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# AI-Powered Plant Disease Diagnosis via Mobile App for Smarter Farming

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***Abstract—*** *Plant diseases significantly reduce the quality and quantity of food, fiber, and biofuel crops, posing a serious challenge as agriculture strives to meet the demands of a rapidly growing global population. Both commercial farmers and hobbyist gardeners face increasing concerns about the health of their plants due to these diseases. Moreover, many regions lack access to agricultural testing facilities or experts who can diagnose and treat plant diseases. To address this issue, we propose a solution that allows users with smartphones and WhatsApp to take images of affected plant areas and send them to a WhatsApp Bot. The bot responds with segmented images highlighting the diseased regions, alongside the disease type and its probability. This system utilizes HSV Filtering, MobilenetV2, and YoloV8 algorithms for disease detection, providing accurate and reliable results. Instance segmentation is implemented to identify multiple diseases on a single plant part. With an accuracy of 95.66% for the classification model and a MAP of 0.756 for segmentation, this system enables easy and accessible plant disease diagnosis. By eliminating the need for physical visits to agricultural centers, this solution promotes early detection and treatment of plant diseases at no extra cost, offering significant convenience to farmers.*
***Keywords—*** *Plant Disease Detection, Neural Network, Yolo, CNN, HSV Filtering, Instance Segmentation, Classification*

## INTRODUCTION

Agriculture is the practice that laid the foundation for civilization. Agriculture is the practice of cultivating natural resources to provide a livelihood for people and to support human life. Agriculture is another type of industry that contributes to the global economy by supplying it with commodities. Commodities are fundamental products that are traded commercially and include things like grain, livestock, dairy products, fiber, and raw materials for fuel. It makes raw materials available, helps establish a supply chain, and promotes economic health and growth.

Plant diseases affect the amount and quality of food, fiber, and biofuel crops produced as agriculture tries to feed the world's constantly expanding population. Even though losses can be catastrophic or recurring, they typically account for 42% of the production of the six crops that are regarded as the most essential [1]. Losses incurred after the harvest can be significant, particularly in cases where farms are located in remote areas, and where insufficient infrastructure and supply chain management are present. Plant infections are caused by bacteria, viruses, fungi, nematodes, parasitic higher plants, and various environmental factors. Both

biological and environmental factors can play a role in the development of plant diseases. The term "biotic plant disease" refers to an affliction of plants that is brought on by the presence of any living organism. These conditions can be further broken down into the categories of bacterial disease, fungal disease, viral disease, and insect attack [2].
Alterations in the environment, such as weather, inadequate moisture, chemical substances, freezing or very hot temperatures, soil pH, soil type, soil moisture, and other factors, can lead to the development of certain diseases. Food grains like rice, wheat, and soybeans, as well as cash crops like cotton and peanuts, are susceptible to diseases caused by fungi and bacteria. One of the most common biotic plant diseases is a fungus, which causes infection in other plants and leaves when the fungus's pores come into contact with those of other plants or leaves. It may spread through the air, on insects, in water, through direct contact, and in other ways as well [3]. Other plant diseases, such as viruses and bacteria, play an equally important role. Some of the most common signs of plant disease include leaf rust, stem rust, Sclerotinia, powdery mildew, birds-eye spot on berries, damping of seedlings, leaf spot, chlorosis, European corn borer, boll weevil, leaf cankers, leaf rots, mosaic virus, and so on. Other symptoms include leaf cankers, leaf rots, and mosaic virus.
Numerous infections can be found after harvest that also release poisons that can be extremely hazardous to the health of consumers. The management of diseases costs farmers billions of dollars annually, and yet they frequently do not receive sufficient levels of technical support [4]. This leads to unintended consequences such as contamination and inadequate disease control. In addition, plant diseases have the capability of obliterating natural ecosystems, which exacerbates the environmental problems that are brought on by the destruction of habitat and improper management of land.
Plant disease management has various challenges associated with it. Some of them are (i) the need to feed the increasing population. Crops are under huge strain to satisfy the needs of the growing community. (ii) With the industries and other projects coming up, fertile lands are being replaced and fertile croplands are reduced severely. (iii) Global warming, calamities, greenhouse effect have changed the weather patterns. These have deteriorated the suitable climatic conditions and depleted the natural resources suitable for plant growth. Plant disease management should improve food security for a stable society while protecting ecosystems and minimizing natural resource dependence. As an initial step, we need to identify the diseased part of the plant, the disease it is suffering from, the causes, and the remedial measures we need to take to protect and prevent the disease.
There are methods such as SVM classifier, K means clustering, and similar to resolve the issue addressed in the problem statement [5]. However, these methods fail to predict more than one disease from a single image. We propose a method that involves the use of instance segmentation, that not only predicts both diseases but also segments the diseased area separately so that the farmer can easily identify both.

