infected cluster was then transformed from RGB to HSI color structure. The SGDM matrices were then constructed for each pixel map of the picture for just HSI images in the next stage. At the final stage, a pre-trained ANN was used to recognize the retrieved feature. The findings demonstrate that the suggested system can accurately identify and categorize illnesses with an accuracy of 83 percent to 94 percent.

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Owomugisha et al. (2014) introduced an automatic diseases detection method for the banana plants. They have worked on Black Sigatoka and Bacterial Wilt Diseases in their study. Authors claimed that ML has been used in farming in a variety of fields, notably plant disease diagnosis and the development of image processing systems for particular crops. The examples of such crops are Cassava, potatoes, tomatoes, wheat, sugar cane, vegetables, grapes, pomegranate and Cotton. Further they added that no ML approaches were used to try to identify infections in banana crop such as banana black sigatoka (BBS) and banana bacterial wilt (BBW), due to which farmers lost a lot of money. This research examined varieties of computer vision approaches, and developed a system consisting of 4 major parts to identify banana diseases. In first part, Photos of banana leaves were taken using digitalcamera. In second part, multiple feature extraction approaches were utilised to acquireimportant data that will be utilized in part three. Part three was implemented to perform the classification. Performance assessment was done in last fourth part.

Authors have retrieved color histograms and converted them from RGB to HSV andfrom RGB to L*a*b format. Max tree was created using peak components. The area under the curve and five attributes related to shape were used to classify the diseases. Input image samples have experimented with several classifiers namely support vector machine, Naïve Bayes, extremely randomized Tree, random forest, Decision tree, and nearest neighbours. Extremely randomized trees offer high accuracy among others. Extremely Randomized Trees have given best result with an area under the curve (AUC) of 0.91 for BBS and 0.96 for BBW among the 7 experimented classifiers. To judge the effectiveness of experimented classification models AUCwas used.

Khirade and Patil (2015) presented a study that looked at several machinelearning and image processing strategies for detecting plant illnesses through leaf photos. The authors have presented 5 steps solution for plant disease detection and classification. They have not illustrated any experiment in their study but only discussed the possible methods used for the detection of plant leaf diseases. First of all, they suggested a color conversion structure, then discussed a colour space conversion that was device-independent. In the second step, Contrast enhancement, picture smoothing, histogram equalization, and clipping pre-processing techniques were discussed to get better visual characteristics for input images. Further, In the third step, they have discussed K-means segmentation, lesion recognition, boundary identification, and Otsu's thresholding segmentation techniques in their study. These segmentation techniques were presented to get infected regions in the input images. Inthe fourth step, they have presented various features extraction techniques in their study. Color, edges, morphology, and texture are among the key discriminating parameters that were highlighted in the paper. The color co-occurrence Method was discussed for achieving unique features related to color and texture from the images. SGDM was suggested to perform the statistical calculations on texture to extract texture features by applying Gray Level Co-occurrence Matrix (GLCM). In the final step, the disease detection and classification approach with ANN was described.

In 2015, Rastogi et al. (2015) presented fuzzy logic and computer vision-based disease recognition and grading techniques. Using DIP and ML techniques, this research presents a simple and efficient technique for identifying and categorizing leafillness. The suggested method consisted of 2 phases. The first phase involves pre- processing of leaves pictures and extraction of features, succeeded by ANN classification model to recognize the leaf. The illness existing in the leaves was classified in the 2nd phase, which involves the “K-Means” technique to segment the infected regions followed by features extraction and then disease classification. GLCM was utilized to retrieve texture information. Disease classification was done using ANN. The illness is then graded based on the intensity of disease found in the sample. Fuzzy logic was applied to grade the illness.

In 2015, Sannakki and Rajpurohit (2015) [46] suggested a disease classificationmodel for the Pomegranate plant. They devised a strategy that was mainly based on the segmentation scheme. Pomegranate leaves were used to provide learning to the developed model. A digital camera was used to capture pictures of normal and diseased leaves samples. To find contaminated parts, the visual appearance of image was improved and segmented. The proposed method applied segmentation technique to locate the defective region and then discovered the texture and color properties of infected lesions. These extracted properties were used as classification features. The categorization was done with the help of an ANN classifier. The classification accuracy was determined to be 97.30%. The biggest drawback is that it can only be utilized for a small number of harvests.

