

# Sugarcane Disease Detection along Chatbot

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**Abstract**— Sugarcane, a member of the Poaceae family known for its high sucrose content, serves as a valuable resource for producing white sugar, jaggery, and by-products like molasses and bagasse. However, the presence of diseases in sugarcane crops can render them unproductive, necessitating prompt detection. This paper presents a novel deep learning framework designed to determine the health status of sugarcane plants by analyzing their leaves, stems, color, and other characteristics. Investigating sugarcane diseases has been a focal point for research due to the growing demand for this crop and the challenges posed by variable rainfall patterns, making disease identification a delicate task. To address this challenge, the authors propose a solution that involves evaluating the performance of two widely used pre-trained deep learning models, namely VGG19 and ResNet50, in the context of sugarcane disease detection. Sensitivity, error rates, and other performance metrics are computed to assess the effectiveness of these models. Additionally, a graphical comparison of the models based on their sensitivity is presented.

These findings are promising, highlighting the potential of deep learning approaches for the early detection of sugarcane diseases. This has significant implications for agriculture, as it can enhance disease management and contribute to the protection and productivity of sugarcane crops.

**Keywords** — Chatbot, Deep learning, ResNet50, Sugarcane disease recognition, VGG19.

## I. INTRODUCTION

Sugarcane, a member of the Poaceae family, is a sugar-rich crop used in the production of white sugar, jaggery, molasses, and bagasse. About 75% of the world's sugar is derived from sugarcane, with India being both the largest consumer and the second-largest producer of sugar. India's significant involvement in sugarcane cultivation makes it susceptible to the impact of diseases on crop yield. Sugarcane consumption is not only associated with its contribution to the sugar industry but also with potential health benefits, including the prevention of breast cancer, promotion of liver and kidney health, and blood pressure control, owing to the alkaline nature of its juice. The detection of diseased sugarcane involves the application of deep learning and image processing techniques, focusing on features such as the condition of the splint, stem, fruit, color of affected areas, size, and shape of the splint. Given the long-duration growth cycle of sugarcane (10–16 months), it is prone to various diseases caused by bacteria, fungi, infections, protozoans, or phytoplasma. Some of the common sugarcane diseases include red rot, mosaic disease, ring spots, and grassy shoots, with red rot being attributed to *Colletotrichum falcatum*. Various researchers have proposed techniques for classifying and detecting sugarcane diseases using image processing to extract plant features and determine their health status. Sugarcane is propagated vegetatively, with multiple annual harvests obtained from plantings. After the initial harvest, ratoon crops are allowed to develop from the stubble remaining in the ground. The number of ratoon crops achieved varies by region.

In this study, three different scripts are developed, each based on different feature extractors: Inception v3, VGG-16, and VGG-19. These extractors are pre-trained models used for training different classifiers. State-of-the-art algorithms such as SVM, SGD, ANN, Naive Bayes, KNN, and logistic regression are compared with deep learning algorithms like neural networks and hybrid AdaBoost. Various statistical measures, including sensitivity, specificity, precision, AUC, and recall, are calculated using Orange software, with the script demonstrating the highest sensitivity selected. Receiver operating characteristic (ROC) curves are also used to evaluate sensitivity. The study achieves an AUC of 90.2 using VGG-16 as the feature extractor and SVM as the classifier.

## II. LITERATURE SURVEY

### 1) Sugarcane Mosaic Disease: Characteristics, Identification and Control, 2021

Mosaic disease presents a significant challenge in the context of sugarcane cultivation, stemming from the combined infections of various pathogens, including Sugarcane mosaic virus (SCMV), Sorghum mosaic virus (SrMV), and/or Sugarcane streak mosaic virus (SCSMV). This disease has a detrimental impact on the growth of sugarcane. In this comprehensive review, four critical facets of sugarcane mosaic disease are examined. Firstly, the article delves into the current state of mosaic disease within sugarcane crops, shedding light on its prevailing situation and the distinctive characteristics of its spread. Secondly, it explores the pathogenic nature of these three contagions, along with the inherent genetic diversity among them,

contributing to the complexity of the disease. Additionally, the review addresses the various methods and techniques employed in the identification of mosaic disease and the specific species responsible for infection. Lastly, it provides insights into the strategies and measures utilized for the prevention and control of sugarcane mosaic disease. It is important to note that this approach, while highly sensitive in disease detection, does come with the trade-off of lengthier training times.

