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DEEP LEARNING BASED PLANT DISEASE DETECTION

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Abstract : One of the most active research fields in agriculture is the early diagnosis of plant diseases. The health of crops depends on the prompt diagnosis of plant diseases. The manual method of identifying and preventing the spread of plant diseases is unreliable. Utilizing AI techniques in agriculture can reduce labour costs, decrease time inefficiencies, and enhance crop quality and overall yield. After revolutionizing the domain of computer vision, machine learning and deep learning can now solve many tasks such as automated plant disease diagnosis, soil fertility management, rainfall prediction, crop yield prediction, etc. To ensure the quality and quantity of crops, it is important to protect plants from diseases. Early identification and prevention of plant diseases are the important aspects of crop harvesting since they can effectively reduce any growth disorders, and thus minimize pesticide application for pollution-free crop production. To this end, various image processing activities such as preprocessing, segmentation, and feature extraction are discussed. For classification, ML and DL based approaches used in the different vegetable plants are elaborated.

***IndexTerms* - Preprocessing, Segmentation, Feature extraction, Classification**

I. INTRODUCTION

Accurate and rapid plant disease detection is critical for enhancing long-term agricultural yield. Various environmental factors lead to plant diseases and thereby result in significant production losses. Disease infection significantly impact both crop quality and quantity, potentially leading to economic losses. Viruses, fungi, bacteria, and other infectious organisms can affect numerous plant parts, including roots, stems, flowers, fruits and leaves [1]. Plant diseases, weeds and pests cause significant ecological and agricultural losses. During the growth stage, apple plants are vulnerable to various diseases including two serious and common fungus diseases: scab (caused by Venturia inaequalis) and rust (caused by Gymnosporangium juniperi-virginianae) [2]. Sunil et al. studied two diseases of cardamom plants, Colletotrichum Blight and Phyllosticta Leaf Spot of cardamom and three diseases of grape, Black Rot, ESCA, and Isariopsis Leaf Spot. Small cardamom is affected by a host of pathogenic bacteria, which seriously damages the crop and is often harmful [3]. Early prediction and recognition of these infections are vital to prevent crop damage and enhance yield.

Plant infections are challenging to spot with the naked eye. Traditional techniques for plant disease detection are time-consuming, require expertise, and resource-intensive. Therefore, automated leaf disease diagnosis using artificial intelligence (AI) with Internet of Things (IoT) sensor methodologies are considered for the analysis and detection. To address the challenges mentioned above that are prevalent in modern agricultural settings, computer-aided automated studies such as machine learning (ML) and deep learning (DL) can be instrumental in facilitating precise, rapid, and early identification of diseases. The advantages of employing these technologies lie in their ability to provide fast and accurate outcomes through computerized detections and image processing techniques [1]. Adopting ML and DL can help in early identification of plant diseases from digital images. Many ML methods have been widely used for the detection of diseases such as leaf blotch, powdery mildew, and rust, as well as disease symptoms from abiotic stresses such as drought and nutrient deficiency but have limitations in accurately identifying subtle symptoms of diseases. In addition, they also struggle to process complex and high-resolution images [4]. Another drawback is that they are not suitable for real-life detection scenarios with non-uniform complex backgrounds. In this regard, DL has made a significant breakthrough in the realm of computer vision with various applications [2]. DL models can handle complex and large images, making them suitable for high-resolution images. However, these methods are computationally expensive, potential for overfitting, require large amount of labeled training data and may not be suitable for unseen diseases.

The different steps to predict plant diseases using AI consist of image acquisition, image enhancement, preprocessing, segmentation, feature extraction, feature selection, and classification. This paper is organized as follows. The image acquisition is mentioned in section 2, and dataset creation is discussed in section 3. Various preprocessing methods are described in section 4, and segmentation techniques in section 5. Feature extraction methods and classification are explained in section 6 and 7 respectively. Before concluding the paper, performance evaluation metrics are placed in section 8.

