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Fusing Deep CNN and Local Binary Pattern for Accurate Plant Disease Diagnosis

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***Abstract*—In today's world where the demand for food increases exponentially, a major thrift has occurred in the agriculture industry to plant those seeds which are convenient and hassle-free to grow. Plants which have the possibility of being infected and which are difficult to cultivate are generally left behind. This in turn will lead to surplus amount of a certain commodity whereas produce scarcity for the others. Moreover , it will affect the economy as a whole. One of the major reasons for this shift is the lack of knowledge and expertise to tackle the unfamiliar diseases that occur in their cultivation. Farmers that are planting new crops with no prior experience will need proper expertise to identify diseases and their treatments for a better yield. But in the present scenario that will have severe overhead costs and thus culminates a lot of risk for the cultivator. In this scenario, an easy to use software that can analyse the issue and give a likeable solution is much desired. Hence, we propose our idea on Leaf Disease Classification and Remedies which can analyse the disease present and suggest probable remedies as well. Our system is built on the traditionally available CNN Models trained on the Field Plant data set to give a better accuracy of the in-field images. During identification, if the possibility of disease is above a threshold then a warning for the same is given. A locally-procured database consisting of treatments for various diseases were made to provide information to users about the identified diseases. And we have also incorporated a predictive analysis system which can (to some extend) give an idea about any possible chances of infection.**

***Index Terms*—deep learning, CNN, plant disease,Field Plant**

I. Introduction

The economic system is heavily dependent on agricultural productivity. As having diseases in plants is relatively natural, this is one of the reasons that disease detection in plants plays a crucial role in the agriculture industry. When this area is not properly cared for, plants suffer major consequences, which have an impact on the quality, quantity, or productivity of the corresponding products. An unsafe disease that affects pine trees in the United States is called small leaf disease, for example. Using an automatic method to identify plant diseases is advantageous since it lessens the amount of work required to monitor vast crop farms and does so at an extremely early stage, when the illnesses' symptoms first appear on the leaves of the plants. Convolutional neural network (CNN), a class of artificial neural network widely utilized in image processing and recognition, is the artificial neural network type that we use in this application. It is made to automatically and adaptively learn feature spatial hierarchies from input photos. The network is made up of several layers of interconnected nodes, such as convolutional layers, pooling layers, and fully connected layers.

A collection of filters are applied to the input image by the convolutional layers in a CNN in order to extract features like edges, corners, and textures. The feature maps are then downsampled by the pooling layers to lower the data's dimensionality and improve the network's computational efficiency. The input image is then classified into one of several categories by the fully connected layers using the retrieved features.

For the detection of leaf diseases, tree identification,plant health monitoring solutions and other purposes, numerous existing systems, such as plantvillage, leafsnap, Agro-cognitive, and many more, have been developed. Our system application employs machine learning and accepts an image as input. It

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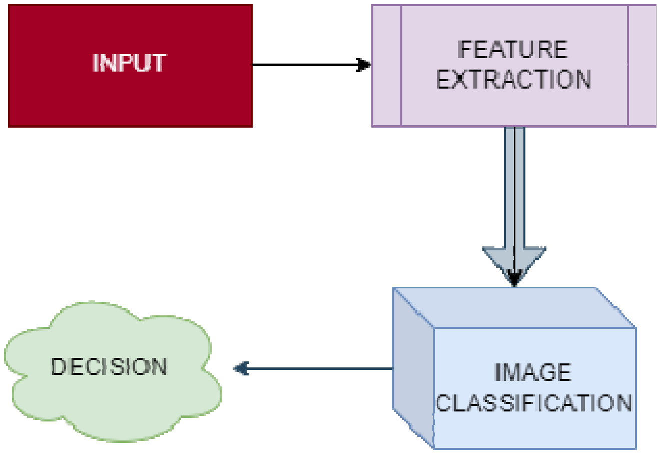

Fig. 1. Basic CNN architecture for an end-to-end image classification

then compares the image to the dataset to identify the disease on the associated image, display the name of the disease, and provide information on any available therapies. In the event that it is determined to be uninfected, it is also performs a predictive analysis.

