Multi-Model Chatbot and Image Classifier for Plant Disease Detection

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Abstract. This study suggests a unique chatbot-assisted plant disease detection system that uses natural language processing (NLP) and image classification methods to give farmers an easily accessible tool for identifying plant illnesses and receiving treatment advice. The three main parts of the system are as follows: a user-friendly chatbot interface that allows for easy image uploading and retrieval of detailed disease information; a knowledge base of plant disease treatments and control measures that offers farmers customized treatment plans; and a strong image classification model that has been trained on an extensive dataset of plant disease images to accurately identify the disease. When the system's efficacy is compared to current techniques, it shows itself to be more accurate at identifying diseases and establishes itself as a priceless tool for raising agricultural output and reducing crop losses.

Keywords: Chatbot · Voice assistant · Plant Disease Detection · Image classification · Convolutional Neural Network (CNN)· Deep Learning · Machine Learning.

1 Introduction

With the global population on a trajectory to surpass 9 billion by 2050, the imperative to meet heightened food demand underscores the critical role of agriculture. But this endeavour is becoming more and more threatened by the growing threat of plant diseases, a problem that became well recognised after 1990. Pathogens, which include bacteria, viruses, nematodes, and fungus, can cause symptoms that vary from wilting to discolouration. These infections can have a major negative effect on agricultural production and put farmers' financial stability at risk. In addition to being costly, traditional techniques like eye examination and lab testing frequently lack the early detection capabilities necessary for prompt intervention.

Recent advances in deep learning and machine learning have emerged as a ray of hope in response to this urgent problem. Chatbots, which make use of artificial intelligence, are helping identify plant illnesses more accurately. Through the smooth integration of sophisticated machine learning algorithms with picture processing from drones or cellphones, these chatbots exhibit an unparalleled capacity to precisely identify a wide range of plant diseases.

Modern-day chatbots transcend mere identification capabilities; they serve as indispensable tools for farmers. These smart bots not only help quickly resolve equipment problems but also offer farmers real-time support with weather forecasts and market pricing, meeting their changing needs. This all-encompassing technological integration, which includes chatbots and recommender systems, creates a strong support system for farmers.

Furthermore, chatbots can now categorise illnesses based on pictures of affected plants thanks to the use of machine learning in illness prediction. As a result, farmers are equipped with up-to-date knowledge and treatment alternatives, enabling a proactive approach to disease control. The integration of these technological developments, as covered in [7], [2], [3], represents a revolutionary step in agricultural practises since it helps with resource conservation and decision-making.

2 Research Gaps

Recent studies have extensively explored the use of chatbots for text-based interactions in plant disease diagnosis. However, a notable research gap exists in the realm of voice-assisted chatbots for the same purpose. Specifically:

Limited Voice-Enabled Plant Disease Detection Tools: Current plant disease detection methods primarily rely on text-based chatbots or smartphone apps, excluding individuals with low literacy skills or visual impairments. The integration of voice capabilities in chatbots can address this accessibility gap.

Scarcity of Research on Voice-Activated Plant Disease Chatbots: Despite the potential benefits, there is a dearth of research on leveraging speech technology for plant disease diagnosis in agriculture.

Accuracy and User Acceptance: The accuracy and user acceptance of voice-activated chatbots for plant disease detection lack thorough examination. More research is needed to assess their viability, reliability, and user satisfaction.

In summary, the research gap in plant disease detection using voice-assisted chatbots stems from a lack of comprehensive studies on the advantages, challenges, and potential applications of this technology. Further exploration of this topic could lead to innovative solutions catering to a broader audience and enhancing precision agriculture.

3 Related Works and Literature Survey

The authors of [10] suggest an effective approach for boosting the effectiveness of question-answering in chatbot apps through the use of TF-IDF and cosine similarity, which is crucial for giving users' inquiries accurate and prompt answers. The authors of [5] assert to have developed a methodology that employs a multilayered Long Short-Term Memory (LSTM) unit to convert the input sequence into a fixed-dimensional vector, hence facilitating the mapping of input sequences to corresponding output sequences. In addition to answering often requested queries, the bot emphasizes weather forecasting and crop disease detection. With the help of natural language processing (NLP) and the TF-IDF approach, [11] suggests developing an intelligent chatbot for text comprehension in the medical sector. The TF-IDF method is used by the chatbot to gather pertinent data from a sizable medical knowledge base while NLP techniques are utilized to read and understand user inquiries.The survey table further highlights the major researches carried out in this domain:

Year	Paper Title	Object	DL framework	Dataset	Sample size	Data Enhancement	Accuracy (%)
2021	Cotton Leaf Disease Recognition Based on a Deep Convolutional Neural Network	Cotton	CNN	Self-acquired	20000	Random rotations, flips and zooms	97.25
2021	A system for automatic rice disease detection from rice paddy images serviced via a Chatbot	Rice	Faster R-CNN, RetinaNet, YOLOv3, Mask R-CNN	Self-acquired	18000	None	95.6
2020	Optimizing Pre-trained CNN for Tomato leaf disease	Apple	ResNet152, IncepetionV3, MobileNet	Self-acquired	334-2004	Random Rotation for cutting and Grayscale	73.5
2020	Image Recognition of 4-Rice Leaf Diseases based in Deep Learing	Rice	CNN-SVM	Self-acquired	6637-8911	Clip	87
2020	Recognition of corn leaf spot and rust based on transfer learning	Corn	VGG16	Self-acquired	600-5400	Rotate-Flip	92.19
2020	Cotton plant disease Identification using CNN and Random Forest Classifier	Cotton	CNN and Random Forest	Self-acquired	1000	Brightness and contrast adjustments	97.8

