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Leaf Disease Detection Web Application Using Deep Learning

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Abstract- Agriculture is under serious threat, and this threat includes diseases that affect plant leaves. Our method pinpoints both the disease that affected the leaf and the region of damage. Both the quantity and quality of agricultural products are impacted by crop diseases, particularly those that primarily harm the leaves. The human eye's ability to see subtle differences in the diseased leaf area is not as strong as it should be. In this study, we provide an automated web-based system for classifying and diagnosing plant leaf diseases. We are using CNN model as a feature extractor and prediction model to swiftly categorise illnesses. Proper treatment can be provided by the study of disease. Along with this we have utilized the docker, POSTMAN API and TF serving server to make the system scalable and improve the working. This study is validated using the Plant Village dataset for plants like tomato and potato. The training and testing results indicate that the CNN model have a greater classification accuracy than the currently in use ANN model. The proposed approach could prove a useful tool for farmers and industry specialists to utilise when making decisions about crop management and disease control.

Keywords— Crop Disease, CNN Model, Docker, POSTMAN API, TF Serving Server, Classification Accuracy, ANN Model, Crop Management.

I. INTRODUCTION

India's economy is heavily reliant on agriculture. 70% of people work in agriculture and related industries. The goals of agricultural research are to increase output and get rid of plant and food diseases. Today's plant diseases are causing a lot of issues for farmers. Climate change and environmental pollution make plants more susceptible to a number of illnesses. Due to awareness of organic crops and food people have started growing crops in their home gardens and such places. The conventional means of disease management implicate farmers and the plant pathologists [1]. The diagnosis and use of the pesticide are more often done in the fields. This process is time-consuming, challenging, and most of the time results in incorrect diagnosis [1]. Because most foliar diseases have a similar form, size, and colour, the current approach is insufficient to identify illnesses in leaves.

The development of automated models enabling, accurate, and prompt diagnosis of the plant leaves disease has advanced with the introduction of Computer Vision (CV), Machine Learning (ML), and Artificial Intelligence (AI) technologies [3]. Due to the availability of several high-performance computer processors and devices during the past decade, AI and ML technologies have attracted enormous interest. It has been clear in recent years that Deep Learning (DL) has mostly been employed in agriculture.

In this era of research, a number of deep learning architectures have been proposed by various authors. Among these, CNN is one of the most popularly deployed deep learning models. CNN is inspired by the biological nervous and vision system. It is an unsupervised deep learning classification model having high classification and recognition accuracy [3]. This model possesses a complex structure as it constitutes large number of information processing layers. This multiple layer architecture differs it from the conventional Artificial Neural Networks (ANN's). Convolutional neural network (CNN), a popular method of target detection, has a wide application prospect in the field of crop disease detection [4]. Therefore, in this study we propose a Convolutional Neural Network (CNN) for classification of plant leaf disease. The performance of the model is validated on the images acquired from the Plant Village dataset.

II. LITERATURE SURVEY

[1] UDAY PRATAP SINGH et al, in Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease study proposes a multilayer convolution neural network (CNN) for the classification of mango leaves infected by anthracnose disease This work is validated on a real-time dataset captured at the Shri Mata Vaishno Devi University, Katra, JK, India consists of 1070 images of the Mango tree leaves. Dataset contains both healthy and infected leaf images. The results of the study demonstrate that the proposed method achieves high accuracy in classification and outperforms traditional machine learning approaches such as support vector machine (SVM) and decision tree (DT). The study shows that the proposed method can be used as an effective tool for the early detection and diagnosis of anthracnose disease in mango trees.

[2] PENG JIANG et al., in the paper Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks describes a deep learning method that uses enhanced convolutional neural networks (CNNs) to identify apple leaf diseases in real time. The suggested method makes use of a collection of images of apple leaves that have been pre-processed to reduce noise and improve contrast. The pre-processed dataset is then used to train an enhanced CNN model, which properly classifies the various apple leaf diseases. The suggested model successfully detects several apple leaf diseases with high accuracy and precision, making it a useful tool for real-time detection of these diseases in apple orchards. The paper also discusses the practical implementation of the proposed approach, including the use of a Raspberry Pi device to enable real-time detection in the field.