## RELATED WORK

Arunangshu Pal, et al discussed the Agriculture Detection (AgriDet) framework that incorporates conventional INCVGGN and Kohonen-based deep learning networks to detect plant diseases and classify the severity level of diseased plants [6]. SivaSivasubramaniam Janarthan, et al thought of a simplified version of the MobileNetV2 architecture is proposed as the embedding module, and an empirical method, of constrained K-Means clustering [7]. Design DoubleGAN for generating plant leaves to expand the data set and evaluate the utility of generated leaves by classification accuracy [8]. Amal Mathew, et al advised a method of SVM classifier which was replaced with a voting classifier. The research lacked detail and basic evaluation metrics were used [9]. Ruchi Gajjar, et used Deep CNN and implemented it on an Nvidia Jetson development board 20 classes were analysed using the algorithm with an accuracy of 96.8%. [10] Shima Ramesh, et al decided to use the Random Forest classifier, the model was trained using 160 images of papaya leaves. The model could classify with approximately 70 percent accuracy [11]. Kapilya Gangadhar, et al propose that disease analysis is more visible on the leaves than on other parts, so automated methods in image processing techniques are required. Two fungal diseases were investigated for identification. Back Propagation Neural Network Classifier and KNN performed better than other algorithms [12]. Houda Orchi et al say that only early automated detection can reduce plant disease severity. Four machine learning algorithms were used, out of which the decision tree algorithm achieved the highest accuracy after 10 cross-validations [13]. Vijai Singh, Namita Sharma, et al discuss how to provide effective measures for the detection and avoidance of plant destruction, the type of plant disease present must be identified early. In this paper, SVM, K-means clustering, Deep learning, and KNN are the main techniques for the early detection and classification of plant diseases [14]. Murk Cho-han, et al in their paper say that we need to identify plant diseases and treat it soon as possible involving the entire planet. On publicly available datasets, the system he proposed achieved an overall testing accuracy of 98%. Based on the accuracy, it was found that CNN is highly suitable for the automatic detection and diagnosis of plants [15]. Prashant Udawant, et al use the object detection algorithm i.e. Mask RCNN and transfer learning to detect the cotton leaf disease. The methods and algorithms used in this paper are Detection, Instance Segmentation, Mask RCNN, Object Detection, and Transfer Learning [16]. Narmadha R.P, et al developed a Deep Learning based rice plant disease diagnosis using Densely Convolution Neural Network (DenseNet) with multilayer perceptron (MLP), called DenseNet169- MLP. The model achieves a very high level of accuracy overall and divides the rice plant disease into three classes: Bacterial Leaf Blight, Brown Spot, and Leaf Smut [17]. Amritha Haridasan, et al in their paper discusses..0 five primary diseases of paddy plants. These diseases were examined, and the proposed approach reveals that softmax along the ReLU (rectified linear unit) function and the PReLU (Parametric Rectified Linear Unit) function provides better accuracy [18]. Koushik Nagasubra manian, et al talk about how plant diseases have a negative potential worldwide and as a result how we must forecast and control disease outbreaks while also developing disease-resistant soybean varieties of economic importance. From the model, it was found that the classification accuracy of 3D DCNN is 95.73%, with an F1-score of 0.87. It was seen that the pixel places of disease symptoms use a saliency map and that in the infrared range, the wavelengths were the most sensitive [19]. Hadi Hosseini and colleagues describe the harm that the fungi Powdery Mildew and Anthracnose do to cucumber greenhouses. This paper develops a non-destructive method for finding these two types of fungal diseases using an image processing technique and an artificial neural network. RGB images of cucumber leaves, 257 of Powdery mildew and Anthracnose, and one healthy 258-leaflet group, were studied. In 6 seconds, an artificial neural network and LM training function achieved an accuracy of 99.95% [20]. Wilian Ramalho Feitosa, et al talk about how the Brazilian Ministry of Agriculture, Livestock, and Supply (MAPA), is faced with constant email and, phone calls, and the need to provide face-to-face interaction with users who have doubts about their plants. To minimize this load, a chatbot was proposed. The method involved creating a virtual platform to exchange messages between user and machine, processing the queries, and lastly responding from the knowledge base. Users found it easier to ask the doubts via chatbot than other methods. It also serves as a medium to share information on plant health [21]. Jun Liu et al in their paper discuss how plant pests and diseases have a significant impact on plant yield and quality. Plants must be protected from disease to be protected and this identification can be accomplished through digital image processing. It was discovered that deep learning algorithms are better than traditional methods. A deep separable fully connected layered structure for the detection of plant leaf diseases is introduced to improve the efficiency of the model [22].