II. IMAGE ACQUISITION

In this phase, relevant images of the object are captured to perform classification using automated approaches. For this, high-resolution digital cameras, smart phones and sensors are used. Sensors are installed in the agricultural field to collect and record plant images. Real-time plant disease detection has some significant challenges, such as complex background and severity of the disease due to the images being captured in real-time scenarios from the farm field. To encourage real-time plant disease classification, images were captured with background, noise, different angles and light illumination [3]. Images are then sent to the image preprocessing stage. If the collected images do not fulfill the processing requirements, there is a need to employ image-enhancing methods [1].

III. Dataset

The agricultural research literature shows plenty of well-known image datasets for various plant species. The datasets include healthy and unhealthy leaves, making it possible to examine and assess the effects of different diseases on plant health. It is necessary to merge data from multiple sources, such as visible, near infrared, and multispectral, to generate a comprehensive dataset on plant diseases. Recording photographs under favorable lighting conditions, such as sunny weather, enhance image quality, but capturing images on overcast days complicates preprocessing and decreases identification accuracy. In addition, it might be difficult to understand even high-resolution photos during the first phases of plant pests and diseases. It is necessary to incorporate meteorological and plant health data such as temperature and humidity to efficiently identify and predict pests and diseases. Several vegetable plant infection-related datasets are available online such as PlantVillage [5], New Plant Diseases [6], IPM Images, APS Images, Plant Doc [7],PLD [8], AgriVision [9], Plant Disease Identification, Plant Pathology 2020, Apple Leaf Disease Dataset. PlantVillage is an open database for plant disease diagnosis that includes images of diseased and healthy leaves of various plants. The dataset is a compilation of 54,306 photos of 14 crops with labels indicating the presence of 38 illnesses. It contains leaves with early blight, and leaves with late blight. AgriVision comprises photos of 14 crops affected by 27 diseases.

An aspect to be considered in connection with dataset creation is data augmentation, which is the process of artificially enlarging the size of a dataset by applying random transformations to the images. This approach has been used to increase the diversity of the data and reduce the dependence on a large amount of labeled data. It involves the use of image manipulation operations including mirroring, translation, shearing, scaling, and contrast alteration in order to create additional training examples for a DL model [2]. Small datasets cannot train an effective recognition model, especially datasets with unevenly distributed disease samples, which can easily lead to overfitting. In order to enrich tiny datasets, generative adversarial networks (GANs) and automated encoders were also utilized to generate fresh, diverse samples. The applications of GAN include image synthesis, semantic image editing, style transfer, image super-resolution and classification. Zhao et al. used DoubleGAN to generate high resolution images of unhealthy plant leaves to balance the datasets. DoubleGAN divides the building task into two stages. In the first stage, the healthy leaf images were used as inputs for the WGAN (Wasserstein GAN) to obtain the pretrained model. Then, unhealthy leaves were used for the pretrained model to generate 64*64 pixel images of unhealthy leaves. Wasserstein distance is used to optimize the loss function of the original GAN, prevent the model training from collapsing, make the training more stable, and provide a clear training index to the model. In the second stage, a SRGAN (super-resolution GAN) was used to obtain corresponding 256*256 pixel images to expand the unbalanced dataset. It increases the residual network, which not only increased the network depth but also prevented overfitting [10]. The efficacy of these strategies is contingent on the quality and diversity of the original dataset.

IV. Preprocessing

Preprocessing allows researchers to maximize the efficiency of their computing resources and maintain uniformity in their image resolutions relative to a set benchmark. Typical approaches include standardization, image size regularization, fit to fixed color scale, distortion removal, and noise removal. The captured images may contain various factors such as noise, blur, low or high illumination, unwanted background, etc. Therefore, it is crucial to process this raw data and make it worthy to classify the disease efficiently using automatic approaches. The quality of plant disease images can be improved using histograms, a technique that changes the power distribution of images [1]. The presence of irrelevant information or noise in the image can negatively impact the performance of the network. In order to address this problem, a region of interest (ROI) based approach can be used, in which the model is taught to categorize specific regions of the image containing lesion [4]. Low-pass filters are used to reduce high-frequency noise. At the same time, the high-pass filter's negative weighting factors increase those regions with a dramatic intensity gradient.