Rothe and Kshirsagar (2015) presented a pattern recognition approach for the diagnosis of infections found in the leaves of the cotton plants. Cotton plant leaf diseases must be recognised early and correctly, since they might have a negative impact on the production. Alternaria, Myrothecium, and Bacterial Blight diseases have been recognized and categorized using a PR system in the suggested study. Images for this study were taken directly from the crop

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fields located at 3 different regions. First site was chosen as crop field of cotton plant located at Nagpur (Central Institute of Cotton Research). Second and third sites were chosen as crop fields of Wardha and Buldana districts, respectively. They have used snake segmentation to separate infected sections and then used Hu's moments as a distinguishing feature. The "active contour model" was utilized to restrict the vitality within the diseased lesion, and the Backpropagation neural network architecture was used to solve a variety of classification issues. The average accuracy of 85.52 percent was achieved by the suggested model.

Further, Ghaiwat et al. (2014) have presented a study of the many classification approaches that may be utilized to classify plant leaf diseases. This work gives an idea of the advantages and disadvantages of several strategies that may be utilized to recognize and classify leaf diseases. A classification strategy involves categorizing each pattern into one of distinct categories. Classification is a method of classifying leaves based on their shape, color, and texture characteristics. ANN and Fuzzy logic, PCA, SVM, Genetic Algorithm (GA), Probabilistic Neural Network (PNN), and k- Nearest Neighbour classifiers were a few well-known examples among available classification algorithms which were discussed in the study. They have realized that choosing a classification technique was really challenging work since the effectiveness of the performance varied depending on the nature of the input samples. For the provided validation cases, the k-NN approach appeared to be the most appropriate and straightforward in all given methods. Further, the author has added limitations of SVM. They have observed that it was challenging to find appropriate parameters in SVM if the data used for model training was not linearly separable, that seems to be its shortcoming.

In 2015, Mokhtar et al. (2015) applied SVM to recognize 2 types of viruses found in tomato leaves. They employed an SVM classifier with varying kernels to the segmented sick parts and used several color and shape-based characteristics. "Tomato yellow leaf curl virus (TYLCV)" is among the most dangerous viruses, causing TYLCV disease around the globe. It leads to yellowing and upward curling of tomato leaves. This study outlines a method for detecting and identifying diseased leaves infected with 2 viruses named "Tomato spotted wilt virus (TSWV) and Tomato yellow leaf curl virus (TYLCV)". "Pre-processing, picture segmentation, feature extraction, and classification are the four primary aspects of the suggested technique". Segmentation was applied to each leaf picture, and a description for every segment is generated. To choose the best features, several geometric metrics were used. For disease categorization, an SVM method with various kernel functions was utilized. 200 contaminated leaves pictures with TYLCV and TSWV were utilized to train and validate the proposed model. The results of the provided strategy are evaluated using the N-fold cross-validation technique. According to the findings of the experiments, the suggested classification strategy had an average accuracy of 90% and a quadratic kernel function accuracy of 92 percent.

Further, Vishnu et al. (2015) examined and discussed the image processing strategies for identifying diseases in plants. They have reviewed various "pre- processing, image segmentation, and feature extraction techniques". Segmentation based on different aspects was discussed in this research paper. They have talked about "model-based segmentation like Markov Random Field (MRF) based segmentation, threshold-based segmentation, edge-based segmentation, region-based segmentation, and clustering-based segmentation". For features extraction, authors have discussed PCA, Gabor filters, Wavelet transform, GLCM, and SGDM techniques. The authors said that BPNN, SGDM, Kmeans algorithm, and SVM are the most familiar methods for detecting the infection in plant leaves. These methods can be utilized to examine the leaves of both normal and sick plants. Further, they discussed the 3 challenges coming during the implementation of these techniques. These challenges are automation of the suggested approach for uninterrupted persistent surveillance of crop diseases under actual field settings, optimization of the approach for particular plant diseases, and the influence of background information in the generated picture samples. According to the review, "these approaches have a lot of potential including the capacity to identify leaf illnesses and certain drawbacks". As a result, there is room for enhancement in the present approaches.