## PROPOSED METHODOLOGY

We propose an idea for plant disease segmentation on an affected plant part. That can be a leaf, stem, fruit, or flower. The existing works on plant disease detection are based on Convolutional Neural Networks which can only classify the kind of disease it has. In such problems, only one disease can be found on a plant while in practical cases, there can be more than one disease for one plant. Detecting these is not possible for the current set of algorithms as these presently available algorithms, fail to detect if more than one disease is present in the plant. The algorithmic flow of the program is given in Fig 1.

An architecture of instance segmentation to take out the diseased plant images and then inspect them along with existing implementation to improve the accuracy of the prediction is proposed in this paper. The disease detection model is based on WhatsApp chats which is a very widespread technology and almost everyone today has it installed on their phone. The user or the farmer takes a picture of their diseased plant using their smartphone. The picture that is taken and sent goes through the server. The API for WhatsApp integration takes in the plant image and then it is forwarded to the Python script for further processing. At this stage, the algorithm splits up into three separate algorithms, each of which runs as a separate thread.

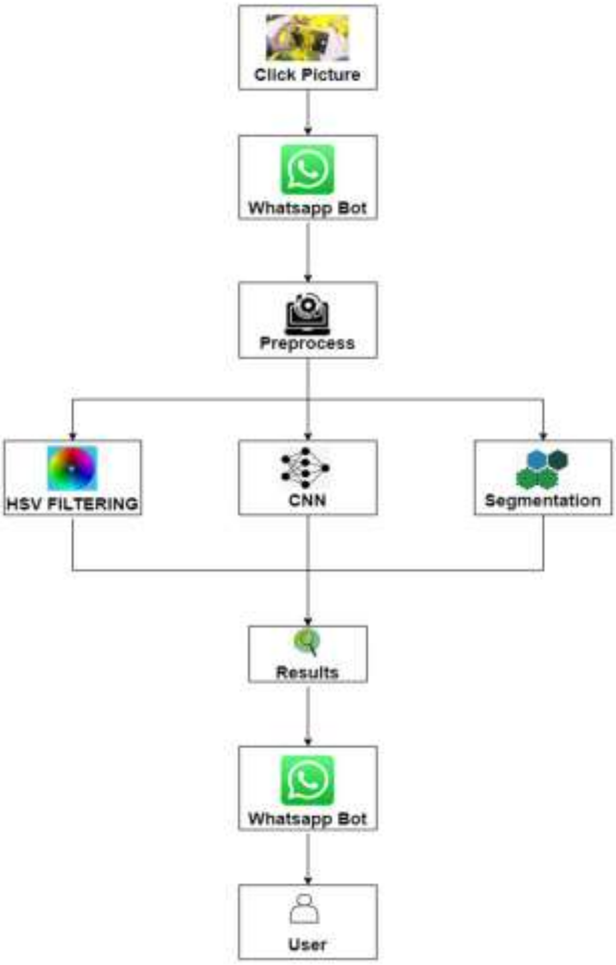



Fig 1: Flow Diagram

The first thread picks the image and then uses HSV filtering to get rid of the part of the plant that is sick or damaged. HSV filtering is based on hue saturation value. This is in other words referred to as colour filtering. We perform HSV filtering, by first loading the images, and then defining the ranges of hue for the diseases, after which we separate the healthy part from the diseased. We can see the healthy and diseased leaves based on filtering. It can visualize both the parts of the plant that are sick and the healthy parts. The user is sent the percentage of disease in that element so he can keep track of it.

The second thread fits the image into a mobilenet model which is a lightweight computer vision model capable of classifying images faster and more accurately than traditional CNNs [23]. A total of 5 classes of leaves namely bacterial, fungal, healthy, parasitic and viral are used as input from the tomato disease dataset for training the model.

