Multi-Plant and Multi-Crop Leaf Disease Detection and Classification using Deep Neural Networks, Machine Learning, Image Processing with Precision Agriculture- A Review

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Abstract- **Globally, more than 19,000 fungi are reported to infect agricultural crops with diseases. As the supplier of human energy, crops are seen as being significant. Plant diseases can harm leaves at any point during planting and harvest, greatly reducing crop productivity and the general market's financial worth. Consequently, the early diagnosis of leaf disease is crucial in farmlands. Agriculture profitability is a key factor in economic growth. This is among the causes why plant disease identification is crucial in the farming sector, as the presence of illness in plants is extremely common. If necessary precautions aren't followed in these regions, plants suffer major consequences, which impact the grade, volume, or production of the corresponding products. For example, the United States has pine trees that are susceptible to a dangerous illness called small-leaf disease and the backbone of the Indian economy is crop plants. It is advantageous to diagnose plant diseases (Black Spot, other leaf spots, powdery mildew, downy mildew, blight, and canker) using an automated method since it lessens the amount of manpower required to maintain megafarms of crops and does so at an incredibly preliminary phase(when they appear on plant leaves). The computerized identification and classification of plant leaf diseases using an imagery segmented system is presented in this work. It also includes an overview of various disease categorization methods that can be applied to the identification of plant leaf diseases. In order to detect disorders in diverse plant leaves, this study provides a review of diverse plant diseases and several classifying algorithms in deep machine learning.**

Keywords- Plant disease, Leaf disease, Plant leaf disease detection, Plant leaf disease classification, Deep Convolutional Neural Network (CNN), Deep machine learning (DML)

I. INTRODUCTION

According to FAO estimations, insects destroy 20 to 40% of the world's food yield each year. Plant diseases expense the world economically over $290 billion annually, and invading parasites cause economic losses of about US$70 billion[13]. At such a stage when the nation has to increase agricultural output as well as assure food supply and nutritional for its expanding current consuming, an approximate 15 to 25% of India's possible crop productivity is destroyed to pests, weeds, and diseases[14]. India is a nation that is expanding rapidly, and agribusiness has historically been the foundation of that prosperity. In India, agriculture is one of the main drivers of socioeconomic progress. The fertile soil, local climate, and crop's commercial benefit are taken into consideration when the farm worker chooses a crop. The farming industry started looking for innovative ways to boost grain productivity as a consequence of growing populace, changing climatic patterns, and geopolitical unpredictability. Unfortunately, the agriculture sector experiences many issues, one of which is the significant decrease in crop yield. Plant leaf infections are among the major causes of output decline, and within the domain of farming, identifying plant leaf disorders is also highly challenging. The human eye approach is outdated, imprecise, time-consuming, and unsuitable for significantly larger farmfields of diagnosing infections. Additionally, it costs a lot because professionals must continuously check it. As a result, deep machine learning, a trustworthy forecasting approach, is utilised to identify numerous infections of plant leaf brought on by bacteria, viruses, and fungi. Yet, as the efficacy fluctuates depending on the raw data, symptom forecasting employing classification techniques seems to be a challenging endeavour.

This makes it possible for investigators to explore novel, highly productive ideas. Farm owners are able to gather knowledge and statistics to determine the best decisions for good agricultural output with the usage of precision farming in information technology. Technological advancement known as precision agriculture (PA) provides advanced methods for increasing farm productivity. Farming can experience socioeconomic prosperity by utilizing these cutting-edge techniques. PA has a wide range of uses, including disease monitoring, weed recognition, crop output enhancement, and insect pests classification. A landowner uses insecticides to reduce bugs, prevent infections, and boost crop production. Because of commercial farming, low yield, financial damage, and plant disease, planters are having issues. As a result, the requirement to describe pathogenicity as necessary is emphasized[1]. Figure 2 shows the sample leaf diseases collected(apple, cherry, corn, grape, potato, peach, orange, strawberry, tomato etc.) from kaggle repository[33].