II. RELATED WORKS

The study [1] investigates the use of deep-learning models that have already been trained on ImageNet object categories, including AlexNet, VggNet, and ResNet. These models are utilized while classifying textures in order to find plant diseases. In this study, texture features are extracted from different layers of these pre-trained Convolutional Neural Network (CNN) models and used in a machine-learning classifier. The TEXTURE DATABASE: OUTEX TC 00013 and the PlantVillage Dataset were both used in the tests by the researchers. The research's conclusions about the OUTEX TC 00013 Dataset show that the best performance is obtained when using features taken from the pre-trained ResNet50 model, whereas the ResNet18 network produced less satisfactory classification results. It is interesting that the AlexNet model showed to be the quickest for feature extraction across all photos within the dataset in terms of efficiency in terms of time and resources.The collected findings for the PlantVillage Dataset show that the pre-trained AlexNet model, especially when taking into account the relu 3 layer, gets the highest classification scores. The researchers used the idea of transfer learning to address the issue of getting relevant classification performance with little datasets. They modified well-known CNN models that had been pre-trained on the sizable ImageNet object-based dataset, such as AlexNet, Vgg16, and ResNet. It should be mentioned that only the pre-trained AlexNet model was used for the PlantVillage dataset because the other investigated models did not satisfy the requirements for real-time processing applications. The paper [2] study the residual network (ResNet) has been changed to create the VRNet, which is intended to be more lightweight and efficient. The attention method is utilized to concentrate on the leaf images' key characteristics, helping to increase the detection algorithm's precision.Four datasets of leaf images with plant diseases were used to evaluate the suggested approach. The outcomes demonstrated that the suggested strategy outperformed other cutting-edge methods in terms of performance.The following are some of the main aspects of the suggested approach: 1. Its lightweight deep residual network foundation makes it easier to train and use than competing techniques. 2. The accuracy of the detection is increased by focusing on the key elements of the leaf images using an attention technique. 3. Four datasets of leaf photos with plant illnesses were used to evaluate it, and it performed well. The following are some of the paper's specific contributions: 1. For the purpose of detecting leaf disease, the authors suggest a new, lightweight VRNet. 2. The authors suggest a brand-new attention mechanism for identifying leaf illness. 3. The authors use four datasets of leaf pictures with plant diseases to evaluate the suggested technique. 4. The authors demonstrate that the suggested strategy outperforms other cutting-edge methods in terms of performance. For farmers and plant scientists, the suggested method is a useful resource. It can be used to detect leaf illnesses early on, helping to stop the spread of disease and safeguarding harvests. This paper [3] investigates the FieldPlant Dataset includes 5,170 painstakingly annotated photos of plant diseases that were directly gathered from diverse plantations. It is the first plant disease dataset to contain annotated cassava photos because all of these images have been expertly categorized by pathologists. The dataset has a huge collection of 8,629 unique annotated leaves dispersed throughout 27 different disease classes. It includes a wide variety of field pictures of tomato, corn, and cassava plants.Although the primary focus of this study is on diseases that harm plant leaves, it also includes a few types of non-leaf diseases, such as cassava root rot (which consists of 78 images) and corn charcoal (which consists of 8 images). The findings of internal testing by the researchers show that when applied to photographs directly taken from the field, the current models for plant disease detection and image classification do not produce adequately accurate results. In contrast to current PlantDoc datasets, the FieldPlant Dataset exhibits superior performance in the classification of these activities.

The research paper [4] proposes a novel method for classifying mango leaves infected by anthracnose disease using a multilayer convolutional neural network (MCNN) model. The paper first explains the importance and challenges of detecting fungal diseases in plant leaves, and reviews the existing methods based on computer vision, machine learning, and artificialintelligence. The paper then introduces the MCNN model, which is a deep learning model that can classify healthy and infected leaves based on their images. The paper also describes the data collection and validation process, and compares the performance of the MCNN model with other state-of-the-art approaches. The paper concludes by highlighting the main contributions of the proposed method, which is automatic, efficient, and cost-effective, and suggesting some

