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PlantHealthAI: An Integrated System for Plant Disease Detection, Severity Prediction with Knowledgebase Chatbot Support

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***Abstract*—Plant Disease detection and severity estimation is crucial for mitigating the impact on crop yield. This research focuses on the development of a deep learning-based model to detect the incidence level of early leaf spot disease in groundnut crops. A real-field dataset is created for evaluating our methodology by inducing the early leaf spot disease to susceptible plants in a controlled and observatory environment. The developed model achieved a precision and recall rates of 98% and 95%, respectively. Additionally, the developed severity estimation model with the custom metric demonstrated promising results, with a maximum absolute difference of 0.5 between the ground truth severity measure and the predicted severity measure. Furthermore, a user-based query feedback system backed by a comprehensive knowledge base was integrated, enabling users to acquire information on various aspects of the detected disease. This feature enhances the usability and accessibility of our solution, empowering farmers to make informed decisions for effective disease management and unlocks new potential in promoting sustainable crop protection practices and thereby positively impacting the agricultural sector.**

***Index Terms*—Deep Learning, Convolutional Neural Network, Image Processing, Segmentation, Knowledgebase, Chatbot.**

I. Introduction

Plant diseases pose a significant threat to farmers, resulting in substantial yield loss and income reduction. Plant disease detection plays a crucial role in ensuring crop health and maximizing agricultural productivity. However, manual identification of plant diseases can be a tedious and time-consuming task, often relying on visual observations by trained experts. Recognizing the limitations of human subjectivity and the need for more efficient methods, there is a growing interest in automating disease detection using advanced technologies such as Artificial Intelligence (AI) and Deep Learning. These technologies offer the potential to improve the accuracy and speed of disease identification, leading to timely interventions and effective management strategies for crop diseases.

Groundnut, a vital oilseed crop cultivated globally, plays a pivotal role in the agricultural landscape, particularly in Asia where it constitutes 60

One of the paramount concerns among these diseases is early leaf spot disease, primarily incited by the fungal pathogen Mycosphaerella arachidis. This affliction primarily manifests through characteristic symptoms on leaves and stems, leading to a decline in overall productivity and significant economic repercussions for agricultural stakeholders [15]. Unfortunately, the reliance on conventional diagnostic techniques introduces an element of subjectivity, thereby impeding diagnostic accuracy and potentially culminating in misdiagnoses. The core objective of this study is to harness the power of advanced deep learning coupled with sophisticated image-processing techniques to establish a precise and efficient disease detection framework. It is worth noting that while disease detection is a critical facet, an effective diagnosis must extend beyond detection to encompass an accurate assessment of disease severity, thus enabling tailored and targeted interventions for the afflicted crops.

Addressing the exigent need for an objective, technologically empowered approach to disease detection and diagnosis in groundnut cultivation, this research endeavor seeks to usher in a transformative era in agricultural practices. By elucidating the potential of cutting-edge technologies, this study strives to provide not only a breakthrough in disease management but also a paradigm shift in the way we safeguard global food security and bolster sustainable agricultural practices.

In our research, we specifically address the Groundnut early leaf spot disease, caused by the fungal pathogen Mycosphaerella arachidis. This disease primarily affects the top of the leaves and can be identified by symptoms such as dark brown lesions with yellow halos and premature defoliation. Our proposed system focuses on detecting the disease from leaf images, estimating its severity, and providing feedback on potential remedial options. While our system primarily targets Groundnut plants, it can be extended to other plant diseases that exhibit symptoms on leaves. Early and accurate identification of the disease is crucial for effective disease control, allowing for timely implementation of necessary precautions to prevent its spread and minimize its impact.

II. Literature Survey

A variety of pertinent keywords, such as “plant disease detection and machine learning”, “computer vision for plant disease detection” and “groundnut leaf disease detection” have been used to find papers to conduct a thorough review of the literature on plant disease detection and severity prediction using AI/ML/DL. During our search, we applied the same filters mentioned above to the popular databases Google Scholar, IEEE Xplore, and ACM Digital Library to ensure we only found pertinent papers.