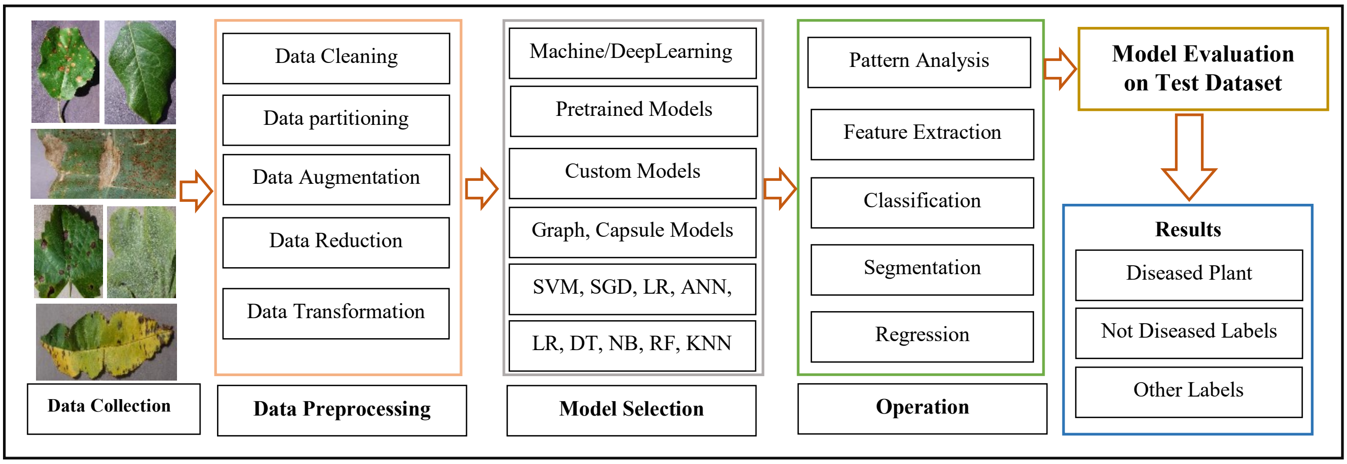


Figure 1. Overall Flowchart of Deep Machine Learning based Plant Leaf Disease Classification

Indian citizens and the country's GDP both heavily rely on agribusiness. Common manifestations include atypical leaf development, blurriness, advancement delays, withering plants, and damaged subunits. Although illnesses and pests can seriously harm crops or spread disease to crops, they can also have a genuinely negative impact on human health. To protect the returns against significant degradation, these call for careful examination and proper handling [2]. Diseases in crops can be detected in a variety of locations, including leaves, stems, and natural remedies. In comparison to flowers and other natural remedies, leaves offer several interesting aspects throughout the year[3], [4], [5]. This work reviews and compares a number of research achievements that contribute to the identification of numerous plant leaf diseases using multiple categorization techniques. The contribution is as follows:

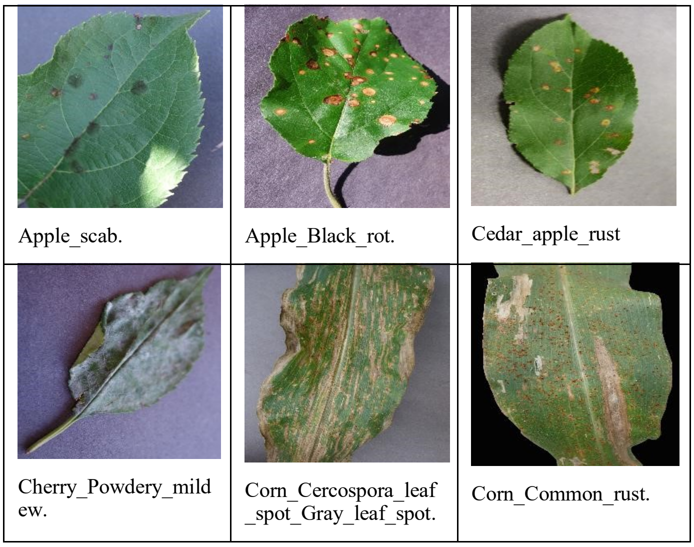
- A state-of-the-art overview of recent work on the classification of plant leaf diseases using DML that highlights numerous benefits, difficulties, and areas for future research.
- The advancement of methods to control serious agricultural diseases while also protecting the ecosystem.
- Farmers will profit from DML approaches for plant leaf disease identification as crop productivity declines.