Table 1: **Literature Survey table**

4 Proposed Methodology

The proposed methodology involves leveraging a comprehensive dataset of non-detached leaves from infected cotton plants, captured using high-quality cameras and smartphones in controlled and natural environments. The dataset encompasses images of Fresh cotton plants, Fresh cotton leaves, Diseased cotton plants, and Diseased cotton leaves, as detailed in Table 2. To predict and classify plant diseases, the approach integrates modern machine learning techniques, particularly deep learning, into a chatbot-supported framework.

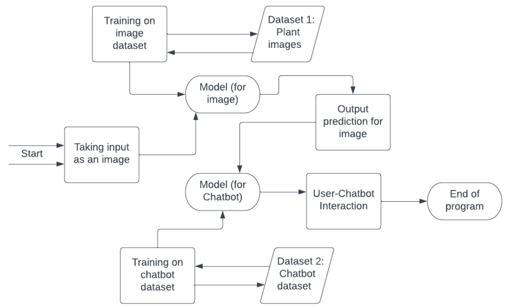


Fig. 1: Flow of Proposed Model

4.1 Pre-processing techniques

Preprocessing plays a pivotal role in elevating the accuracy and efficiency of chatbots by refining both input and output data quality. This involves the removal of unnecessary characters, punctuation, white spaces, and common stop words. Adjusting text case (lowercase or uppercase) and implementing tokenization further aids in breaking down text into smaller units, be it words, sentences, or characters, facilitating the chatbot's comprehension of input data. Techniques such as lemmatization and stemming, as highlighted in [8], are crucial. They work to condense words into their basic forms, not only enhancing chatbot performance but also ensuring consistency and correctness in input-output interactions. The collective application of these preprocessing steps establishes a robust foundation for precise classification, responsive chatbot interactions, and overall effectiveness in AI systems for both text-based and voice-based chatbot support.

Moreover, preparing images for machine learning also involves several essential steps. Image resizing is deployed to ensure uniform resolution and aspect ratio preservation, simplifying data handling and feature extraction. Noise reduction algorithms have enhanced the image clarity by removing undesirable distortions and abnormalities. Moreover, data augmentation introduces controlled variations to the dataset, such as cropping and flipping, diversifying the training data, and thus has also been used by us for reducing the risk of overfitting and improving model generalization.

4.2 Model for Image classification

The various models used have been trained on the dataset using transfer learning. Three pre-trained CNN architectures are used for training the cotton disease classification model. Then, model accuracies, precisions, and several other parameters are compared. A pre-trained Inception V3 model has been used without the top layer. On the top of the base layer, a Dense layer of 512 neurons with ReLU activation is used in conjunction with a GlobalAveragePooling2D layer. Only the top layers have been trained by freezing the base model. The model has been compiled using Adam Optimizer. Besides Inception V3, a pre-trained VGG model as the base model is applied, without the top layer. On top of the base, a flattening layer and 2 fully connected Dense layers with ReLu activation have been added. Further, a softmax layer for output is present. The Resnet50 is implemented as a base model for the dataset. The flattened output from the base has been passed through two fully connected layers with 512 and 256 units respectively. Moreover, the model uses the ReLU activation function. The final output layer has four neurons in a dense layer and the softmax activation function has been used to predict the probability of the image belonging to each of the four classes. Based on these experiments, the Inception V3 architecture has demonstrated superior performance when compared to VGG16 and ResNet50. Inception V3 improves the power of the original Inception model by using a deep architecture with several convolutional and pooling layers to extract features from input images.[4] [1].

4.3 Model for Integrated Chat-bot

The proposed model for chatbot makes use of the tfidf approach for text classification and vectorization. TF-IDF (term frequency-inverse document frequency) is used for information retrieval and natural language processing. First, the user's input is tokenized and broken into individual words or phrases. Calculation is then done for the document and term frequency of each word. Then, the TF-IDF score is subsequently computed for each word in the user's input by combining the term frequency and the inverse document frequency. The inverse document frequency is calculated by dividing the logarithm of the total number of feasible solutions by the document frequency of the word. The possible responses are ranked by their TF-IDF ratings, and the response with the highest score is selected as the chatbot's response. TF-IDF aids chatbots in selecting better responses by choosing the most applicable one based on the user's input. It also helps to avoid meaningless responses and give users a more personalized experience as mentioned in [9], [6], and [12]. Moreover, the chatbot uses a multimodel approach to take in questions and give responses. The chatbot can take in speech input and give out speech output. It uses the audio of a person to take in the input, converts it to text internally, and feeds it to the neural network for its processing. Then, the text response generated is converted back to audio and given out as an answer.