After presenting the review, the authors have proposed a disease recognition and classification method. First, they converted RGB images into HSV image format. Then K-means algorithm was utilized to segment leaves before calculating texture characteristics for the separated diseased items. Finally, a neural network classifier was used to process the extracted features.

Using photos of damaged and normal leaves, Prajapati et al. (2017) developed an SVM-based diagnosis system to diagnose illnesses in rice plants. They employed DIP algorithms on input samples to obtain a high-quality picture and then used ML to create a disease prediction model based on pre-processed samples. The background of the sample pictures was removed during pre-processing. To find the sick region of the leaves, they employed the K means clustering technique. "The size, color, and texture information" of damaged parts of the leaf were utilized as indicators of illness. The suggested approach has a training

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sample accuracy of 93.33 percent and a test sample accuracy of 73.33 percent.

Using rice leaf digital photographs, Jayanti et al. (2019) built a prediction system to diagnose rice leaves illness. DIP techniques were used to remove noises from the image samples and to locate the infected regions in leaf images. To remove noises from the input image samples, a median filter has been used. These pre- processing operations helped to achieve high-quality photographs of rice leaves. The fuzzy C-mean clustering approach was used to find the borders of sick sections. Speeded-up robust features (SURF) and texturing approaches were used to retrieve important features from infected regions of input samples.

To diagnose illnesses, these collected features were fed into an ANN model to recognize and categorize the diseases. They claimed to obtain a good outcome but did not specify the method's exact accuracy.

Crop disease identification algorithms depend on capturing several types of information from infected plant leaves photos. Leaf infections are key factors because it significantly reduces the amount and quality of farming products. As a result, diagnosing and comprehending illnesses are essential. In conclusion we can say that presented reviews generally suggest two steps to recognising diseases based on leaf images: First collecting morphological, texture, and color attributes from infected regions (ii) applying ML algorithms to categorise unhealthy leaf samples. Similar approach was also utilised by Nandhini et al. (2020) . Based on the collected attributes, this study examined the efficiency of categorization of diseases using decision Trees, SVM, and KNN.

.2.1.4 Related to Deep Learning Approaches for Plant Disease Recognition and Classification with Transfer Learning

Agriculture is a common domain that is susceptible to viral, bacterial and fungus illness.

To increase agricultural productivity, crop diseases must be detected accurately and early. The Deep learning is useful in detecting crop diseases utilising a large quantity of plant leaf photos. Convolution Neural Network (CNN) is among the most widely used architectures in deep learning. But, utilising deep learning approaches to recognise illness with limited and small databases is a difficult task. One of the most prominent deep learning algorithms for correctly detecting the plant illnesses with small dataset is transfer learning. Deep convolution neural network model based on transfer learning is proposed by the researchers for disease identification in various crops.

In this subsection, we have presented literature review of various research papers that focus their study on transfer learning.

Zhang et al. (2018) used deep learning techniques to provide maize disease detection system. They felt that the automated detection and characterization of diseases found in maize leaves are widely wanted in the domain of agriculture. Therefore, the revised Cifar10 and GoogLeNet deep learning architectures were suggested for maize leaf disease recognition in this study to increase detection performance and minimize the number of model parameters. Modifying the pooling choices, incorporating ReLu layers and dropout processes, tuning the network parameters, and lowering the number of classifiers result in two better models that were utilized to train and evaluate 9 different types of maize leaf pictures. Furthermore, the enhanced architectures have a substantially lower number of parameters than the AlexNet and VGG architectures. The GoogLeNet architecture has an average accuracy rate of 98.9% when recognizing 8 types of diseases in maize plants, whereas the Cifar10 architecture obtained 98.8% average accuracy.

Transfer learning strategy is not only being used in leaf disease recognition, but also being used by different researchers in recognition of plant types.