The following is a summary of the upcoming sections. The taxonomy used to prepare this work is described in Section 2 of the article. According to various Deep Machine Learning and image processing approaches, Section 3 describes the classification of leaf diseases. Finally, sections 4 and 5 respectively provide the discussion and conclusion.

II. REVIEW TAXONOMY

The detection of leaf diseases utilizing imagery methods and DML approaches is the focus of this review of the literature. By obtaining understanding and expertise through straightforward approximations, ML and DL techniques are able to handle complex issues. The capacity to create accurate renderings is the crucial component that has led to the extensive use of neural network and ML techniques. As a consequence, a layered sequencing of CNN employs a number of layers and maximizes the advantages of learning in-depth information for the best simulation results [27]. Machine learning classifier requires the utilization of features, which is a challenging procedure that has a significant impact on classifier. In fields including medicine, agriculture, and computer vision, DL techniques are often used to classify images [28]. Moreover, DML is being used in medical imaging disease classification [25] [26] [27] [28]. Figure 4 shows the taxonomies employed within the chosen platforms under study are divided between ML-based evaluation, DL-architectures, and image-processing mechanisms. Figure 1 depicts the general flowchart of plant leaf disease classifications, and Figure 3 illustrates the corresponding disease subtypes.

In order to retrieve the studies, a list of eligibility parameters was established, and searching behaviors on Elsevier, IEEEXplore, ScienceDirect, SpringerLink, ArXiv, Google Scholar, or other journals up until December 2022 were examined. For the preparation of this review article, the most common phrases, such as "Plant leaf disease," "Detection and or classification," and "Deep and or Machine learning," were employed.



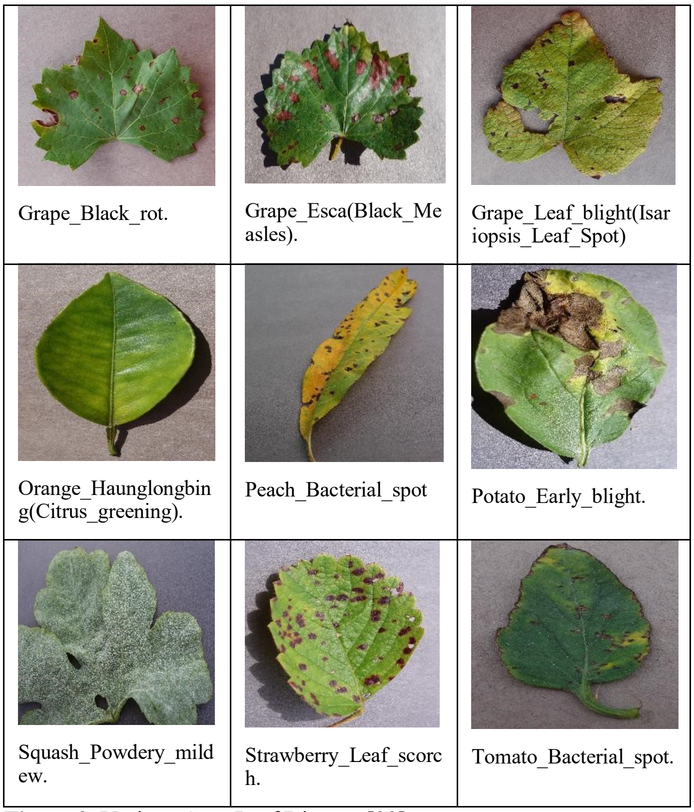


Figure 2. Various Crop Leaf Diseases[33]