The third thread fits the image into a YoloV8 instance segmentation model that is custom-trained on the images from the tomato disease dataset of PlantVillage[24]. The multiclass model with four classes namely bacterial, fungal, parasitic, and viral segments the diseased part in the plant and then classifies it making it capable of finding more than one disease in an image rather than the traditional classification approach. The specified three approaches return the results in different formats and types making it difficult to create an ensemble model hence they are separately considered for deriving the conclusion on the plant disease. The hsv filtering approach visualizes the diseased part and the rest which gives a sense of what fraction of the plant is diseased. The mobilenet model classifies the image and returns the predicted class of disease from the total 5 classes. The CNN- based approach being a more widespread and accepted approach for plant disease detection, gives more sense to the user on what disease is affected on the plant. The chances of confusion still pertain in terms of multiple diseases on the same plant, hence a multiclass model for segmenting and visualizing multiple diseases in the plant is used. All these results are sent to

the user to make sure that diseases are not missed because of the wrong prediction of the disease or bugs in the model.
The novelty of the idea is the instance segmentation done over the plant image, the use of lightweight models for classification for processing efficiency, and a mathematical model for filtering the healthy part based on a predefined green pixel threshold and this creates the requirement for relabelling of the images. The instance segmentation datasets are unavailable creating the requirement for manual labeling of a handpicked image set from PlantVillage.

## RESULTS AND DISCUSSION

The CNN and the Mask-RCNN models are trained using the collected dataset. There was no dataset containing the labels for YoloV8 instance segmentation, so that was created for selected images from the PlantVillage dataset. HSV filtering uses math to filter out pixels falling under a range of HSV values for which it is assumed that the plant part is always green and any deviation from it is a disease.

### *A. HSV Filtering*

The image is cleaned and cropped to get the plant part by removing all the noises in and around the captured picture for better processing. From the leaf image, all pixels falling in the HSV range from (36, 25, 25) to (70, 255,255) are masked and labeled as the healthy part. Anything outside the range is considered unhealthy which can be dried off either because of natural causes or by some disease. Fig 2 shows the processing of the image using this technique. From the input image given in Fig 2a, the range is masked and for the user to easily observe, the masks are replaced with their original pixels and Fig 2b is obtained. The ones outside this range are masked by inverting the mask and Fig 2c is obtained by replacing those mask values.