One such experiment was conducted by Ghazi et al. (2017) to detect the species of plants.In their work, Ghazi et al. employ deep CNN models to recognize the plants types for given leaf picture. They have investigated different network parameters and assessed the effects of various parameters on the results of these models. This task of plant recognition was accomplished using 3 successful and well-known CNN variants: VGGNet, AlexNet,, and GoogLeNet. LifeCLEF 2015 plant task databases were utilised to apply transfer learning on these pre-trained networks. Problem of overfitting was minimised by applying data augmentation. To boost overall accuracy, the hyperparameters of networks were modified and CNNs are fused. Suggested system achieved validation accuracy of 80%.

InceptionResNetV2 is a form of CNN architecture that was used with a transfer learning strategy to recognize leaf diseases by Krishnamoorthy et al. (2021). The parameters of suggested model were tuned in such a good manner that they achieved a high accuracy of 95.67 percent. This study takes into account 4 classes of leaf samples: healthy class as well as 3 diseased classes (bacterial blight, leaf blast, brown spot). The authors have implemented 2 experiments to show the effectiveness of transfer learning. One experiment was conducted with simple CNN and the other with InceptionResNetV2. By performing fifteen epochs, multiple network parameters were tested on basic CNN and reached an accuracy of 84.75 percent. On the other hand, by applying ten epochs with transfer learning InceptionResNetV2 was able to achieve an optimal accuracy

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of 95.67 percent.

Chen et al. (2020) investigated Deep CNN architectures with a transfer learning approach for the detection of leaf diseases. Already trained CNN models were used to initialize the weight and biases of a suggested network. In this study, VGGNet pre- trained model was used with the inception module. These pre-trained networks were trained on huge data set namely ImageNet. On the public repository, the suggested technique obtains a test accuracy of at least 91.83 percent, which is a significant enhancement over previous state-of-the-art approaches. The suggested technique achieves an average classification accuracy of 92.00 percent even with a noisy background. Experiments show that the suggested technique is viable and that it may be used to identify plant diseases quickly.

Tomato is a common food item that is susceptible to illness. The introduction of ML and deep learning (DL) approaches have made it simpler to identify agricultural diseases. Sangeetha et al. (2020) introduced a transfer learning strategy using 2 deep learning architecture namely VGG19 and VGG16. DL has become a strong technology for data analytics and image processing in recent times, with promising outcomes. DL has been used in a wide range of fields, notably farming. Convolution Neural Network (CNN) is among the most widely used architectures in deep learning. Transfer learning is a novel method in deep learning that uses pre-trained architecture to train a fresh database to speed up the learning process. The goal of this study is to create a Transfer Learning-driven classification model for detecting leaf illness. A novel composite and detailed prediction system for tomato disease assessment is established in this research. Proposed classification system was created by combining 2 DL models, namely VGG19 and VGG16. Accuracy, F1-score, recall, and Precision, were used to analyse the performance. The higher accuracy of Transfer Learning demonstrated in this published study supports its use in the disease classification and recognition.

In order to assist the farmers and crop owners for increasing the agricultural productivity, Thangaraj et al. (2021) introduced a DCNN model based on TL for disease identification in tomato crops. The system detects disease by combining stored photos and real-time acquired pictures of the leaves of tomato plants. They have used 3 different kinds of optimizers one by one to check the performance of the proposed model. "RMSprop optimizers, stochastic gradient descent (SGD), and Adaptive moment estimation (Adam)", are used to assess the results of the suggested model. This exercise was done to get the best possible results and to analyse the effect of several optimizers on the suggested network. The validation results show that the suggested system, which employs a transfer learning technique, is accurate in classifying tomato diseases automatically. When contrasted to RMSprop and SGD optimizers, the Adam provides higher accuracy.

Further, Hasan et al. (2019) felt that the farming industry in India is affected by challenges such as poor crop productivity, widespread usage of pesticides and fertilisers, outdated production practises. Using a CNN, Hasan et al. created a precision farming system based on drone to successfully detect high infectious region in a crop field. With the use of drones, they have planned to apply targeted insecticides on the infected region. Authors have collected 2100 samples from online sources and combined it with 500 samples captured from the crop fields. To develop the detection system, Google's inception model was retrained using transfer learning strategy. To decide the proper insecticide dosage, leaves are divided into three classes: bad, nominal, good. When the proportion of training dataset is raised to 85 percent, 99 percent accuracy is obtained.