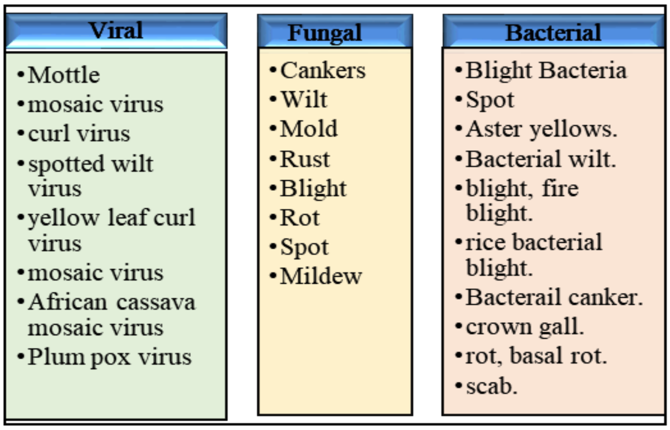


Figure 3. Classification of Plant Leaf Diseases with its types.

III. RELATED WORK

This section describes the taxonomies created for plant leaf disease classification based on DL, ML and image processing techniques.

A. Deep Learning-based approaches for Plant Leaf Disease classification

DL-based plant leaf disorder screening utilizing an EfficientNet version was reported by Atila et al. [15]. To empower the classifiers, the PlantVillage database was utilised. The initial and enlarged collections, which contained 55,448 and 61,486 photos, respectively, were utilized to train all of the classifiers. 38 subclasses of 14 distinct varieties of crops overall are included in the database, 12 of which are healthy and 26 of which are afflicted. All of the network stages in the EfficientNet are made to be trainable. The test database findings revealed that EfficientNet architecture's B5 and B4 networks had the greatest accuracy and precision scores of 99.91% and 99.97%, respectively, when comparing to all deep learning algorithms in the initial and supplemented datasets.

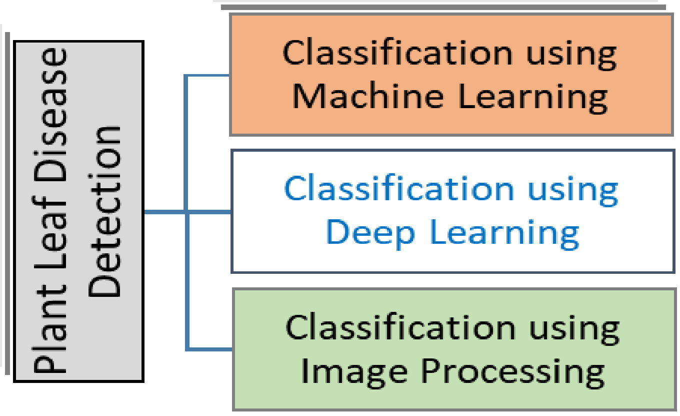


Figure 4. Plant Leaf Disease Classification Taxonomy.

DTL-based AlexNet framework by Singh et al. [16] for quick and precise diagnosis of leaf disease in maize plants. Two types of maize infections are contained within this PlantVillage data source: typical rust-based illnesses and leaf-spot (Cercospora and Gray). Pictures of maize are enlarged evenly in a 224x224x3(224:height, 224:width, and 3:colour channels). Additionally, maize photos are subjected to data augmenting processes such as rotation, zooming in and out, fading, ambient noises, luminance, and blackness. 1363 photographs are in the first group, while 929 photos are in the second. The ability of CNN to dynamically extract the characteristics by using the raw pictures directly is one of its greatest benefits. Using different trials (25-100), AlexNet was able to achieve a 99.16% accuracy.