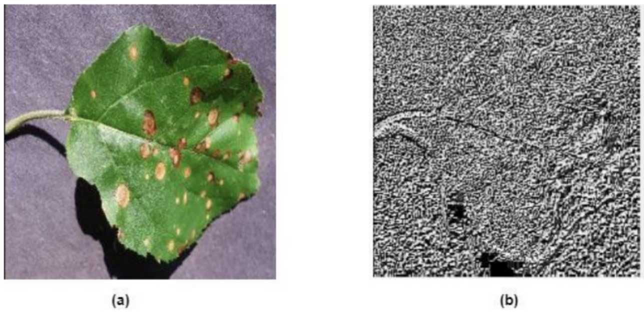

Fig. 2. LBP Feature Extraction

future work to improve the model and apply it to other plants

The research paper [5] presents a new method for classifying plant leaf diseases using a hybrid approach of deep learning and traditional image processing techniques the paper first examines the current methods and their challenges such as the reliance on expert inspection the use of low-level features and the high computational demand of deep learning models the paper then proposes a new deep convolutional neural network dcnn model that learns high-level features from plant leaf images the paper also employs local binary pattern lbp features to capture the local texture information of the leaves the paper combines the deep and handcrafted features to form an integrated model that can better represent the plant leaf images the paper tests the proposed model on three publicly available datasets of apple tomato and grape leaves and demonstrates that it surpasses the existing methods in terms of accuracy and efficiency the paper summarizes the main contributions and suggests future work. In paper [6], The transfer learning approach serves as the foundation for the PiTLiD methodology. Transfer learning is a machine learning technique where a model that has been built on a big dataset is used as the foundation for a model that has been trained on a smaller dataset.Utilizing the ImageNet dataset, a sizable array of photographs of real-world objects, Kangchen Liu and Xiujun Zhang trained a pre-trained CNN dubbed Inception-V3 to perform their analysis. After that, a collection of leaf images with plant illnesses was used to fine-tune the Inception-V3 model.A potential new technique for detecting plant diseases from leaf photos is the PiTLiD method. Since it can be challenging to train a model from scratch on such short datasets, it is particularly helpful for plant diseases that have limited sample numbers.The PiTLiD approach has the following salient characteristics: 1. It is based on transfer learning, which makes training it more effective than approaches that do not use transfer learning. 2. It has been tested on several datasets using tiny samples, and the results have been promising. 3. It is a flexible technique that can be used to identify a range of plant diseases. Plant scientists and farmers can benefit greatly from the PiTLiD technique. Early detection of plant illnesses with this method is possible, aiding in the protection of crops and the reduction of disease transmission. This paper [7] discusses how to forecast and enhance various agricultural operations using IoT and machine learning methods. The farmer can choose from a variety of alternatives, including crop forecast, feedback on crop improvement, and plant disease detection. The farmer is provided with the sensors which can be used to regularly check values and receive recommendations. They discuss the different types of IoT sensors that can be used to collect data on soil conditions, weather conditions, and plant health, as well as the different types of ML algorithms that can be used to analyze this data and make predictions. The authors discuss the different applications of these technologies in precision agriculture and highlight the challenges and opportunities for their future use. Crop yield prediction uses IoT sensors to collect data on soil moisture, temperature, humidity, and other factors that affect crop yields. This data is then used by ML algorithms to predict crop yields for individual fields or even for entire farms. This information can help farmers to make better decisions about crop management, such as when to sow and harvest crops, and how much fertilizer and water to apply.Plant disease detection uses ML algorithms to analyze images of diseased and healthy plants to detect plant diseases early on. This can help farmers to take corrective action quickly and prevent the spread of disease. For example, if a farmer detects a plant disease early on, they can treat the affected plants before the disease spreads to other plants in the field.