Various research has been done on plant disease detection, and it has been found that image-based classification methods have more accurate results than visual classifications[11]. Hitherto, agricultural scientists have proposed many approaches to predict whether the plant has been affected or not using different machine learning, deep learning, and image processing techniques[12]. It is of utmost importance to promptly and accurately detect this disease to effectively implement control strategies and mitigate its detrimental effects on agricultural productivity.

Mohanty et al. propose a methodology for the identification of powdery mildew on grape leaves using deep convolutional neural networks (CNNs)[14]. The methodology involves training a CNN model on a dataset of annotated grape leaf images, consisting of both healthy and powdery mildew-infected samples. The trained CNN model is capable of automatically learning and extracting relevant features from the input images, enabling accurate classification of disease presence. The authors evaluated the performance of the CNN model using various metrics such as accuracy and F1-score. The results showed that the deep CNN-based approach achieved high accuracy in detecting powdery mildew on grape leaves, showcasing the potential of deep learning techniques for disease classification in plants.

The methodologies described in the Deep Plant Phenomics (DPP) platform [13] and the powdery mildew identification on grape leaves using deep convolutional neural networks (CNNs)[14] showcase the potential of deep learning techniques in accurately classifying plant diseases and phenotypic traits. However, several limitations should be considered. The performance of deep learning models relies heavily on the availability of high-quality and annotated datasets, which can be labor-intensive and may limit the generalization to new plant species or rare diseases. Additionally, deep learning models require significant computational resources and training time, posing challenges for implementation in resource-constrained environments or real-time applications. The grape leaf methodology[14] also faces challenges related to the availability of diverse and representative datasets and potential variations in lighting conditions and image quality. Robust validation on larger and more diverse samples is necessary to assess generalizability.

The advantage of incorporating Deep Learning algorithms into smartphones for plant disease detection is that it enables rapid and convenient image recognition, allowing farmers and individuals to detect diseases early and improve food security[2]. Additionally, linear regression analysis helps understand how factors such as the number of images in the dataset can positively impact the accuracy of the Convolutional Neural Network (CNN) algorithm.

Hyperspectral imaging can be used for segmentation by leveraging its ability to capture a wide range of spectral bands, allowing for the differentiation and delineation of objects or regions based on their unique spectral signatures[1] and it can be utilized for early disease detection in plants by detecting specific spectral signatures associated with diseased or infected areas, enabling timely intervention and treatment to prevent further spread and damage.

Another study on Vermicompost and vermi-leachate states that, they can be used for disease control in plants by suppressing diseases through the presence of beneficial microorganisms and enhancing plant immunity[3]. This is done after identifying the disease in the plant in its earlier stage. The microorganisms in vermicompost compete with pathogens, while the organic matter and bioactive compounds in vermileachate stimulate the plant’s natural defense mechanisms, resulting in healthier and more resistant plants aiding in better yeild.

We built the system on a custom dataset, in which plants are grown in a filed which simulates the real case scenario and incorporating various practical aspects. Researchers from Amrita School of Agricultural Sciences, deliberately infused diseases into plants and cultivated them in both controlled and uncontrolled environments. Daily multi-dimension photographs of the diseased and healthy control plants were captured from day after induction of disease, ensuring a comprehensive and authentic dataset for analysis.

The developed system demonstrates three key functionalities: early disease detection, severity estimation, and providing feedback to farmers. Using advanced image processing techniques, the system effectively identifies the initial establishment and spread of leaf spot in plant, we developed a light weight computer vision based accurate disease detection system. Furthermore, it accurately calculates the severity of the diseases, enabling farmers to assess the extent of damage to their crops. Based on this information, the system generates actionable feedback for farmers, offering recommendations and guidance on appropriate treatment strategies and management practices at right time to mitigate the impact of the disease and maximize crop yield. By providing a comprehensive solution encompassing disease detection, severity assessment, and tailored feedback, the system empowers farmers with valuable insights to make informed decisions and take timely actions to protect their crops.