A standard preprocessing methodology in agricultural research uses the type, capacity, and value (HSV) method, closely mimicking human observers' capabilities [11]. To improve processing efficiency and accuracy, agricultural researchers frequently use masking and background removal techniques [12]. Due to its resemblance to the perceptual traits of human vision, the conversion of a coloured image into the renowned HSI (Hue, Saturation, Intensity) color space representation is used. Removing the background from an image is a challenging task without explicit pre or post-processing. If the item has a very similar colour to the background, it tends to be highly challenging to track down a perfect form because of soft edges or shadows. Sunil et al. proposed a cardamom plant leaf disease detection approach by employing a background removal technique to remove the complex background of the image by using U^2-Net. It takes the input image to produce a mask of the ROI. Further, it applies a bitwise operation on the original image and the mask produced by U^2-Net. Cardamom plant leaf images are of RGB, collected with a complex background with different dimensions and resolution. In this work, EfficientNetV2 deep learning model is used for classification [3].

V. Segmentation

The primary goal of segmentation is to analyze each object in more detail, extracting beneficial features that might enhance our understanding and knowledge. Distinguishing between unaffected and infected regions is possible based on the retrieved features. Segmenting the preprocessed images to classify diseased leaves is crucial to extract the helpful features. Traditional approaches, such as thresholding, edge detection, region-based, and clustering, rely on mathematical and image processing knowledge to segment the images. Thresholding is one of the most effective segmentation approaches based on pixel intensity values. It is widely used in various applications such as classification, detection, and remote sensing. Edge detection is a process where objects are partitioned based on their edges. Some of the famous edge detection methods are Sobel operator, Canny edge detector, and Laplacian of Gaussian (LoG) filter. Region-based segmentation divides the image into multiple regions based on the similarity of pixels in terms of intensity value, colour, and shape. Two well-known region-based segmentation methods are

Region Growing and Region Splitting. The clustering technique groups pixels together based on their similarity in texture, colour, or other required features. K-means and Fuzzy C-means are the famous clustering algorithms widely used in various applications. In recent years, DL-based automatic segmentation approaches have outperformed traditional methods in terms of performance. Two well-known DL-based segmentation approaches are Semantic Segmentation and Instance Segmentation [1]. Tassis et al. proposed segmentation and removal of the background using semantic segmentation by employing U-Net on coffee plant disease detection [13]. Singh et al. proposed a segmentation approach by employing K-means clustering, watershed segmentation, and threshold-based exemption on coconut leaf image datasets to detect leaf blight disease [14]. Chouhan et al. proposed a neural network model with superpixel clustering for segmentation [15].

The segmentation network transforms the task of detecting plant and pest diseases into semantic segmentation, which includes separating lesions from healthy areas. By dividing the lesion's area in half, it calculates the position, rank, and associated geometric properties (including length, width, surface, contour, center, etc.). Traditional plant and pest disease segmentation methods are categorized as conventional FCN, U-Net, and SegNet according to variations in the architecture of the FCN network. A fully convolutional network (FCN) is used to segment the image's semantics. FCN uses convolution to extract and encode the input image features, then deconvolution or oversampling to gradually restore the segmented image's resolution, resulting in the output of the segmentation process. U-Net is a popular convolutional neural network (CNN) architecture for image segmentation tasks. The architecture is named U-Net because it is U-shaped, with encoder and decoder sections connected by a bottleneck. The encoder section of the network consists of a series of convolutional and clustering layers that extract entities from the input image. These features then pass through the bottleneck, where they are up sampled and connected to the feature map from the encoder. This allows the network to use both superficial and fundamental image attributes when making predictions. The decoder part of the network then uses these connected feature maps to generate the final segmentation map. U-Net is able to handle class imbalance problems, where some areas of the image contain more target objects than others [4].