[3] MOBEEN AHMAD et al. in the paper Plant Disease Detection in Imbalanced Datasets Using Efficient Convolutional Neural Networks with Stepwise Transfer Learning proposes an approach for plant disease detection in imbalanced datasets using efficient convolutional neural networks (CNNs) with stepwise transfer learning. The proposed approach overcomes the issue by utilising a lightweight, effective CNN architecture that has less training parameter requirements. Additionally, a stepwise transfer learning strategy is used to transfer learned features from previously trained models to the new CNN architecture, enhancing performance and speeding up training. The proposed approach is examined using a number of unbalanced datasets. The article's conclusion is that the suggested approach offers a potential option for plant disease detection in unbalanced datasets, which is essential for efficient disease management and crop yield improvement.

[4] JUN SUN et al. in Northern Maize Leaf Blight Detection Under Complex Field Environment Based on Deep Learning proposes a deep learning-based approach for detecting northern maize leaf blight under complex field environments. A prevalent disease that damages maize crops and causes major economic losses is northern maize leaf blight. In the proposed approach, images taken in challenging field situations are used to automatically identify northern maize leaf blight. To improve the quality of the input photos, the system first performs pre-processing. Next, it employs a convolutional neural network (CNN) to extract features and identify diseases. A dataset of images of maize leaves taken in various environments is used to evaluate the suggested method, and the results show good accuracy in identifying northern maize leaf blight.

[5] RESHMI A.M et al. in Leaf Disease Detection using CNN discusses the use of image processing and a convolutional neural network (CNN) algorithm for leaf disease detection. The steps of implementation, which include dataset collection, training, segmentation, feature extraction, testing,

and classification, are described in the article. The suggested technique is capable of determining if a leaf is healthy or sick, and it can also pinpoint the specific illness, such as fungus, viruses, bacteria, black spots, powdery mildew, downy mildew, blight, and canker. The system also offers treatments for curing various illnesses. The system's accuracy is 99.5%. The paper focuses on the value of a large dataset for training and the effect of dataset quality on model performance. By identifying and halting crops diseases, the system can aid farmers and people in averting future losses.

[6] SAHANA UDAY NAIK et al. in Plant Disease Detection using Leaf Images describes the use of convolutional neural networks (CNN) to identify and categorise plant diseases in images of leaves. The suggested approach gets over this restriction by automatically learning features with CNNs. To improve the quality of the input photos and increase the model's accuracy, the system makes use of image pre-processing techniques such image scaling, normalisation, and data augmentation. The Plant Village dataset provides the foundation for the suggested technique. The system's uniqueness resides in its capacity to automatically identify and classify plant diseases from leaf photos, offering a quick and precise replacement for manual detection techniques that are frequently cumbersome and prone to mistakes.

[7] YANG ZHANG, et al. in Deep Learning-Based Object Detection Improvement for Tomato Disease describes Deep Learning- Based Object Detection Improvement for Tomato Disease, they improved the anchoring according to the clustering results. They improved anchor frame tends toward the real bounding box of the dataset. Finally, they carried out a k-means experiment with three kinds of different feature extraction networks. The experimental results showed that the improved method for crop leaf disease detection had 2.71 percentage higher recognition accuracy and a faster detection speed than the ANN model. Finally, the authors discuss some of the challenges and future directions for research including the need for more diverse and comprehensive datasets, the development of more efficient and accurate algorithms, and the integration of other sources of information such as weather and soil data to improve the accuracy of disease diagnosis.

Author	Network used	Plant name	Disease	Dataset	Accuracy	Advancement
UDAY PRATAP SINGH et al. in [1]	CNN	Mango	Anthracnose	Mango leaves and PlantVillage	97.13%	To develop an appropriate and effective method for diagnosis of the disease and its symptoms
PENG JIANG et al. in [2]	INAR-SSD	Apple	Multiple	Apple leaf disease dataset (ALDD)	78.80%	Real-Time Detection of Apple Leaf Diseases
MOBEEN AHMAD et al. in [3]	CNN	Pepper crop	Multiple	Plant Village	99.53%	Plant Disease Detection using CNN With Stepwise Transfer Learning

JUN SUN et al. in [4]	CNN	MAIZE	Maize Leaf Blight	NLB	91.83%	Maize Leaf Blight disease detection in real time
RESHMI A.M et al. in [5]	CNN	Multiple	Multiple	Leaf	99.5%	Automatic leaf disease identification model
SAHANA UDAY NAIK et al. in [6]	CNN	Multiple	Multiple	Plant Village	97%	Detection of non-real time plant diseases
YANG ZHANG et al. in [7]	RCNN	Tomato	Multiple	AI Challenger	98.54%	Make use of the Faster RCNN algorithm to detect diseased tomato leaves and used ResNet101 in place of VGG16.