III. Dataset Creation

The plants utilized in the dataset were cultivated by the Amrita School of Agricultural Sciences, including both controlled environments within polyhouse setups and open agricultural fields. This section delves into the intricate details concerning the generation and collection of the dataset, a crucial aspect of the study.

A. Inducing the Disease

The available plant disease data sets worldwide represent only the manifested and established symptoms of infections, which may not be relevant for determining effective management measures prior to crop failure. Nevertheless, early and accurate disease diagnosis at the field level under favorable climatic circumstances should be the primary focus of all plant disease control initiatives. In this planned study, crops were cultivated under favorable conditions for the establishment of disease and monitored daily basis, and disease progression was imaged from the entry and onset of pathogen colonization on the leaf surface. The controlled environment assured that the features developed in the plant are only because of the early leaf spot disease. This will significantly support farmers' early detection before disease injury level, precise identification, and forewarning capabilities using the Android app.

Inside the polyhouse, cultivating soil has been cleansed with cypermethrin to eliminate soil-dwelling microorganisms and treated with compost to enhance fertility. The mud pots have been filled with sandy soil, FYM and red earth mixture and arranged. A healthy, uninoculated control seedling has been included as a reference point, while susceptible varieties of groundnut have been intentionally infected for research purposes. Each container has been planted with 6-7 seeds, and after germination, three seedlings have been selected per container. Immediate picture acquisition of diseased leaves has commenced. Pathogen establishment and histological alterations are being routinely observed under microscopic examination.

B. Dataset Collection

The symptoms of Early Leaf Spot disease[8] in Groundnut plants is identified by dark brown lesions surrounded by a yellow halo on top of the leaves. Using professional and mobile cameras, we have captured normal RGB photographs at multiple scales, both at leaf and at plant level, to facilitate this study. We captured daily images of groundnut plants in two ways: leaves-wise and canopy-wise. In order to enable effective disease detection and severity estimation using supervised learning, we employed preprocessing techniques to clean and enhance the dataset. This involved enhancing the images when cropping them to focus on the leaves, as well as reducing noise, normalizing the images, and resizing them to ensure a standardized dataset. These steps were undertaken to minimize unwanted variations and facilitate the development of accurate machine learning models for groundnut disease detection and severity prediction.In Groundnut, Early Leaf Spot pathogen will be inoculated on the 25th day; progression and imaging had been continued throughout the crop period of 100-120 days along with the healthy control. We have 480 healthy leaf images, 700 diseased leaf images, 330 healthy leaf videos and diseased leaf videos. The ground truth for severity prediction has been generated by using QuPath [10] software and employing the ResNetUNet model for robust background removal.

IV. Methodology

This section details the methodology and our architecture which is proposed for disease detection, severity estimation and knowledge support.

A. Methodology for Disease Classfication

1) Dataset for Disease Classification: As discussed in the Dataset Creation section, we have captured photographs of both healthy and diseased leaves for the supervised disease detection system. Altogether, we have used a balanced dataset of 1130 photographs containing equal number of healthy and diseased leaf images. For the training of the classification model, the dataset was split into 70% images for training, 20% images for validation, and 10% images for testing. The images were captured on a daily basis with high quality DSLR camera which captures each and every detail.

In our pursuit of developing an effective disease detection and severity estimation system for early leaf spot disease in groundnut crops, we explored multiple methods to enhance our model's performance which are discussed in the following sections.

2) Transfer Learning with VGG 16: In addition to the custom CNN models, we also explored transfer learning using the VGG-16 architecture. By leveraging pre-trained weights from VGG-16, which was trained on a large-scale dataset[7], we could benefit from the knowledge and features learned from the vast image dataset used during its training. Transfer learning allows us to leverage the rich representation capabilities of pre-trained models and adapt them to our specific disease detection task. The advantages of transfer learning include faster convergence, reduced requirement for large training datasets, and improved generalization.