Sliding window approach, thermal map technique, and multitasking learning network methods involve analyzing the input image and identifying specific regions that correspond to lesions through a systematic and formal analysis process. The sliding window method is a widely utilized technique for identifying and arranging elements within an image. This method involves moving a small window across the image and analyzing each window using a classification network. This technique is particularly useful for detecting localized features, such as lesions in plant photos [4]. In [16], a CNN classification network incorporating the sliding window method was utilized to develop a system for the identification of plant diseases and pests. In [17], a CNN was trained to generate thermal maps of corn disease images, which were then used to classify the entire image as infected or non-infected. A multitask learning network is a network that is capable of both categorizing and segmenting plant afflictions and pests.

Faster Region based CNN (Faster R-CNN), Region-based FCN (R-FCN) and Single Shot Multibox Detector (SSD) are three families of object detection algorithms that can be used for localizing the affected areas in the plant [18]. Single stage networks such as SSD and YOLO (You Only Look Once), and multistage networks like YOLOv1 are commonly employed in the identification of plant lesions and pests. The single-stage network makes use of network features to directly forecast the site and classification of blemishes, whereas the two-stage network first generates a candidate box (proposal) with lesions before proceeding to the object detection process. Both SSD and YOLO use a single CNN to predict the type and position of objects in an image. However, SSD makes predictions about the size of objects based on multiple feature maps that are scaled differently, making it better suited for identifying small objects with greater precision than YOLO [4]. In [19], the Faster R-CNN was used to accurately locate tomato diseases and pests infestation. It is a two-stage object detection system that uses a common feature extractor to obtain a map of features from an input image. The network then utilizes a Region Proposal Network (RPN) to calculate anchor box confidences and generate proposals. The features maps of the proposed regions are then connected to the ROI pooling layer to enhance the initial detection results and finally determine the location and type of the lesion. In [20], a modification was suggested for the Faster R-CNN framework to automatically detect beet spot lesion by altering the parameters of the CNN model. Zhou et al. proposed a rapid detection system for rice diseases by integrating the FCM-Kmeans and YOLOv2 algorithms [21]. For real-time applications that prioritize speed, YOLO may be the best option, but for applications that require a higher level of accuracy, SSD and Faster R-CNN may be more suitable.

Mask R-CNN is an effective DL model that is perfect for plant pest detection. It is an extension of the Faster R-CNN model and can recognize objects and segment instances [22]. The primary advantage of Mask R-CNN over other models such as YOLO and SSD is its capacity to produce object masks that allow more precise image object location. This is especially beneficial for detecting plant pests, as it enables for more precise identification of afflicted areas. In addition, Mask R-CNN is able to handle overlapping object instances, which is a common issue in plant pest detection due to the presence of several instances of the same pest and disease in a single image.

There has been debate over whether detection networks can replace classification networks in this field. The primary goal of a segmentation network is first to identify the presence of plant maladies and infestations, whereas the goal of a predictive model based on a classification scheme is to categorize these diseases and pests. The detection network includes the steps of the classification network. While the detection network may provide accurate results in different patterns, these patterns may not accurately represent the individuality of specific plant maladies and infestations, and may only indicate the presence of certain kinds of illness and bugs in a specific area. In such cases, the use of a classification network may be necessary. In conclusion, both classification networks and detection networks are important for efficient plant disease and pest detection, but classification networks have more capabilities than detection networks [4].