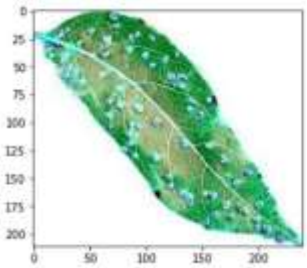



Fig 2a: Sample Input

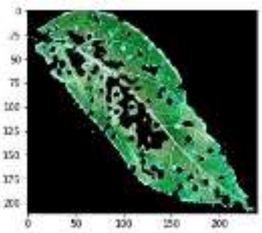


Fig 2b: Healthy Part

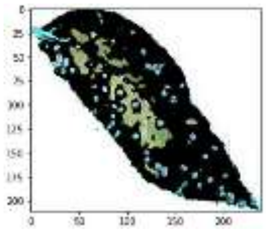
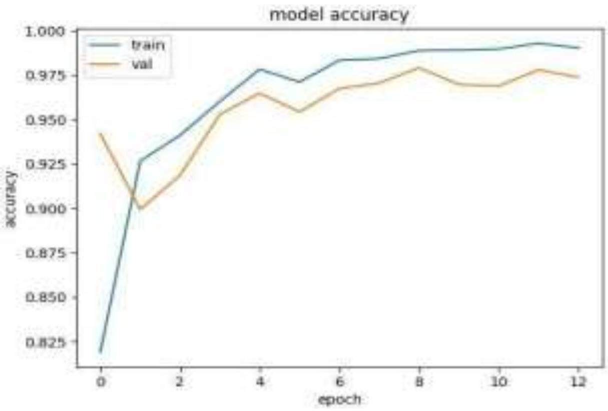


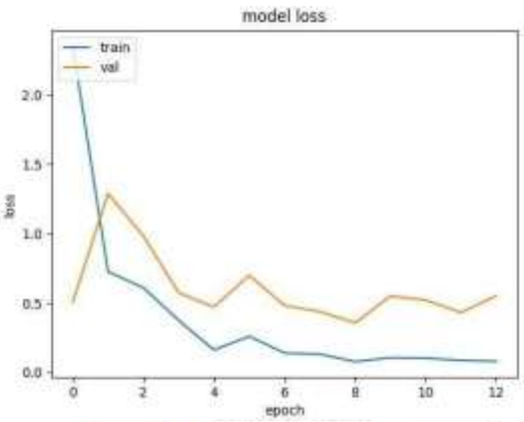
Fig 2c: Diseased Part Fig 2: HSV Filtering process

### *B. Image Classification*

A mobilenet_v2 model was trained on a handpicked dataset derived from the PlantVillage dataset on 5 different classes bacterial, fungal, healthy, parasitic, and viral as mentioned in the above section. A total of 5000 images equally distributed on all 5 classes which were split in the ratio of 8:2 to train and test showed an accuracy of 95.66%, recall of 94.65%, and precision value of 95.19% on the test dataset. The model accuracy plot given in Fig 3 and the model loss plot in Fig 4 show the accuracy and loss of the train and validation sets for all the epochs in the training phase. The confusion matrix in Fig 5 shows that the classification is very good with a very high number of True positives. Fig 6 shows the predicted leaf diseases