III. METHODOLOGY

A. Working

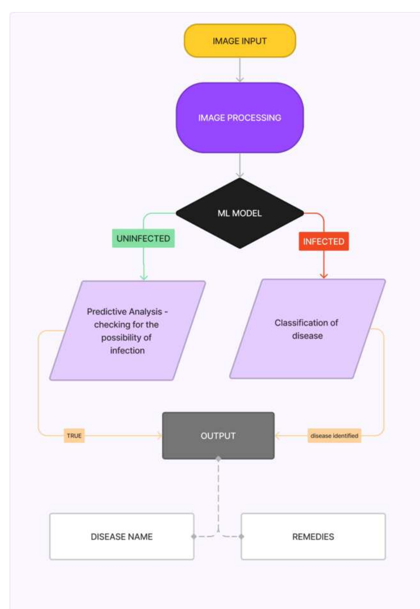

Fig. 3. Flow Chart for the Implemented Methodology

The basic flow of the entire process is illustrated in the fig:3. The proposed model takes an image as the input, does the required pre-processing and then processes the image using our ML algorithm. The ML model first classifies it as infected or uninfected. Then if it is classified as infected, displays the name of the specific disease, and provides information to any accessible treatments. And also to do a predictive analysis in case its classified as uninfected. The detailed description of the ML Model and its working is stated in the below paragraph. The decisions and outputs of each step were chosen after reviewing multiple papers [1] [2] [3] [4] [5] [6] [7] and multiple internal review sessions. This architecture is both simple and straight to the point. And is less likely to cause unwanted overheads when analysing the image.

B. ML Model

Our ML Model is based on the existing architecture [5] involving Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern as it promised a high accuracy as per our literature survey. The architecture is shown in fig.4.

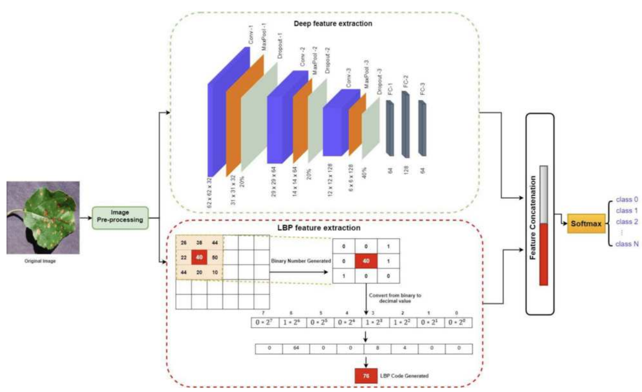

Fig. 4. CNN+LBP Architecture [5]

Here, the Deep CNN model will capture the deep features whereas the local binary pattern extracts the local texture information. Then, the extracted features are concatenated together before being fed into the FC layer. Classification is done using the Softmax activation function. After using picture pre-processing techniques such image filtering, image sharpening, and image scaling, the proposed model is fed input images that are 64 x 64 sized. The model consists of four dense (completely connected) layers, three convolutional layers with kernel sizes of 3 x 3 and 2 x 2, and three max-pooling layers. One of the most potent texture descriptors is known as local binary patterns (LBP). It is used to illustrate an image's regional characteristics, which are its focal points. A 3 x 3 pixel window is the definition of the traditional LBP operator. This window's center pixel serves as a threshold; if a surrounding pixel's value is less than the threshold value, the pixel is considered to be outside the window.