Similar kind of approach was utilized by Abas et al. (2018) to classify plant varieties. The possibility of using VGG16 deep architecture for plant categorization is discussed in this research. Due to similar characteristics of colour and shape of leaf of many plants, flower photos were utilised as input sample in place of leaves. Earlier studies have shown that employing data augmentation, dropout and transfer learning minimise the overfitting issue of deep network when used to a small set of samples. With 2800 flower photos, authors were able to effectively develop and train the VGG16 model. The model had a validation accuracy of 93.93%.

In Thailand, Mathulaprangsan et al. (2020) attempted to solve the challenge of manual rice disease recognition. Authors suggested a two-phase rice disease identification paradigm. They began the research by capturing photos of rice plants in order to create the dataset. Then DenseNets and ResNets pre-trained deep learning (DL) architectures were used to categorize the rice illnesses in the second phase. On the collected datasets, some alternative DL architectures were also tested to compare the outcomes of the suggested strategy. The suggested model attained an average accuracy of 95% in experiments, according to the results. The authors say that their technique will be simple to adopt in the future and will be capable of helping Thai farmers.

To diagnose 4 kinds of rice diseases, Islam et al. (2021) introduced a CNN-based automated disease recognition technique. Leaf smut, leaf blight, leaf blast and brown spot diseases were included in this study. To provide the learning to the CNN models, they have utilized healthy leaf photos as well as these unhealthy leaf images. The authors

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tested 4 types of CNN models: ResNet-101, Xception, VGG-19, and Inception-Resnet-V2. They discovered that Inception-ResNet-V2 outperformed the others. Inception-ResNet-V2 obtained an accuracy of 92.68 percent.

Jadhav et al. (2020) introduced a pathogen recognition method for the soybean plants using a TL methodology. To create illness detection models, they utilised 2 deep CNN architectures (AlexNet and GoogleNet). They have created 2 detection models. The GoogleNet architecture was used in one model, while the AlexNet architecture was used in the other. The suggested system was developed using photos of soybean leaves that were obtained from dataset. The training set included 649 photos of sick leaves and 550 images of healthy leaves. The suggested system was put to the test on 80 very new leaf photos. In result analysis, GoogleNet-based model has given 96.25 percent accuracy while accuracy of AlexNet-based model was observed as 98.75%.

Further, Ghosal et al. (2020) used a TL approach to develop a deep CNN model for rice illness identification. authors They have produced a little dataset of their own. The introduced CNN model was built utilising a VGG-16 architecture pre-trained-on massive dataset. Learned information was transferred to train and verify the proposed model using a field dataset that was created by the authors. Their recommended model has a 92.46 percent accuracy rate.

Deng et al. (2021) suggested an ensemble learning strategy based on DL architectures for automated identification of 6 kinds of rice illnesses. Authors have conducted experiments with ensemble learning using several deep learning models. To verify the model, a large database of 33,026 photos was utilized. False smut, leaf blast, neck blast, bacterial stripe disease, sheath blight, and brown spot diseases were tested in this study. Ensemble learning using the ResNeSt50, DenseNet-121, and SE- ResNet-50 deep CNN models outperformed other methods in result analysis. The proposed strategy has 91 percent accuracy.

4. Conclusion

Various relevant studies related to plant disease diagnosis and classification is selected for literature review of this research. These studies have been published in various reputed journals and conferences. The main purpose of literature review is to recognize unexplored areas that could be further explored. The conclusion and future scope section of all reviewed research papers are carefully studied to identify the research gaps. We have identified following research gaps during the literature review:

1. In all the reviewed methods, very few methods have given 99% or more accuracy.
2. Since maximum of the benchmarked plant disease dataset consists of image samples labelled with disease name only, but not contains image samples labelled with disease intensity or severity. To overcome this issue, an infection severity estimation method can be developed to derive new dataset labelled with disease intensity from existing plant disease dataset.
3. Even with small datasets and complex background images, better accuracy can be achieved.

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