from the classification model.
Fig 3: Model Accuracy Plot



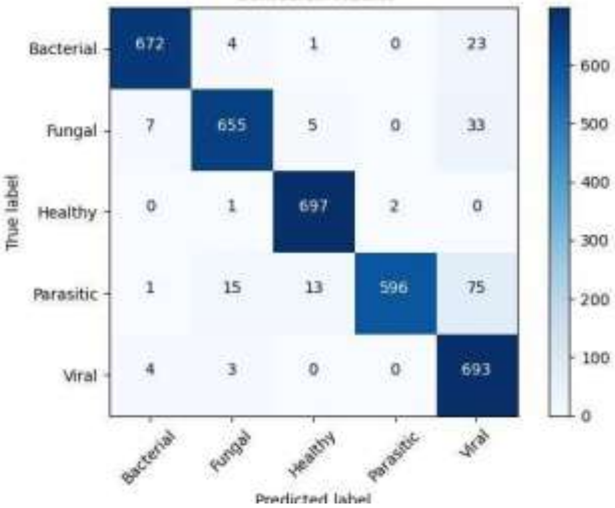




Fig 5: Classification Confusion Matrix



Fig 6a: Bacterial Leaf Fig 6b: Fungal Leaf



Fig 6c: Healthy Leaf Fig 6d: Healthy Leaf



Fig 6e: Parasitic Leaf

Fig 6f: Viral Leaf Fig 6: Classification Results of the mobilenet model

### *C. Instance Segmentation*

The technique of instance segmentation is applied to find the diseased area in plants using a multiclass state-of-the-art Yolov8 segmentation model which is trained over the dataset mentioned above containing a total of 400 images, which was split in the ratio of 8:2 to the train and test dataset. The F1- Confidence plot in Fig 7 shows that the optimal performance can be obtained at a confidence of 0.595 confidence when the f1 score value is 0.76. Considering the Precision-Recall Curve in Fig 8, all classes show that the model performance is quite impressive with the parasitic and viral classes showing nearly perfect behavior. While the bacterial and fungal shows average performance. The model has 0.756 mAP @ 0.5. The confusion Matrix on the test dataset given in Fig 9 shows that the model shows a very good performance in the detection of viral and parasitic diseases. The model showed a test accuracy of 94.65% on the test dataset. A few sample output images from the instance segmentation model with the segmented part, bounding boxes, classes, and confidence score can be seen in Fig 10.

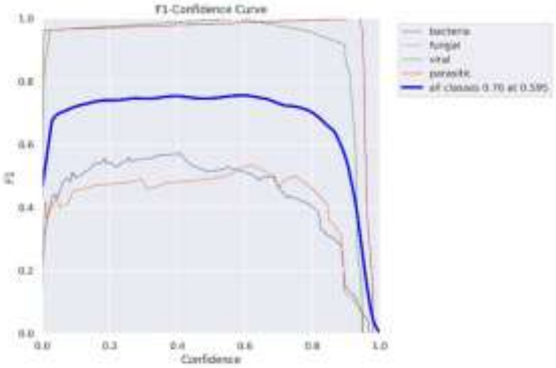



Fig 7: F1 confidence Curve

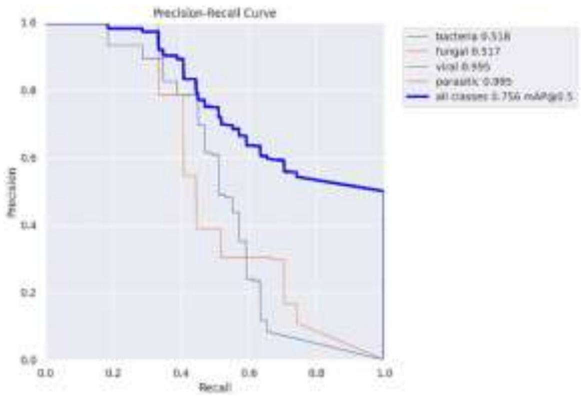
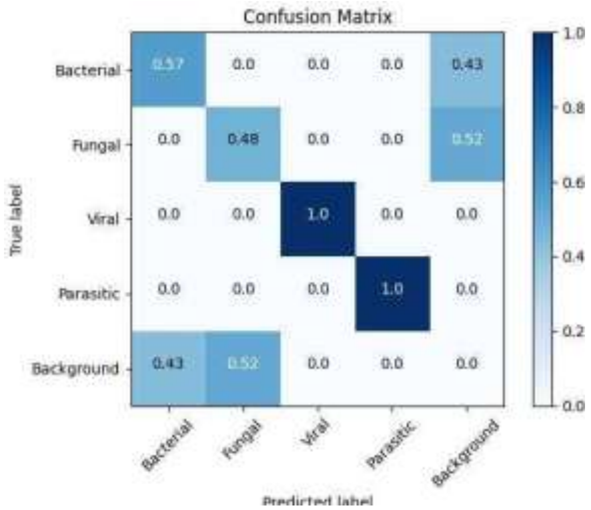