For the classification and segmentation of diseased leaves, Vallabhajosyula et al. [17] presented a deep ensemble neural network (ResNet50/101, InceptionV3, DenseNet121/201, MobileNetV3, NasNet). The effectiveness of the suggested strategy is assessed using the 54,305 photos from 38 subclasses that make up the plant village dataset. 80 percent of these photographs, or 43,456, are utilised to develop models, while the other 10,849 images are utilized to assess how well the suggested strategy is working. The recommended ensembles (MobileNet+Densenet121+DenseNet201) achieved 100% accuracy for classifying plant leaf diseases. InceptionResNetV2-based disease categorization was suggested by Kaur et al[18]. This platform's typical input size is 224x224x3. 9600 tomato leaf samples were gathered from the underlying data and Plantvillage repository, while 9025 samples with 256x256x3 dimensions were from PlantDocdataset. Additionally, 575 pictures from a ground-truth collection with 256x256x3 dimensions are included in this study. These samples cover a variety of leaf diseases, including leaf mould, yellow leaf curl virus, late blight, septoria leaf spot, target spot, spider mites, mosaic virus, and healthy leafs samples. From each type of dataset, there are 840 and 360 images in the validation and testing sets(i.e. 70:30 ratio), respectively. The suggested MIR-V2 network yielded exceptional efficiency and F1score of 98.92% and 97.94%, respectively.

The CNN model was suggested by Gajjar et al. [19] for the categorization of 20-leaf diseases. They took 338 samples from their university's campus and 21,978 samples total from the PlantVillage collection of apples, maize, potatoes, and tomatoes. The train, validate, and test sets were each given an allocation of 80%, 10%, and 10% of the classification dataset, respectively. They first train the entire model on a standard computer before subsequently deploying features on the Nvidia Jetson TX1. The proposed CNN model achieved 96.88% accuracy, 95.34% F1-score, 94.91% recall, and 93.78% precision.

B. Machine Learning-based approaches for Plant Leaf Disease classification.

The k-nearest neighbor (KNN) method was developed by Geeta et al. [20] to diagnose tomato leaf disease. A total of 200 leaf images—50 each for healthy, early blight, bacterial spot, and YLCV—make up the gathered dataset. They used data preparation methods including noise filtering, image resizing, and flattening. The authors used HOG and GLCM to produce compact features during the extraction phase. The difference among the querying instance and the provided present instance from the given dataset for classifications is determined using the KNN. Full-featured applications with an Android-based web server communication mechanism are used for categorizing tomato leaf diseases. IoT-FBFN framework for automatic disease diagnosis from plant leaves by Chouhan et al. [21]. The effectiveness of using k-means and SVM is demonstrated by the extracted features using SIFT and the obtained result with specificity(0.7088, 0.7292) and sensitivity(0.7137, 0.7353). Time test were taken for leaf samples of 21.95s and 19.10s for SVM and k-means.

Sujatha et al. [22] conducted a study comparing the effectiveness of DL and ML in classifying leaf diseases in plants. The dataset for citrus leaf disease was used to do the DML-based classification. The snapshots were personally taken by the authors using a DSLR and have a 7-DPI resolution and 256x256 pixel size. There are 609 total samples, with black spot(171), canker(163), greening(204), melanose(13), and healthy(58) labels. In terms of citrus plant disease identification, the ML-based (SVM, RF, SGD) and DL-based (InceptionV3, VGG16, VGG19) approaches are both effective. The disease recognition rate (CA) we achieved through testing is pretty good, with DL approaches outperforming ML methods in the following disease recognition tasks: RF (76.8%), SGD (86.5%), SVM (87%), VGG19 (87.4%), InceptionV3 (89%), and VGG16 (89.5%). From the result, RF is attained the lowest accuracy whereas VGG16 attained best results.

ML-based Plant Leaf Disease screening was suggested by Tulshan et al. [23]. The personally gathered dataset includes hardly 150 leaf samples with the labels Early Blight, Mosaic Virus, Down Mildew, White Fly, and Leaf Miner. The grey-level co-occurrence matrices (GLCM) approach was used for extracting features. Since the GLCM technique solely accepts 13 elements at a stage, only 13 elements were employed throughout the whole experiment. Steps including picture pre-processing, image segmentation, and feature extraction were part of this procedure. On the results of these three phases, KNN and SVM classifiers are further used. SVM and KNN have demonstrated 98.56% and 97.6% accuracy in forecasting plant leaf disorders, respectively, in the proposed implementation. Matlab was used to carry out the simulation.