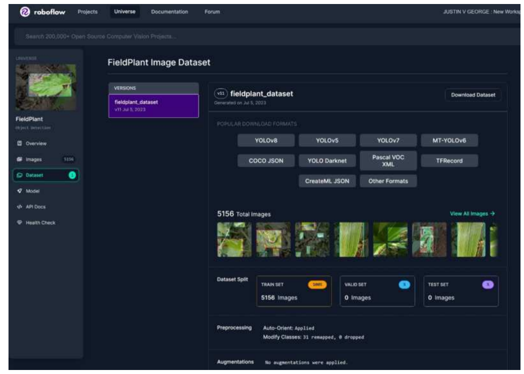

Fig. 5. FiledPlant dataset as available on Roboflow Website

C. Dataset Used

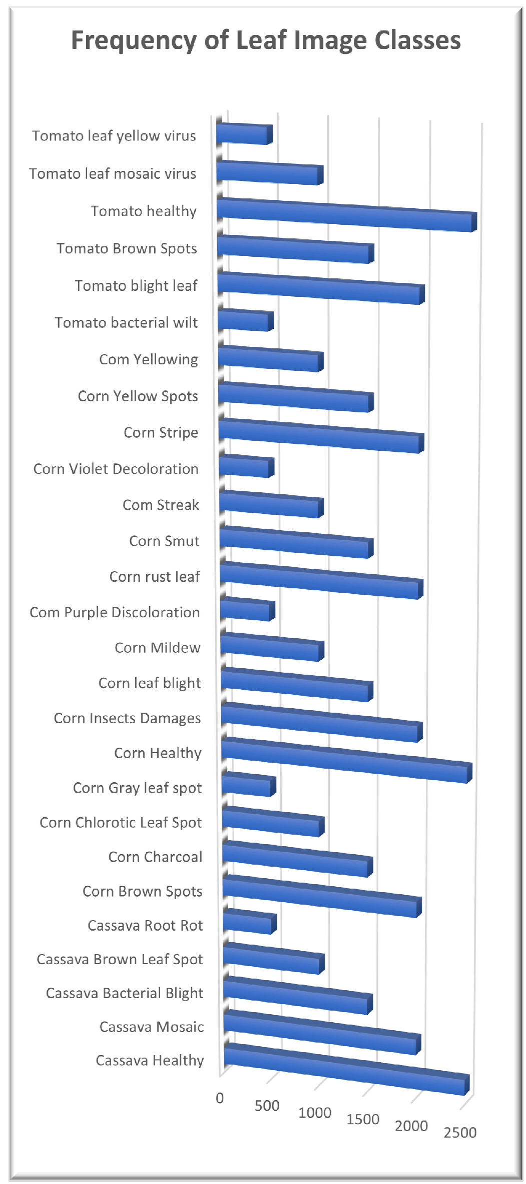

Fig. 6. Frequency of Image Classes in Field Plant Dataset [3]

- Name: FieldPlant Dataset
- It consists of 5170 annotated plant disease images collected directly from plantations , classified by expert pathologists for cassava , tomato , corn.
- The FieldPlant Dataset can be downloaded from RoboFlow Website .
- According to the paper [3] the dataset has 8,629 individual annotated leaves across the 27 disease classes The different varieties of the available plant images in FieldPlant are illustrated in the following fig :6

Fig. 7. FieldPlant dataset image sample

- The different diseases represented in the data set for cassava crops are as follow: Cassava Bacterial Disease, Cassava Brown Leaf Spot, Cassava Healthy, Cassava Mosaic and Cassava Root Rot.
- The different diseases represented in the data set for corn crops are: Corn Leaf Blight, Corn Brown Spots, Corn Gray Leaf Spot, Corn Charcoal, Corn Chlorotic Leaf

above mentioned model to classify the plant diseases of Cassava, Corn and tomato plants using their leaf images.
- In addition to the classification of disease, we developed our model to provide adequate information on the avail-

Spot, Corn Healthy, Corn Insects Damages, Corn Mildew, Corn Purple Discoloration, Corn Rust leaf, Corn Smut, Corn Streak, Corn Stripe, Corn Violet Decoloration, Corn Yellow Spots and Corn Yellowing.
- The different diseases represented in the data set for cassava crops are: Tomato Bacterial Wilt, Tomato Blight Leaf, Tomato Brown Spots, Tomato Healthy, Tomato Leaf Mosaic Virus, Tomato Leaf Yellow Virus.
- A sample illustration of some of the available images is shown in fig: 7.
- The Remedies to be displayed for the diseases were locally sourced and added to the data set before the training was done on our model.

D. Result Analysis

- An instance of a processed image is shown in Fig:8 .