Fig 8: Precision-Recall Curve



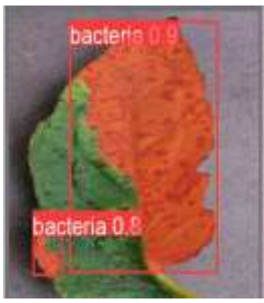





Fig 10a: Bacterial Leaf Fig 10b: Parasitic Leaf

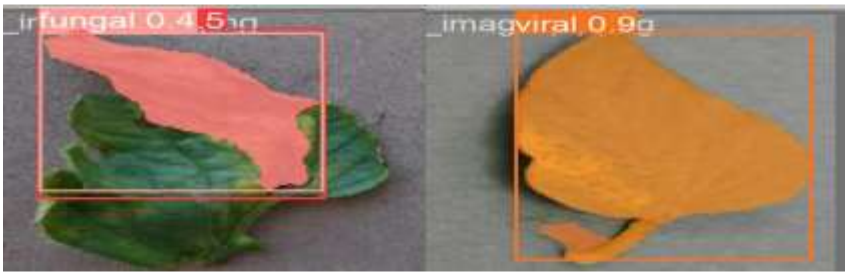



Fig 10c: Fungal Leaf Fig 10d: Viral Leaf Fig 10: Instance Segmentation output of the Yolo model

***D. Whatsapp Bot***

Having all three algorithms applied and the disease found with high accuracy using different techniques, the next move is to send all the results to the end-user or the farmer using the bot. The WhatsApp bot is created using open-source Python libraries. A separate server is maintained to keep the application running all the time. Using a Python function the image sent is read and it goes through all three processes as mentioned in previous sections. All the results are further sent to the user and then the disease is identified with the probability. Fig 11 shows a sample WhatsApp process of sending the plant image and receiving the Disease probability.

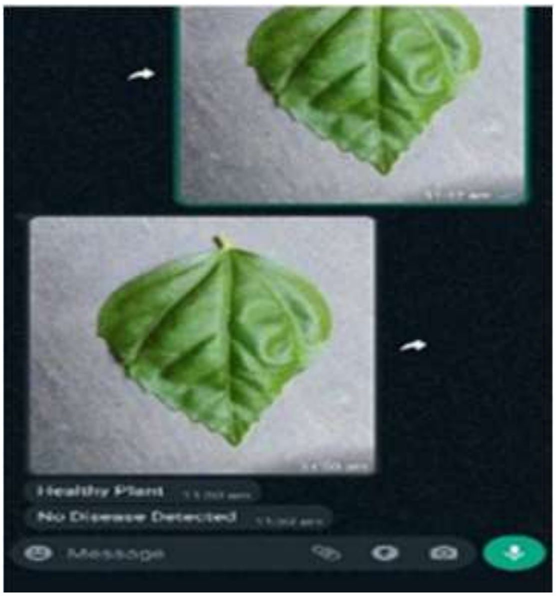



Figure 11: WhatsApp Screenshot

**CONCLUSION**

In this paper, proposed chatbot assists the user in identifying plant diseases using three different approaches. The mobilenet classification model and the yolov8 segmentation model showed very good classification results in real data making an efficient system for plant disease detection. Any farmer or gardener can take a picture with their smartphone of a plant that has been infected with a disease and send it as a regular message to the bot which will identify the disease, recognize the affected area, and identify the type of disease and sent to the user as a reply. The classification model showed an accuracy of 95.66% and the instance segmentation model showed 94.65% accuracy on the test dataset. The future scope of this paper includes improvement in the HSV filtering technique with a more generalized masking rather than static threshold-based filtering and a more varied and structured dataset for the segmentation.

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