C. Image Processing based approaches for Plant Leaf Disease classification

Fuzzy Based Functional Networks were developed by Chouhan et al.[21] for IoT-based leafy disease categorization. 35 plants were identified in the Pauropsylla tuberculategalls database on the Alstonia Scholaris, of which 27 had the infection and 8 did not. The SIFT technique was employed to capture the image's features, and the firefly technique then optimizes the retraining of the databases employing those features. Then the FBFN is used to do the illness categorization and detection. For the job of identifying the infuriates, the suggested technique achieved mean specificity of 0.8066 and sensitivity of 0.8018. For the task of classifying the galls, mean Vpc and Vpe were assessed to be 0.7452 and 0.2617, respectively. The performance is assessed using the Validation Evaluation Partition Coefficient(Vpc) and Entropy(Vpe). To test separate leaf, 17.35s was taken by the suggested methodology. Gavhale et al.[24] studied on the identification and categorization of leafs disease. All of the samples underwent 512x512 preprocessing, colour separation and clustering, and SVM classifications to complete the operation. An analysis of the DSS approach for classifying leaf diseases was given out by Dhaware et al. [29]. Segmentation techniques including region, edge, and threshold-based techniques are used for image preprocessing to convert RGB to grayscale HSV. Gabor filters, wavelet transforms, and PCA can all be employed for feature mining. Finally, KNN, RBF, ANN, SVM, BPNN, and CNN may be utilized to classify diseases.

Jumb et al. [30] addressed segmented victimization approaches. K-means clustering and Otsu's thresholding. The 5 component is utilized for multi-thresholding since the primary picture area units regenerated to HSV colour scheme. The proposed analysis contrasts this segmentation method with others, including fuzzy C-means, region growth, and others. Peak signal-to-noise ratio(PSNR) and mean square error(MSE) are the two measures used to evaluate these approaches. The diagnosis of damaged grape plant leaves using image processing was proposed by Kamlapurkar [31]. Author gathered Powdery Mildew and Downey Mildew labels for grape plants from a private dataset in the Nashik region. Major axes, minor axes, and other leaf characteristics are taken from the leaf and provided to the classifiers for categorization in order to identify infection. Lastly, ANN was implanted for leaf disease classification.

In another study contains a different leaf disease categorization analysis of infected leaves carried by Jagtap et al.[32]. Anthracnose, Black Spot, and Red Leaf Blight are listed on the disorder label. The length and ratio of the primary axes, the center of gravity, the orientation, the equivalent diameter, the eccentricity, the solidity, the extent, the hydraulic radius, the complexity, and the Euler number are used to extract the morphological properties of the spot features. The first is the improvement, that consists of luminance correction, histogram monitoring, and HIS transformation. Segmentation takes place in the second phase and involves adapting the fuzzy c-means approach. The third phase, known as feature extraction, deals with 3 factors: colour, size, and spot form. The classification step, which is the fourth, uses neural networks with deep networks as its foundation. With one and two layers, the recommended model's accuracy for anthracnose in sample sets of 50–250 and 150–150 was 0.86 and 0.83, respectively.

IV. Discussion, Challenges and Future Work

In the near future, precise diagnosing techniques that may be applied to bacteria to identify crop infection must be created, evaluated, and refined in addition to leaves infection monitoring. Genotyping may be used in new fungi leaf disease detection methods intended for field use[12]. It may be operationally difficult to sample and apply this equipment in the format of compact biosensors. Additionally, because leaves contain extensive and intricate genomics, it could be challenging to get the remote location of DNA bioinformatics experts [6]. Systems microbiology and bioinformatics with significant productivity will be crucial for data mining and assessment. There are currently no plans to develop transportable DNA sequence nanosensors that can pinpoint fungi planting diseases. Further genomics using microfluidic technologies should make it easier to identify many fungi phytopathogens. The utilization of biosensing in fungi diagnoses will make it possible to create compact, affordable, precise, easy, and quick equipment that even unskilled employees can utilize in fieldwork and remote plants-locations [7].