4.4 Data-set Description

Data-set for Chat-bot: The Chatbot uses data in the form of tags, patterns, and responses. The intents.json file is widely used in chatbot development to give the intents—or prospective user intentions—that the chatbot is meant to manage. The goal or aim a user has in mind when interacting with a chatbot is known as their intent. The intentions.json file usually contains a list of all the intents that the chatbot has been trained to identify, along with a list of training phrases for each purpose. This file consists of domains as tags (such as fertilizers, pesticides, crop types, soil, etc.), questions as patterns, and answers as responses.

	Fresh Cotton Plant	Fresh Cotton Leaf	Diseased Cotton Plant	Diseased cotton leaf
Training	42100	42700	81500	28800
Validation	8100	8000	10100	5500
Test	42100	42700	81500	28800

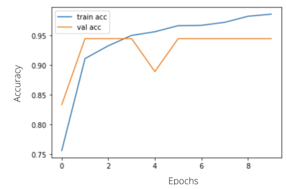
Table 2: **Dataset Description for Sample Leaves**

5 Results and Conclusion

In this work, we thoroughly evaluated our chatbot using a dataset of 1100 questions and their corresponding domain-specific replies. The evaluation was performed using accuracy and loss graphs, as demonstrated by Figures 5a and 5b. The three image classifiers, InceptionV3, VGG16, and Resnet50, were also assessed for efficiency. The figures 2a, 2b, 3a, 3b, 4a, and 4b illustrate classification reports that consist information on observed support, f1-score, precision, and recall. These graphs and reports have indicated that Inception V3 performs the best in terms of accuracy. The inception modules use parallel convolutional operations of different filter sizes, allowing the model to capture both fine and coarse details in the cotton images. These observations and metrics have demonstrated that the results generated by the image classifiers are promising and encouraging. Moreover, the use of TF-IDF also enhances the performance of the chatbot to understand user's questions. TF-IDF assigns higher weights to words that are frequent in a specific document but less frequent across all documents in the collection. This helps identify words that are distinctive to a particular user's speech, thus, allowing to focus on more important words rather than trivial ones. Consequently, using these language modeling techniques and insights from the validation dataset, the chatbot has shown to exhibit two-fold functionality: to provide information on the ideal conditions for plant care, and provide recommendations for preventing or slowing the spread of illness. Furthermore, the chatbot when conjuncted with the image classifier becomes capable of classifying new plant images and delivering insights into ailments and potential therapies using the trained CNN model. This integrated CNN-aided chatbot emerges as a valuable tool for farmers, facilitating swift and accurate plant disease diagnosis and enabling timely measures to mitigate the spread, ultimately enhancing crop yield.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	3
1	0.83	1.00	0.91	5
2	1.00	1.00	1.00	5
3	1.00	0.80	0.89	5
accuracy			0.94	18
macro avg	0.96	0.95	0.95	18
weighted avg	0.95	0.94	0.94	18

(a) Classification Report of Inception model

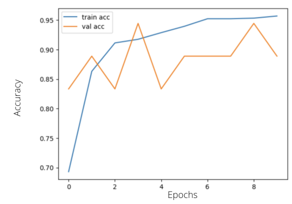


(b) Accuracy VS Epochs Plot for Inception model

Fig. 2: Inception Model

	precision	recall	f1-score	support
0	1.00	1.00	1.00	3
1	0.83	1.00	0.91	5
2	0.83	1.00	0.91	5
3	1.00	0.60	0.75	5
accuracy			0.89	18
macro avg	0.92	0.90	0.89	18
weighted avg	0.91	0.89	0.88	18

(a) Classification Report of VGG16 model

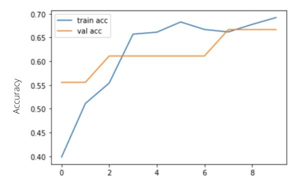


(b) Accuracy VS Epochs Plot for VGG16 model

Fig. 3: VGG16 model

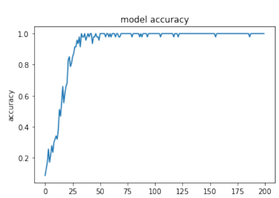
	precision	recall	f1-score	support
0	0.50	0.33	0.40	3
1	0.75	0.60	0.67	5
2	1.00	1.00	1.00	5
3	0.43	0.60	0.50	5
accuracy			0.67	18
macro avg	0.67	0.63	0.64	18
weighted avg	0.69	0.67	0.67	18

(a) Classification Report of Resnet50 model

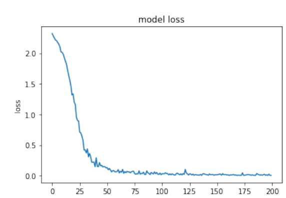


(b) Accuracy VS Epochs Plot for Resnet50 model

Fig. 4: Resnet50 Model



(a) Accuracy of Chatbot over Validation Dataset



(b) Loss of Chatbot over validation dataset

Fig. 5: Model Validation

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