3) Custom CNN Models: We employed custom CNN architectures for our experiments, these custom models were designed to optimize the learning process.The model architecture includes three convolutional layers with decreasing filter sizes, accompanied by max pooling, activation functions, and batch normalization. These layers extract and capture important features from the input images. After the convolutional layers, a flatten layer transforms the features into a 1-dimensional representation. Two dense layers follow, with the first having 256 units and ReLU activation for learning complex patterns. Dropout regularization is applied after the first dense layer to prevent overfitting. The final dense layer has 2 units and uses the softmax activation function to generate class probabilities. This architecture, comprising convolutional, pooling, activation, and dense layers, is designed to effectively classify the input images. The custom model offers advantages over pre-trained models by allowing specific tailoring to the task, incorporating regularization techniques to improve generalization, and learning directly from the provided dataset for potentially better task-specific performance.The custom CNN was preferred over pre-trained models due to its superior accuracy of 98% compared to the pre-trained model's accuracy of 70%.

At the end of training, the metrics are impressive. We achieved a remarkable 99.68% training accuracy, with a training loss of 0.349, using the robust categorical cross entropy loss function. Additionally, our model demonstrated an outstanding 98.537% validation accuracy, accompanied by a validation loss of 0.3309, based on the same categorical cross entropy loss. These numbers highlight the effectiveness of our approach and the model's ability to accurately classify and optimize the selected loss function.

B. Methodology For Severity Prediction

1) Dataset for Severity Prediction: The dataset for the segmentation of the leaf is generated by using the software QuPath which is an Open Software for Bioimage Analysis. A total of 100 images were used and the masks were generated for the 100 images. This method of obtaining the masks for the dataset is suggested by StarDist[5] which has set a benchmark for segmentation.

Figure 1 represents the original input image of leaves captured from the plant. This image serves as the initial data input for further analysis and processing. Label GT is generated using QuPath software[10]. It represents a mask that highlights specific regions or objects of interest within the input leaves image. The mask is derived through segmentation techniques, which identify and separate the desired elements from the background or other unwanted components. The generated mask assists in subsequent analysis tasks, such as

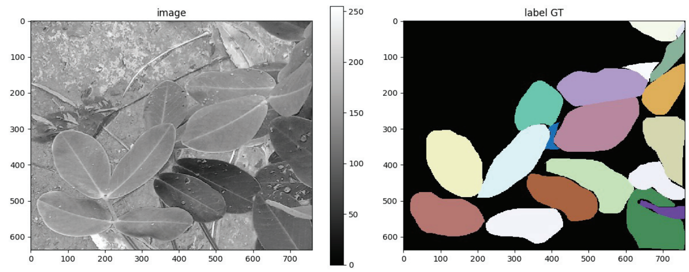

Fig. 1. Input Image and its mask generated using QuPath

disease detection, by isolating and focusing on the relevant areas of the leaves.

2) ResNet-UNet Segmentation: The combination of ResNet and U-Net is a robust solution for background removal in leaf segmentation tasks. It combines ResNet and U-Net architectures to provide an effective and original approach. ResNet extracts high-level features and details from leaf images while overcoming the vanishing gradient problem through residual connections. U-Net captures global and local contextual information for accurate segmentation. The combination of ResNet and U-Net yields remarkable results for complex leaf backgrounds. ResNet U-Net's capability to learn rich representations and capture fine-grained details, along with its contextual understanding of leaf structures, makes it ideal for background removal in leaf segmentation. The model offers advantages such as multi-scale feature fusion through skip connections and upsampling layers. This enables capturing fine-grained details and contextual information. Efficient upscaling is achieved using bilinear interpolation in upsampling layers, preserving spatial information and accurate boundary delineation. ResNetUNet benefits from adaptive learning mechanisms, utilizing convolutional layers with ReLU activation to capture complex patterns and distinguish leaf regions from the background. Optimization is achieved using the Dice loss function, resulting in accurate and visually appealing segmentations. ResNetUNet combines ResNet and U-Net architectures, efficient feature fusion, adaptive learning mechanisms, and optimized training for accurate leaf segmentation and background removal.