III. PROPOSED METHODOLOGY

In our Proposed System "Web-Based Application for Plant Leaf Disease Detection," the input is an image, uploaded from either mobile or PC. The application is intended for all types of user weather it be a farmer or a person interested in plants. This paper proposes a Convolutional Neural Network-inspired method for identification of plant leaves diseases. The model is trained and tested for potato, tomato and bell pepper plant leaves. The training and testing were successful, and we achieved a good accuracy that is shown in the further part of the paper. A multilayer CNN model is implemented for better results and a user-friendly UI is also made available. The application is developed by using ReactJS and POSTMAN API is also used in the system. We tried to use the most suitable technology for the application so that the product can be tested with other application similar to it. The CNN model being the base for detection we have made the UI more refined and user-friendly and added features where users can get information about the plants and increase their knowledge base in the same domain.

A. System Architecture

The system architecture leverages the Postman API, Docker containerization, a CNN model, and TensorFlow serving to create a scalable and efficient solution for analyzing taking an input image, sending through a Postman API to the model, processing the image using a CNN model hosted within a Docker container, and generating a result to determine if the image is classified as healthy or not healthy. This modular and flexible architecture enables seamless integration of the different components and facilitates the processing and classification of images in a robust and reliable manner.

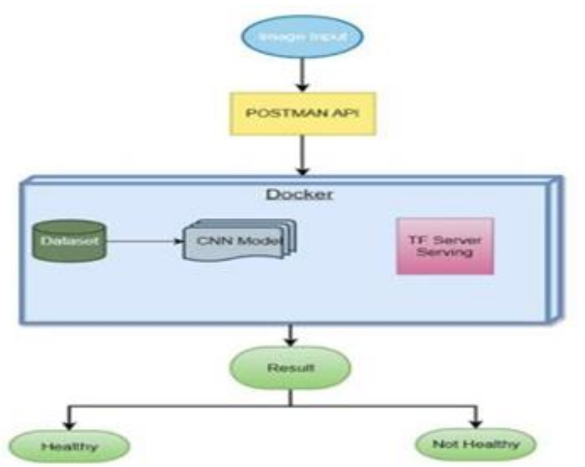

Fig. A System Architecture The system architecture consists of the following components:

1. Front-end Website:
Users can interact with the system using the front-end website's user interface. The website allows users to upload plant images for disease diagnosis. It is designed using ReactJS.

2. The Postman API:
The TensorFlow Serving server and the front-end website are connected using the Postman API. It enables exchange of information between the server and the website, enabling the sending and receiving of requests and answers.

3. TensorFlow tf Serving:
In order to provide a scalable and effective serving infrastructure for machine learning models, TensorFlow Serving is deployed as a Docker container. It keeps the Convolutional Neural Network (CNN) model that has been trained and offers an API endpoint for forecasting fresh plant photos.

4. Trained CNN Model:
Identifying plant diseases is the responsibility of the trained CNN model. It has been taught to recognise patterns and traits linked to various diseases using a collection of plant picture data. The algorithm analyses input photos and generates predictions indicating whether or not the plants are infected.

5. Plant Dataset:
The training data for the CNN model comes from the plant dataset, here we have used Plant Village Dataset. It includes examples of both healthy plants and plants with various diseases, as well as a collection of labelled photos. The CNN model is trained using the dataset, allowing it to discover and generalise patterns for disease detection.

B. Flow Structure of Model
The flow structure of the model involves acquiring images, pre-processing them to enhance their quality, assigning class labels to represent their content, and then splitting the dataset into training and testing subsets for training and evaluation purposes, respectively.

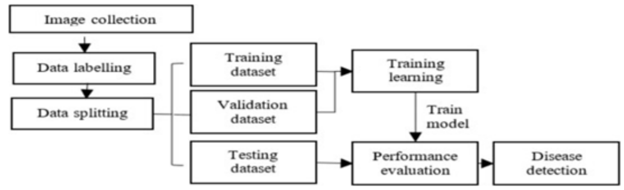

Fig. 1 Flow Structure of Model

1. Image Acquisition: Leaf is captured through high resolution camera. Image will be in the form of RGB (Red, Green, Blue) form. To improve the precision of the disease detection and classification process, device dependent colour space is required. The procedure includes obtaining pictures from any equipment sources or from any database. This is the initial phase in the process of image processing. The obtained image is in RGB format. It is not always possible to get huge amounts of images for a specific crop disease pair. This data shortage problem and class imbalance problem are addressed by using data augmentation techniques which can make CNNs able to learn representative features of disease classes [3].