VI. FEATURE EXTRACTION

Feature engineering is a fundamental technique that includes transforming raw data into a set of meaningful and relevant features. The basic features in an image include colour, texture, morphology, and other related characteristics. When identifying the spot on a leaf that has been damaged, morphological traits prove more effective than others. The methods such as colour histogram, colour correlogram, colour R moment, etc., are used to obtain features like colour moments and Gabor texture [1]. For plant disease identification, texture feature yields more favorable outcomes [23]. By using the grey-level co-occurrence matrix (GLCM) method, one may determine the area's energy, entropy, contrast, homogeneity, moment of inertia, and other textural features [24][25]. Texture characteristics may be separated using Fourier Transform and wavelet packet decomposition. Additional features such as the speed-up robust feature, the Histogram of Oriented Gradients, and the Pyramid Histogram of Visual Words (PHOW) have shown greater effectiveness [23]. Vadivel and Suguna used K-means to extract the features such as contrast, correlation, energy, homogeneity mean, standard deviation, and variance from diseased leaves [26].

In traditional manual image classification and recognition methods, the underlying characteristics of an image are extracted through the use of hand-crafted features. These methods are limited in their ability to extract information about the deep and complex characteristics of an image. This is because the manual extraction procedure is extremely reliant on the expertise of an individual conducting the analysis, and can be prone to errors and inconsistencies. Additionally, traditional methods are not able to extract information about subtle or hidden features that may be present in an image. In contrast, DL-based image classification and recognition methods use artificial neural networks to automatically extract image features. These methods have been shown to be highly effective in extracting complex and deep features from images, and have been utilized in numerous applications such as object recognition, facial feature recognition, and image segmentation. Among the primary benefits of DL-based methods is its capacity to learn features autonomously from input data, rather than relying on manual feature engineering. This allows the model to learn more abstract and subtle features that may be present in the image, leading to improved performance and greater accuracy. Additionally, DL-based methods are also able to handle high-dimensional and complex data, making them particularly well-suited to handling large-scale image datasets [4].

VII. Classification

Machine learning and deep learning algorithms are widely used to classify healthy and diseased plant leaves. Decision tree (DT), random forest (RF), k-nearest neighbor (KNN), k-means clustering, support vector machine (SVM), artificial neural network, naïve Bayes, linear regression (LR), and linear discriminant analysis are the frequently used ML approaches. DL has significantly impacted areas such as image classification, object recognition, plant disease diagnosis, segmentation, and natural language processing. It employs neural networks for autonomous feature selection, eliminating the intensive feature engineering requirement. It improves accuracy and generalizability in tasks such as image recognition and target identification by combining low-level information to build abstract, high-level features. Several pre-trained models tailored to deep neural networks (DNN) already exist within agricultural research. These models are deployed in agriculture to aid in prediction, feature extraction, and tweaking. Image classification has seen the development and study of several well known CNN architectures - VGG16, GoogleNet, ResNet, GeneticCNN, SqueezeNet, LeNet, Inception, MobileNet, and Xception [1]. All these models have been shown to be effective in detecting plant diseases and pests based on different characteristics such as size, shape, and colour [4].

A visualization and classification architecture (Teacher/Student) based on aggregate learning of two deep classifiers was proposed by Brahimi et al. Teacher/Student is a deep interpretable architecture that simultaneously classifies the disease and envisions symptoms. This architecture is a trainable mechanism of visualization for the classification of plant diseases. It uses an autoencoder for preserving the important features in the image. Autoencoder handles the deconstruction and reconstruction of the image so that the noise is removed and only the salient features remain in the image. The teacher is a classifier working as an encoder in the autoencoder. Decoder depletes the inherent representations from the Teacher i.e. the encoder to reconstruct the image. A classifier (Student) learns from this reconstructed image and classifies the disease with finer accuracy [27]. In Teacher/Student, standard VGG16 architecture is employed in the Teacher and the Student components. VGG16 is a linear architecture with no residual connections. Apart from the U-Net skip connections in the autoencoder from the encoder to the decoder, there are no residual connections to preserve the gradients in Teacher/Student. Shah et al. proposed an architecture ResTS (Residual Teacher/Student) which uses residual/skip connections in encoder and decoder components. To achieve this, the authors implemented standard Xception (Extreme Inception) architecture as Teacher and Student. They have introduced residual/skip connections along with batch normalization in the decoder part of the autoencoder which helps in achieving state-of-the-art accuracy for classification and visualization tasks. This architecture also contains U-Net skip connections in the autoencoder which become beneficial in reconstructing the image [18].