C. Methodology For Knowledge Base Integrated Chatbot

1) Creating a Knowledge base: We have created and developed a knowledge base with information regarding groundnut early leaf spot disease in specific, as model applicable for other plant diseases. The format of the knowledge base is a "Question and Answer" format, where questions are gathered and curated from the most frequently searched topics on Google about plant diseases and their treatments. The questions were chosen from some of the most recognized forums in the agriculture industry, and the answers were given by our very own researchers and professors from Amrita School of Engineering, Coimbatore. The Knowledge base contains expert responses to roughly 20 queries regarding the groundnut plant leaf spot disease, each of which is linked to an article from a reputable academic publication or forum.

2) Implementation of Chatbot: We devised a method by which our chatbot can access the information in the knowledge base and give out the answers that are particular to the domain automatically. We achieved this flow of the chatbot by using the technique of in-context learning[9].

Our chatbot can even tackle questions that are absent in the knowledge base and give answers with a significant confidence score that is convincing enough to consider the responses as true. In our study, confidence scores were obtained from the pretrained ChatGPT model itself, which inherently provides internal confidence estimation for its responses. These scores reflect the model's level of certainty or reliability in its generated answers, serving as an indication of the model's confidence in the correctness and relevance of its responses. All this is possible because of the enormous data Text Davinci [OpenAI Model] is trained on, and leveraging the technique of in-context learning. Additional insights and in-depth analysis are mentioned in the results section.

V. Results

A. Results of Leaf Detection and Classification Model

The classification model for detecting infected leaves is a custom CNN model that uses Efficient B1 architecture[16] as a feature extractor. The MobileNetV2[17] model achieved an impressive testing accuracy of 91.98%.The model was trained using the categorical loss function, which is commonly used for multi-class classification tasks. The categorical loss function helps to optimize the model's parameters and minimize the discrepancy between the predicted class probabilities and the true class labels. When compared with the proposed model, the custom CNN exhibits exceptional performance, achieving a remarkable testing accuracy of 98.32%

The below table represents the precision, recall, and f1-score of each class' classification of the disease classification custom CNN model.

Leaf Image class	Precision	Recall	f1-score
Diseased	0.98	0.95	0.97
Healthy	0.95	0.98	0.97

This model is later integrated to a YOLO V5 architecture(leaf detection model) to identify and classify the leaves in a given image or video.

In Figure 2, we can see that the leaf detection model is working perfectly by detecting most of the leaves in an image. The algorithm detects most of the diseased leaves and also displays the severity level of the leaf.

Figure 3 depicts the results from the final model which is the combination of the classification model and YOLO V5 model that classifies good and diseased leaves. This annotation makes it simple for the model to pass the bad annotated leaves into the severity model for predicting the severity of the leaf.