2. Pre-processing: We scaled the images to the required size before feeding them to the network. We normalized the picture pixel value as well in order to enhance model performance (keeping them in range 0 and 1 by dividing by 256). Both during training and inference, this occurs. In order to account for this, we added a layer to our sequential model. To improve the quality and quantity of data, data augmentation is carried out. Cleaning data is one of the processes of a data model, which is essential for high-accuracy models. However, the model cannot make accurate predictions for inputs from the real world if cleaning decreases the representability of the data. The overfitting problem in the training stage of CNNs can be overcome via data augmentation. The overfitting problem occurs when random noise or errors, rather than the underlying relationship, are described [2].

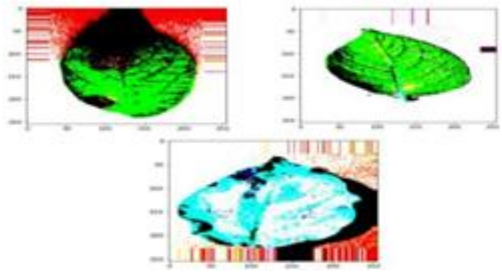

Fig. 2 Image Preprocessing

3. Dataset: The database repositories have been employed in the proposed work; the plantVillage dataset repository, which contains leaves from various plants.

These images have been split into two groups: plant leaves that had the disease and plant leaves that didn't. These images are assigned to their relevant classes according to the category. PlantVillage dataset is a public dataset containing 38 crop disease pairs. In total there are 14 crops with 26 disease classes and 14 healthy plant classes [3]. The purpose of using a publicly available dataset was to evaluate our system for comparative analysis with other existing methods [3]. The example dataset depicted in Fig. 3 is made up of pictures acquired from the plantVillage dataset.

Fig. 3 Sample of images

4. Convolutional Neural Network: Deep learning-related applications have seen exponential growth due to the advent of computationally efficient hardware like the Graphics Processing Unit (GPU). Deep learning has the advantage of directly extracting classification features [7]. The traditional artificial neural network is what inspired the notion of deep learning. The number of pre-processing layers in the deep learning model is stacked, and they are used to extract information from the initial raw input to the final output that is task specific to the job at hand. The deep learning model utilised for difficult pattern recognition and classification issues with a large number of datasets is a convolutional neural network. Convolution Neural Network is a Feedforward Neural network, which is always better in the field of image recognition. Networks consists of three layers i.e., convolution layers, pooling layers, and fully connected layers [7]. The architecture's ability to configure itself based on task-related findings is what makes it innovative. There are several CNN models available, including AlexNet, VGG, GoogLeNet, ResNet, and others. The depth, configurations, nonlinear function, and number of units of these models vary. In

the proposed method we have used different layers and activation.

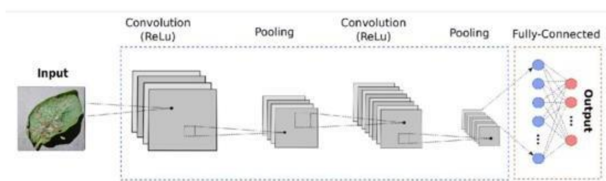

Fig. 4 Convolutional Neural Network

5. Training and Testing: The complete dataset is initially split into the training, testing, and validation datasets. This is accomplished by randomly dividing the dataset into training (80%) and testing and validation (10% each) sets. Most neural network applications employ this ratio distribution.

Running training examples through a CNN from the input layer to the output layer while generating a prediction and analysing the outcomes or mistakes is known as training a CNN. If the prediction is inaccurate, the error is back-propagated from the topmost layer to the bottommost layer in reverse order. In order to improve the outcome, we employ the backpropagation technique to slightly modify the weights of the network. This entire process is regarded as one epoch.