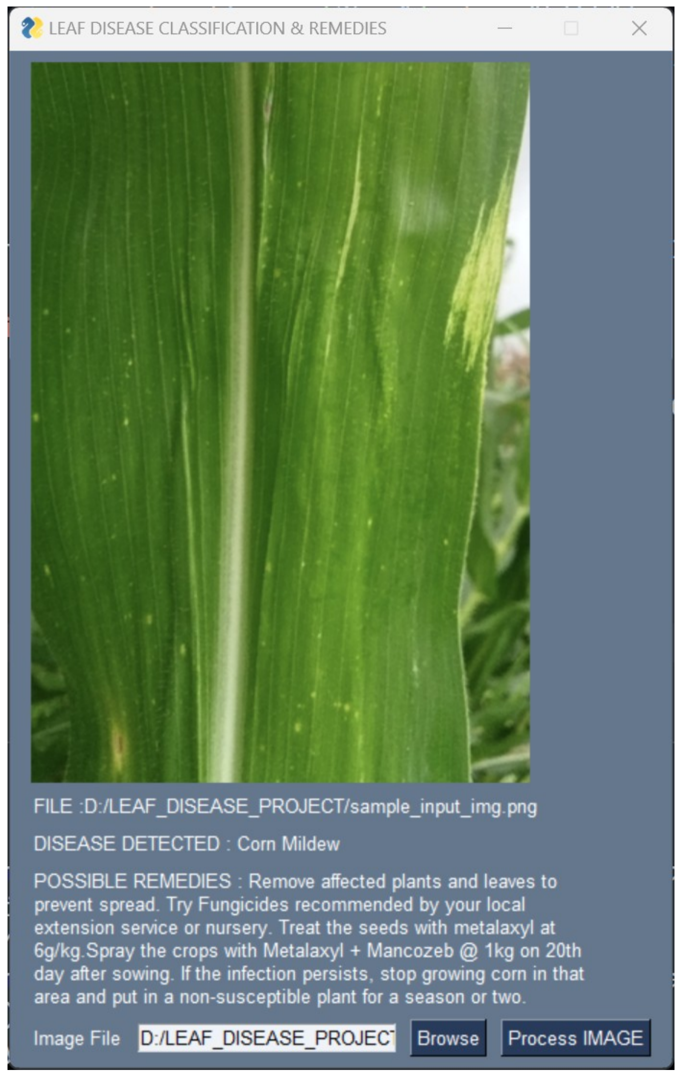

Fig. 8. Instance of a processed image

- The authors of this research paper conducted reasonable research on the related areas and came up with the

able remedies as well.
- By creating another lowered threshold value in the analysis, the authors were also able to provide a prediction system in their model, which in reality can benefit the agriculturalist in early detection of diseases, which in turn

lowers their net expense on mitigating of the disease.

- The model was trained using in-field images collected directly from plantation's and hence as per the research [3] will have better accuracy in comparison to similar models when fed with in-field images.
- The data set was divided into a 64:16:20 partition for the training, validation and testing purposes.
- It was noted that for the model the following end results were observed .

TABLE I
PERFORMANCE ANALYSIS

Model	Accuracy	Precision	Recall	F1 Score
Proposed model	97.0	96.9	96.5	96.7
VGG16	96.1	96.7	96.6	96.4
GoogleNet	96.5	96.2	96.5	96.4

The performance analysis listed in Table I was carried as per the standard valuation criteria as stated in (1),(2),(3),(4).

$$Accuracy = \frac{TP + FN}{TP + FP + FN + TN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\,Score = \frac{2TP}{2TP + FP + FN} \quad (4)$$

Where TP,TN,FP,FN stands for True Positive, True Negative, False Positive,False Negative respectively and are obtained from the overall confusion matrix values. It can also be noted that the proposed system has better performance values in comparison to the presently available systems.

- Both the CNN and LBP results are combined and depending on the output value the following scenario can occur.
- If it is classified as Infected by a disease, the model would output as "infected" and would display the name of the disease along with the available remedies that can be taken.
- if it is classified as Uninfected, then the model runs a predictive analysis to check for possible chances of infection, if so, the message : "a probable chance of disease" , along with disease name and remedies are given as output.
- if the predictive analysis also returns negative, model classifies it as uninfected.

IV. CONCLUSION

The model shows potential to be used in the real world for identifying plant diseases and their corresponding remedies, using leaf images as input. The model, having many implementation areas ranging from Mass agriculture to Home grown plants, from Laboratories to Research fields and many more; can help in easy mitigation of plant diseases, especially in places which lack experts in the field. Having a reasonably good accuracy in comparison to similar models, our model shows a promising potential for usage in real life situations. This is further backed up by the fact that our model is by far (as per our research) the only one that simultaneously gives remedial solutions for the identified disease ; which in reality is as crucial as the identification process in itself. Also , Since the model is trained using field plant dataset which has in-field images over laboratory images; the model has a better identification rate when fed with in-field images as well.

The research has shown promising advancement to detecting plant diseases using in-field images but the lack of more varieties of in-field images of other plant types dose impose a major limitation. Also the Effective yield of mixing laboratory images(single leaf infections with solid background) along with this dataset can be considered for future research. A through performance analysis of the same along with different newly developed techniques will surely benefit in decreasing plant loss in the near future.

V. ACKNOWLEDGEMENT

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