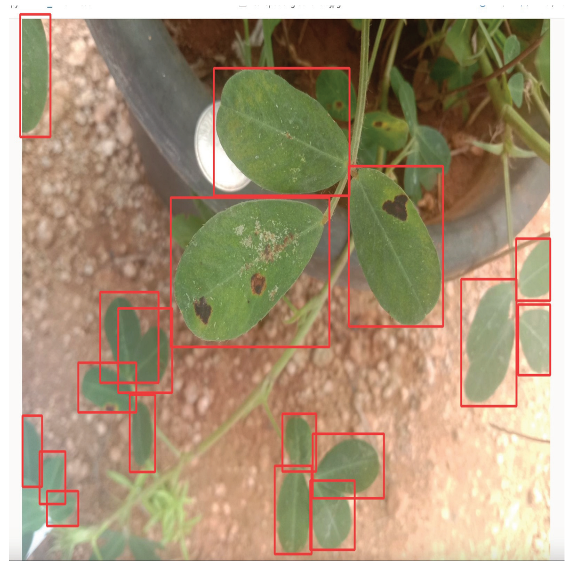

Fig. 2. Leaf Detection

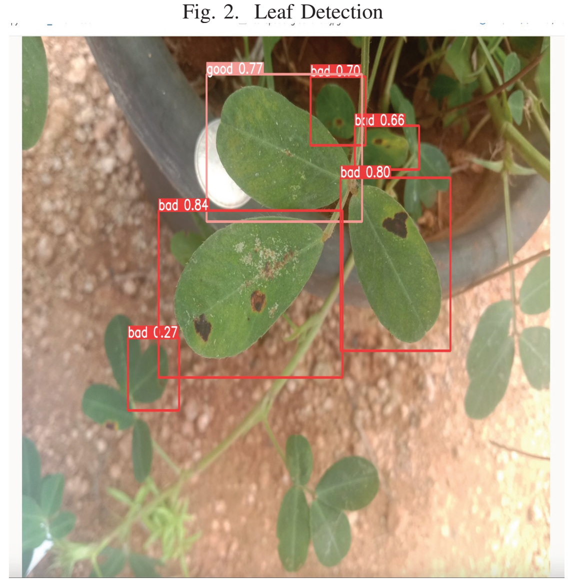

Fig. 3. Good Bad Classification

B. Results of Severity Prediction Model

Figure 3 depicts that the segmentation is working fine but there is a minimal loss of leaf area. But it is better than the original image which has additional green areas of other leaves which would be more inaccurate for severity.

To quantify and compare the results of severity prediction with a particular benchmark, we have found the ground truth of severity manually by selecting the infected and uninfected region of a leaf manually using MATLAB function 'imsegfmm' and divided the area of infected by uninfected and got the ground truth values. This process was done on 200 leaf images and saved the obtained value to a CSV file. The ground truth value corresponds to the number of diseased pixels in a leaf divided with the total number of leaf pixels.

Later, after getting the result of the same ratio (Infected

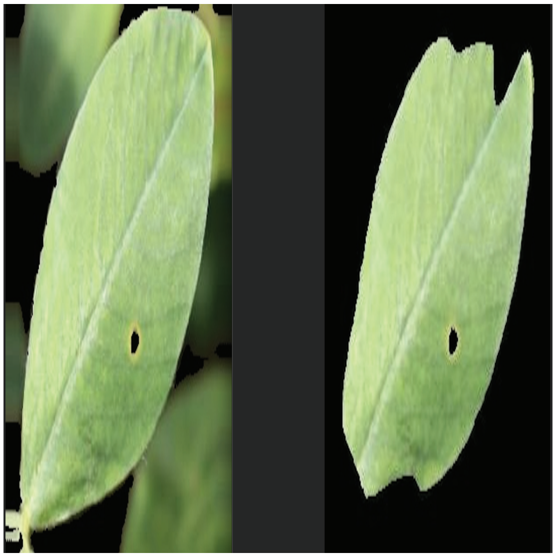

Fig. 4. Background Removal using ResNet U-Net

region/uninfected region) from our proposed model for the same set of images, we found out the mean absolute difference of ground truth and values from the proposed model, and the result was 0.5229.

In our experimentation, we examined a set of approximately 100 leaves to determine the severity of disease. The severity was measured as the ratio of diseased leaf area to the total leaf area. Comparing the ground truth severity values, calculated manually, with those obtained through our proposed methodology, we found that the average severity values were 14.9315 and 14.9499, respectively. The minimal difference between these averages indicates the accuracy of our results, suggesting that our proposed methodology provides reliable assessments of disease severity in plants.

C. Results of Chatbot

The system integrates a leaf scanning feature that displays disease details upon scanning a leaf. By providing an option to explore more details, users can access comprehensive information about the disease, its symptoms, severity, and corresponding treatments using fertilizers. Additionally, users have the choice to engage with the NLP bot for further assistance and guidance. This integrated functionality enhances the system's usability and empowers users with comprehensive knowledge and treatment options for effective disease management on edge devices.

The results of the chatbot are shown below in figures 5 and 6. Figure 5 shows the answer given by the chatbot when asked about the name of the disease of the plant, and also some of the common symptoms of it. This data is already present in the dataset, and the chatbot is presenting us much more comprehensively.