Roy and Jayabrata proposed a multi-scale disease detection model based on improved version of the state-of-art YOLOv4 algorithm and applied to real-time apple plant disease identification. YOLOv4 is a high-precision one-stage object detection model that transforms the object detection task into a regression problem by generating bounding box coordinates and corresponding probabilities of each class. In the proposed model, CSPDarkNet53 has been modified to be Dense CSPDarkNet53 by introducing DenseNet blocks to improve feature transfer and reused for small-target detection. The algorithm not only has high detection speed but also performs with high precision and accuracy for different real-time object detection applications in a complex environment [2]. The following are the methods used to identify diseases in different crops.

The *tomato* crop is vulnerable to several diseases brought on by bacterial infections, microbes, and pest infestations. Francis and Deisy proposed a CNN model to discriminate between healthy and diseased tomato and apple leaves [28]. Basavaiah and Anthony observed the practice of various ML algorithms such as KNN, LR, DT, RF, and SVM to identify tomato plant disease, of these RF model performed better [29]. K B and Rao use KNN and probabilistic neural networks (PNN) to detect and categorize different diseases affecting tomato leaves. The model accurately identified Verticillium wilt, powdery mildew, leaf miners, Septoria leaf spot, and spider mites [30]. Chakravarthy and Raman used ResNet and Xception to identify early blight disease in tomato leaves [31]. Kumar and Vani analyzed four common transfer learning-based architectures - LeNet, Xception, ResNet50, and VGG16 to identify diseases in tomato leaves [32].

The *chilli* disease such as Down curl, gemini virus, cercospora, leaf spot etc. are caused by bacteria, virus, and fungus causative agents. In a work by Naik et al. VGG19, squeeze-and-excitation-based CNN, and DarkNet53 (with augmentation) models showed better performance [33]. Kanaparthi and Ilango investigated the efficacy of the SqueezeNet CNN architecture in identifying Gemini virus and Mosaic-infected Chilli leaves [34]. KM et al. used YOLOv5 model to diagnose two primary illnesses, leaf spot, and leaf curl in chilli crops [35].

The *potato* is one of the most widely affected crops in agriculture due to the prevalence of diseases such as Black scurf, common scab, black leg, pink rot, etc. caused by different causative agents. Arya and Rajeev investigated the viability of using CNN and AlexNet architectures for disease detection in potato and mango leaves [5]. Mahum et al. used an Efficient DenseNet model to detect various potato plant leaf diseases [36].

Cucumber plants are particularly susceptible to diseases like mildew, bacterial, downy mildew, and powdery mildew. Zhang et al used EfficientNet-B4-Ranger architecture to detect and categorize diseases affecting the leaves of cucumbers [37]. Wang et al. introduced DUNet, a two-stage model that combines the benefits of DeepLabV3+ and U-Net for disease classification in cucumber leaves against diverse backgrounds. Disease spots on leaves can be identified with U-Net, while DeepLabV3+ segregates healthy parts from complex backdrops [38]. Zhang et al. proposed a method to diagnose cucumber plant diseases by separating images with diseased patches by combining K-means, and separating unhealthy leaf images using scant resentment [39].

A region-based single-shot multi-box detector was used with Visual Geometry Group (VGG) for cotton plant disease detection [40]. In [41][42], pre-trained ResNet was employed for coffee and soybean plant disease detection. Jiang et al. proposed a multi-task approach by employing transfer learning with VGGNet, in which the authors extracted the independent features from multiple datasets and trained independently for multiple related tasks on wheat and rice plant datasets [43]. In [44], the Internet of Things was employed with fuzzy networks to detect pauropsylla disease.