In this study, the stochastic gradient descent approach is used for optimizing the weights. The proposed ternary classification model based on convolutional neural networks is then trained for the detection and classification of plant leaves such as potato and tomato. This ternary model has three scenarios:

a) Classifying the provided picture as a plant leaf or not.
b) Classifying the image as a healthy plant leaf.
c) Classifying the image as a sick plant leaf.

Each class label's training images were acquired while keeping an image ratio of 80%. All of the other 20% of the images remained unmodified throughout the whole process. The Convolution Neural network model receives each image from the normalised training dataset as an input to extract the features. Every training image's class label is predicted by this model.

The results of testing came out to be positive. The accuracy achieved by the system after 1st phase of training was 98%. The sample images used for training purpose are depicted in the following figure.

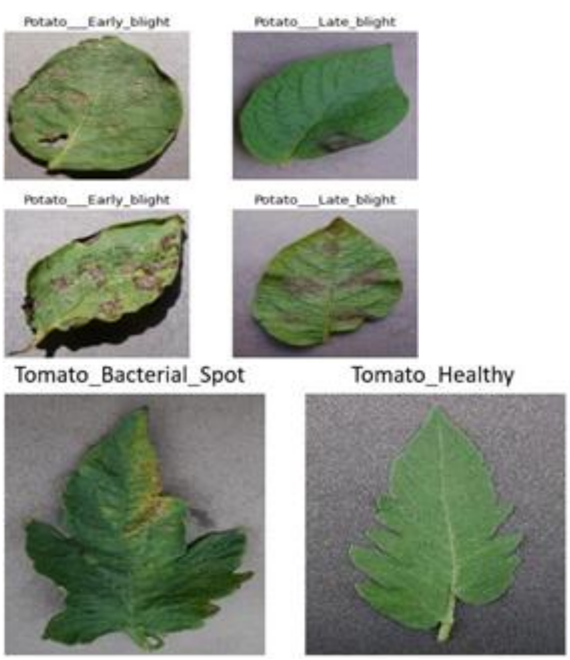

Fig. 5 Sample images for training model

6. Experimental Results: The proposed model's training and testing procedures were put into practice making use of the Python programming language and the TensorFlow open-source software framework. The testing and training were carried out on Jupyter Notebook. While doing so 100 epochs were used and the results obtained were as shown in the following figure.

Fig. 6 Experimental results The results of the proposed methodology mainly focus on:

- Primary task is to identify the leaf image is of which plant.
- Second task is to check whether the image is of diseased leaf or not.
- If the image is having disease, then predict which disease it is and give proper cure for the disease.
- If the image is found to be healthy, then give response as healthy.
- The figure 6 also shows the accuracy of the testing of disease prediction model. The overall accuracy is calculated to be 98.44% as shown in the figure 7.

Testing the Model

```
In [25]: print("[INFO] Calculating model accuracy")
         scores = model.evaluate(test_ds)
         print(f"Test Accuracy: {round(scores[1],4)*100}%")

[INFO] Calculating model accuracy
8/8 [==============================] - 1s 15ms/step - loss: 0.0519 - accuracy: 0.9844
Test Accuracy: 98.44000000000001%
```

Fig. 7 Accuracy of the model

Along with the accuracy we have plotted the graphs for training and validation accuracy and training and validation loss. In the accuracy graph the training accuracy is found to be increasing along with the validation accuracy. The training and validation loss graph showed decrease in the loss in the later phase.

C. Overview of system

The below diagram is the overview of the system. The system comprises of the component's as shown in the figure. These components work in unison to produce the desired result. The input is taken in the form of image. The image is given to the model with the use of API and the trained model use the Plant

Village dataset to give the output.The TensorFlow Serving framework hosts the trained CNN model, which uses a plant dataset for training. The result of the system is the classification of the plant in the input image as either healthy or diseased.

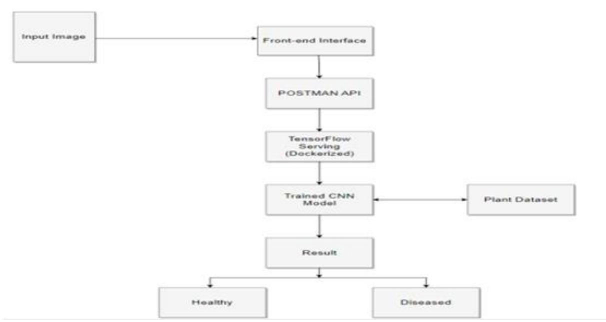

Fig. 8 Overview of system

The overview of the system can be described as follows:

1. Input Image: The system takes an input image as its main input. This image represents a plant that needs to be classified as either healthy or diseased based on its visual characteristics.
2. Front-end Interface: The front-end interface is the user-facing part of the system where users can interact with the application. It provides a user-friendly way to upload the input image and initiate the classification process.
3. Postman API: Postman is a popular API development and testing tool. In this system, it is used to handle the communication between the front-end interface and the TensorFlow Serving API.
4. TensorFlow Serving: TensorFlow Serving is a framework for serving machine learning models in production. It allows you to deploy trained models and provides an interface to make predictions or inferences using those models. In this system, TensorFlow Serving is used to host the trained Convolutional Neural Network (CNN) model.
5. Trained CNN Model: The CNN model is a deep learning model that has been trained on a plant dataset. The model has learned to recognize visual patterns and features associated with healthy and diseased plants. It takes an image as input and produces a prediction indicating whether the plant is healthy or diseased.
6. Plant Dataset: The plant dataset is a collection of labeled images of plants, where each image is associated with a class label indicating whether the plant is healthy or diseased. This dataset is used to train the CNN model, allowing it to learn the distinguishing features of healthy and diseased plants.
7. Result (Healthy or Diseased): The final output of the system is the classification result for the input image. Based on the trained CNN model's prediction, the system determines whether the plant in the image is healthy or diseased. This result can be displayed to the user through the front-end interface, providing valuable information about the plant's health status.

D. Testing of the User Interface:

The UI is designed using React. The UI is easy to use interface where we can insert image for disease detection. The user just needs to either drag or drop image or select image from any file available. The user gets the output along with the confidence level.

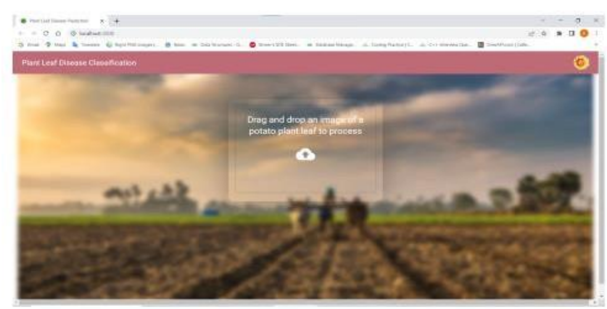

Fig: 9 UI to give input image

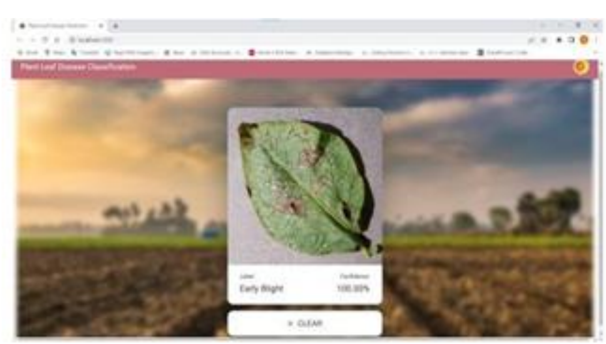

Fig: 10 UI showing output

IV. CONCLUSION AND FUTURE WORK

In this study, the convolutional neural network was used to identify diseases in tomato and potato leaves. Crop protection in agriculture is a difficult endeavour that requires in-depth knowledge of the crop being farmed and any pests. The issue of manual non-real-time plant leaf disease detection is addressed by the application that was created. The experiment shows how CNN is used to identify plant diseases in artificial environments. The test shows that CNN achieved 98% accuracy while operating outside of real time. To identify plant diseases and its treatments, CNN and leaf images are employed.

The proposed approach combined several phases, such as data preparation, data augmentation, and disease detection. Data pre-processing was primarily done to increase detection precision and lessen the impact of high-intensity light on picture identification. By adding new instances for underrepresented classes, data augmentation was utilised to combat overfitting and balance the dataset, enhancing the model's overall performance. The model used for this study proved helpful in identifying leaf disease. The disease detection model might take the role of on- site identification by human specialists since it was effective and accurate. It might lessen labour while removing the subjective nature of feature selection. This technique may be improved even more by using alternative algorithmic pairs to identify plant diseases more precisely. In the future, we may work with additional economically significant plants and determine the disease's severity while also taking other plant components into account.

V. ACKNOWLEDGEMENT

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