For further genetic modification and practical applicability, in-depth research is required. The use of marker-aided selection in crop immune function, though, is achievable as shown by the detection of genetic techniques linked via disorder gene products and quantifiable character loci [8]. In the future, PCR and flowing cytometry could be used to detect emerging infections and recognise current ones genetically [9]. Genomic research might reveal the origins of platform and pathogenic tolerance in conditions like powdery mildew. Root rot fungi infections like Trichoderma have already been tested for biocontrol agents via seeds coating [8]. Multi-stranded RNA decoding can be used to identify only fungi-specific genomic indicators.

The control of foliar fungal infections requires physical and agricultural methods, such as modifying plant tolerance, using chemical pesticides, biomaterials like natural substance solutions, and defense stimulators or biostimulants. Because temperature sensor is so receptive to changes in various climatic circumstances, its use for illness assessment is constrained and flawed[8], [9]. The investigation of certain targeting compounds is an additional choice. Since it merely reveals a small portion of the overall chemical composition, it is not widely acknowledged. Selective unstable inorganic substance testing offers a more comprehensive understanding of the host biochemical structure[11]. This method can be used particularly where it's necessary to identify and quantify very different volatile organic molecules in real-time. Tracking fungus agricultural diseases may potentially benefit from remote sensing techniques [10].

A. Technical challenges are as follows:

1) Large amount of leaf disease dataset for training deep machine learning models.

2) Presence of intra-class leaf-diseases variation.

3) Diseased leaf image variation in scale, perspective, illumination, Clutter in the background.

4) Properly annotated leaf disease dataset.

5) Automatic leaf-disease detection under limited data and big data situations?

6) Automatic leaf-disease detection of single case involving multiple diseases?

7) Manage uncertainties in automatic leaf disease classification.

8) In case when researcher have very little information about new disease environment.

9) In case of short time, when researcher have very few number of data to live environment.

10) Deep machine learning model parameter and values optimization.

B. Future Work

1) Biomaterials, microfabrication techniques, and Genetic analysis could be used to create and operate biosensors for maximum precision.

2) Remote sites should host IoT deployable DML-based GUI apps (Agricultural fields)

3) Globalization and adaptive trends in leaf disease in response to shifting climatic situations and agricultural needs.

4) The effects of the environment on disease resilience and agricultural productivity.

5) Assessment of the societal and economical costs and benefits of managing leaf disease epidemics.

6) The advancement of technology to handle severe agricultural pests while also protecting the ecosystem.

7) As global populace increases and life expectations rise, the guarantee of food sovereignty, stability, quantity, and diversity is needed.

8) Falling agricultural output as a consequence of intensive farming practices, competing field utilization, and soil properties nutrients deficiency.

C. Performance metrics

To test the efficiency of any DML models, most preferred method is plotting confusion matrix(CM). It offers 2d-plot showing true and predicted labels. It has TN, TP, FN, FP values. These four attributes are used to calculate precision, recall, accuracy, F1-score, etc.

$$Accuracy = TP+TN/(TP+TN+FP+FN) \text{ ----------------------- } (1)$$

$$Precision = TP/(TP+FP) \text{ -- } (2)$$

Recall = TP/(TP+FN) ---(3)

F1 Score =2[(Precision*Recall)/(Precision+Recall)] -----(4)*

V. Conclusion

Here, we analyzed a number of the most prevalent plant diseases as well as the climate diversification and habitat switching mechanisms that underlie diseases. In economically significant plants all throughout the earth, fungi leaf infections cause significant production losses. The development of techniques that allow for the quick identification of such illnesses is important in additional to assessing the agronomic relevance of viral, bacterial, and fungi leaf diseases. The discovery of environment diversification in such infections is one strategy that is conceivable. The multifaceted issue, which involves the societal and economical aspects as well as atmospheric engineering, calls for the administration of leaf disease in a balanced way. The hosting leaf disease strategic plan might be effective for investigating not only specific qualities but also for protecting the environment. We hope that, suggested future work will be useful for further research in plant leaf disease detection and to minimize the farmers losses due to pests.

Declaration

The contributors did not disclose any probable conflicts of interest.

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