Machine learning algorithms, such as C4.5 classifier, tree bagger, and linear SVM, have been applied to the classification of plant diseases. Recently, transfer learning and ensemble methods have emerged as popular trends in plant disease detection using ML and DL. Transfer learning involves fine-tuning pre-trained models on a specific dataset to enhance the performance of DL models. This method is less computationally intensive and requires less labeled data due to the fact that the pre-trained network has already acquired generic characteristics from huge datasets. It can increase model performance and minimize model development expenses. Ensemble methods, on the other hand, involve combining multiple models to improve overall performance and reduce dependence on a single model [4]. DL approaches based on RNN have demonstrated success by achieving high accuracy in identifying various plant lesions from images [45]. Deep Denoising Autoencoder (DDA) is a variant of autoencoder, which is a neural network architecture composed of an encoder module along with a decoder. It has been used for two different purposes - noise removal and to identify plant disease [46]. Sachdeva et al introduced a Deep CNN model with Bayesian learning to improve plant disease classification. A Bayesian procedure has been built into the structure of a residual network [47]. Zhang et al. introduced a unique Global Pooling Dilated CNN (GPDCNN) for plant disease identification [48]. Katafuchi and Tokunaga proposed a framework for plant disease detection which operates a conditional adversarial network - pix2pix [49].

VIII. Performance Evaluation Metrics

The following metrics are used for evaluating the performance of plant disease classification, detection, and segmentation models [4].

Accuracy: This is the proportion of correctly classified instances out of the total number of instances.

$$Accuracy = \frac{True \quad Positive \quad Ratio + True \quad Negative \quad Ratio}{Total \quad number \quad of \quad samples}$$

Precision (P): This is the proportion of correctly classified positive instances out of the total number of predicted positive instances.

$$\Pr ecision = \frac{TP}{TR + TP}$$

Recall (Sensitivity): This is the proportion of correctly classified positive instances out of the total number of actual positive instances.

$$\mathrm{Re}\, call(R) = \frac{TP}{TP + FN}$$

Average Precision (AP): It is the area under the PR-curve.

$$\text{AP}= \int_0^1 P(R)dR$$

Mean Average Precision: It is average of all APs [2].

$$\text{Mean Average Precision}= \frac{1}{N}\sum_{i=1}^{N} AP_i$$

F1-Score: This is the harmonic mean of precision and recall.

$$\text{F1-Score}= \frac{2 * (\Pr ecesion * \mathrm{Re}\, call)}{\Pr ecesion + \mathrm{Re}\, call}$$

Intersection over Union (IoU): This is used to evaluate the performance of segmentation models.

$$\text{IoU}= \frac{TP}{TP + FP + FN}$$

Dice Coefficient: This is also used for evaluating segmentation performance.

$$\text{Dice Coefficient}= \frac{2 * TP}{2 * TP + FP + FN}$$

Jaccard Index: This is another metric used for evaluating segmentation performance.

$$\text{Jaccard Index}= \frac{TP}{TP + FP + FN}$$

Receiver Operating Characteristic (ROC) curve: It is a graphical representation of the performance of a binary classifier. The area under the ROC curve with a value of 1 indicating perfect performance and a value of 0.5 indicating no better than random.

Area Under the Curve: AUC is also used to evaluate the performance of the binary classifier. It goes from 0 to 1, where 1 corresponds to a perfect classifier and 0.5 corresponds to a random classifier. A greater AUC value suggests superior classification ability.

IX. CONCLUSION

The use of ML and DL techniques in plant disease detection can reduce the need for manual labour and the cost of plant disease detection. Most of these techniques have focused on a specific type of disease or a specific plant species. Therefore, more research is needed to develop a generalizable and robust model that can work for different plant species and diseases. It is also important to gather images from various plant growth stages, seasons, and regions. It is required to include more plants, their diseases and datasets for study to cover the entire field. Further, it is yet reach the accuracy of disease prediction up to a dependable level.

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