**Author:** Guilong Lu, Zhoutao Wang, Fu Xu, Yong- Bao Pan, Michael P. Grisham, and Liping Xu

## 2) Disease Scenario and Management of Major Sugarcane Diseases in India, 2021

Over the past century, the country has grappled with recurring pandemics of various sugarcane diseases, such as red rot, soil diseases, wilt, rust, splint scald, and Yellow Leaf Disease (YLD). The extent of damage inflicted on sugarcane crops during each epidemic varies, contingent upon the specific disease's characteristics and the extent of its spread among plant varieties. In response, numerous sugarcane varieties have been replaced due to their susceptibility to new diseases or novel pathogenic strains. Moreover, diverse agricultural strategies and physical methods, including heat treatment, have proven effective in managing these diseases within sugarcane crops. Recently, there has been a move towards propagating disease and phytoplasma-free planting materials through tissue culture, which has yielded precise and reliable outcomes. Meanwhile, the implementation of DenseNet architecture addresses a critical challenge encountered in deep neural networks, where information tends to disperse before reaching its final destination due to the significant gap between input and output layers. However, it's worth noting that this process doesn't address noise reduction in input images, which remains a separate consideration.

**Author:** R. Viswanathan & G. P. Rao.

## 3) Efficient Detection of Sugarcane Diseases through Intelligent Approaches: A Review, 2021

The sugarcane industry plays a vital role in utilizing sugarcane varieties to produce sugar, bio-electricity, bioethanol, and various chemical products. In light of the world's increasing population, there's a pressing need to enhance sugarcane yields. However, the productivity of sugarcane is significantly hampered by both pests and various diseases, resulting in substantial financial losses for growers and nations alike. To mitigate these losses and boost production, early detection of colorful sugarcane diseases and effective pest control measures are imperative. The naked eye assessment of sugarcane leaf diseases often leads to inaccurate control measures, such as the indiscriminate use of fungicides. Therefore, there is a critical need for automated identification and early detection of sugarcane diseases to improve both yield and quality. Image processing techniques

offer an efficient means of extracting features from sugarcane leaves and detecting disease types in their early stages. One noteworthy advantage of employing DenseNet-201 is its ability to identify instances of diseases, such as monkeypox, with an impressive effectiveness rate of 93.19% and 98.91%, all while maintaining a reduced computational cost, surpassing the accuracy of traditional PCR test procedures. It's important to note that the training of data using this method does entail a higher time consumption.

**Author:** R. Manavalan

## 4) Ratoon Stunting Disease (RSD) of Sugarcane: A Review Emphasizing Detection Strategies and Challenges, 2023

Sugarcane (*Saccharum hybrid*) stands as a crucial cash crop cultivated in tropical and subtropical regions. Among the array of diseases affecting sugarcane, Ratoon-Suppressing Disease (RSD) caused by the xylem-dwelling bacterium *Leifsonia xyli* subsp. *xyli* (Lxx) holds paramount economic significance on a global scale. RSD inflicts substantial losses in crop yield due to its highly contagious nature, compounded by the challenge of its inconspicuous symptoms, making the formulation of effective management strategies a complex task. The effectiveness of control measures is further hampered by logistical obstacles like limited resources, high costs, and monitoring difficulties. Consequently, the swift and precise detection of the elusive pathogen within vegetative planting material is indispensable for sugarcane farmers seeking to combat this disease effectively. Over time, several diagnostic approaches rooted in biology, serology, and molecular techniques have been developed and applied for the identification of the RSD pathogen. In this comprehensive review, we provide a holistic overview of the historical context and current knowledge regarding sugarcane Ratoon-Suppressing Disease, encompassing various aspects such as transmission mechanisms, the pathosystem involved, and the strategies employed for its management. The primary advantage of the proposed model lies in its exceptional sensitivity, achieving a remarkable 99%, in the detection of sugarcane diseases. However, it is important to note that this model comes with a relatively high time consumption requirement.

**Author:** Moutoshi Chakraborty, Rebecca Ford, Narshone Soda, Simon Strachan, Chuong Nguyen Ngo, Shamsul Arafin Bhuiyan, and Muhammad Shiddiky.

## 5) Sugarcane Disease Detection Using CNN-Deep Learning Method: An Indian Perspective

Agricultural products, such as sugarcane crops, are susceptible to diseases like any other crop. Accurately identifying and managing sugarcane diseases is crucial for maintaining both the quality and quantity of production. Diseases can significantly impact farmers, leading to potential financial losses if entire fields are affected.