Figure 6 shows the answers given by chatbot to the questions that are not in the given dataset. This clearly depicts that it uses the context given in the dataset and searches for the relevant answer on the internet just like ChatGPT and gives out accurate answers

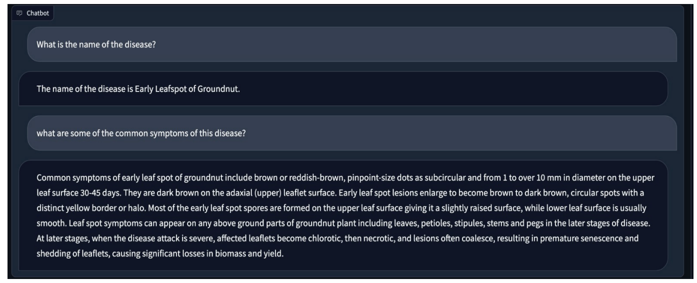

Fig. 5. Answers to questions inside the dataset

Fig. 6. Answers to questions which aren't in the dataset

VI. Contributions and Limitations

The proposed research needs to address a location-specific issue in agriculture; project outcomes are applicable worldwide, particularly for the early detection of plant diseases in the targeted crop plants. We propose a pilot study with the early leaf spot of groundnut crop widely cultivated across India, especially in the Coimbatore district of Tamil Nadu.
The Groundnut (Arachis hypogaea L.) is revered as the king of oilseeds and is cultivated globally. The groundnut leaf has four leaflets, making it trifoliate. The leaflets have an oval form with a pronounced midvein. The leaf spot disease is severe in Tamil Nadu in regions where Groundnut is produced. The dots appear on the leaves of the host plant when it is 1 or 2 months old. Groundnut early leaf spot, represent four distinct leaf lets, pathogens, culture factors, and symptom types, favoring the proposed model's validation. As mentioned in the abstract, our goal is to build a scalable and usable automated system for Indian farmers that can identify plant diseases and assess their severity and progression. By reviewing the literature, CNN has produced state-of-the-art disease detection and severity estimation results. A plethora of work in this regard happened in the last five years. In the proposed project, an expert knowledge base about the diseases will be integrated to share details about the disease, its effect, and intervention mechanisms. We aim for a mobile application that farmers can readily use. We will train a good model offline after collecting proper datasets. We will use methods such as pruning, quantization, and knowledge distillation to convert the heavy CNN to lightweight models with little loss in accuracy. The App, once developed, will

enable the farmers to hover over leaves and get the prediction done. The images that were taken, if needed and allowed by the user, can be sent periodically to the server for an update.

VII. Conclusion

Detection of crop diseases is a very challenging task. Farmers benefit from early identification and detection of early spot disease as they can implement suitable management practices to reduce the detrimental effects of the disease and prevent or minimize potential yield losses. We were able to automate this detection using state of a art Deep Learning based Convolutional Neural Network trained on custom images collected daily by Amrita School of Agricultural Sciences, Coimbatore. The images of leaves have been collected from especially infected plants in a controlled environment. The collected images are labeled and then used in object detection and image classification task. We used a state-of-the-art YOLO model to detect leaves and a custom Convolutional Neural Network architecture to classify the detected leaves into diseased or healthy. Ultimately, we deployed this model as a mobile android application that can take live camera feed from the mobile's camera, import a video or image of leaves, and then detect and classify them as diseased or healthy. The app even shows the overall severity of the disease if the plant/crop is infected. From the Fig. 5 we can depict that the absolute difference between the disease severity calculated by our program and ground truth is less than 1.5. This means that the severity predicted that is our way of approach is satisfying and can be used by the farmers to predict the disease severity of the plants. Integrated mobile applications will provide farmers with valuable assistance by incorporating disease detection, severity estimation, and chatbot functionalities. This will aid farmers to effectively manage crop diseases and enhance agricultural productivity in a sustainable manner[4].

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