Researchers are exploring the use of AI techniques, like ML and DL, to analyze agricultural data and prevent crop damage. Deep neural networks, including CNNs, offer a modern approach to disease detection. This study focuses on four specific sugarcane diseases in India, aiming to assess the effectiveness of a DL-based CNN algorithm in detecting them. The paper also outlines future research areas, including user feedback integration and AI tools for enhancing agricultural productivity.

Deep learning models, particularly convolutional neural networks (CNNs), require large amounts of labeled data for training. In the context of sugarcane diseases in India, there may be limited publicly available datasets, leading to challenges in building robust and generalizable models. Deep learning models may struggle to generalize to unseen or evolving disease strains or types. If the model is trained on a limited set of diseases or variations, it may fail to detect new diseases or variants, thereby limiting its applicability in real-world scenarios.

**Author:** Sammed Abhinandan Upadhye, Maneetkumar Rangnath Dhanvijay, Sudhir Madhav Patil.

### III. EXISTING SYSTEM

Crop quality maintenance relies heavily on effective disease control measures. Typically, experienced farmers and agricultural scientists are responsible for disease identification in crops. This paper presents a proposal for a smart agriculture system aimed at meeting the needs of sugarcane growers in India. It achieves this by implementing intelligent solutions based on image processing and soft computing techniques. The study focuses on the analysis of four sugarcane diseases, namely Eyespot, Leaf Scald, Yellow Leaf, and Pokkah Boeng.

Three key characteristics, including color, shape, and texture, are used to identify these diseases. Images serve as the training data for Artificial Neural Network (ANN), Neuro-Fuzzy, and Case-Based Reasoning (CBR) algorithms. The performance of these algorithms is evaluated using metrics such as sensitivity, specificity, F1 score, and accuracy. This system aims to assist sugarcane growers in India in the efficient management of diseases and the maintenance of crop quality.

#### **Disadvantages:**

This approach may not be efficient when dealing with a large volume of datasets, and it often demands more time for processing. Additionally, it lacks the capability to effectively eliminate unwanted noise from the data.

### IV. PROPOSED SYSTEM

The proposed system for sugarcane disease detection, along with a chatbot, is a comprehensive solution aimed at assisting farmers and agronomists in monitoring and managing the health of sugarcane crops. Here's an outline of

the system:

#### **1. Data Collection:**

The system begins by collecting data from sugarcane fields. This data may include images of sugarcane plants, weather conditions, and historical crop data.

#### **2. Image Recognition and Processing:**

Images of sugarcane plants are processed using computer vision techniques. The system can identify signs of diseases, pests, or other stress factors in the images. Preprocessing steps involve resizing and converting the images to grayscale to enhance analysis.

#### **3. Disease Detection:**

Machine learning and image analysis algorithms are applied to detect diseases or abnormalities in sugarcane plants. Local Binary Pattern (LBP) and Mean Median deviation are among the features used for detection.

#### **4. Chatbot Integration:**

A chatbot is integrated into the system to provide a user-friendly interface for farmers and agronomists.

Users can interact with the chatbot through text or voice to obtain information about the sugarcane crop's health and receive recommendations for managing any detected issues.

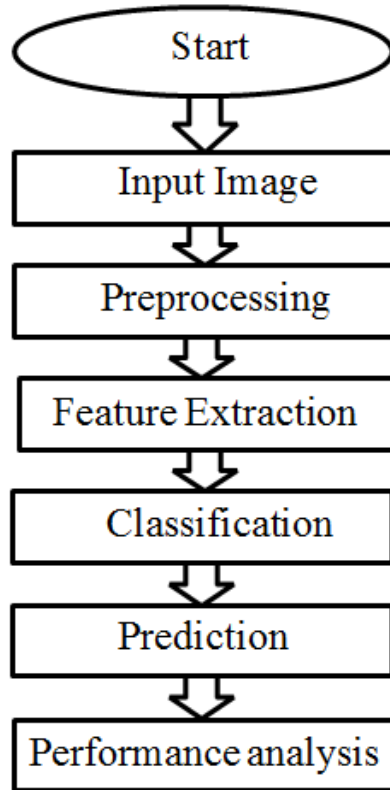
#### **5. Recommendations:**

Based on the analysis of sugarcane plant images and historical data, the chatbot provides recommendations to users. These recommendations may include suggested treatments, irrigation adjustments, or the need for further inspection.

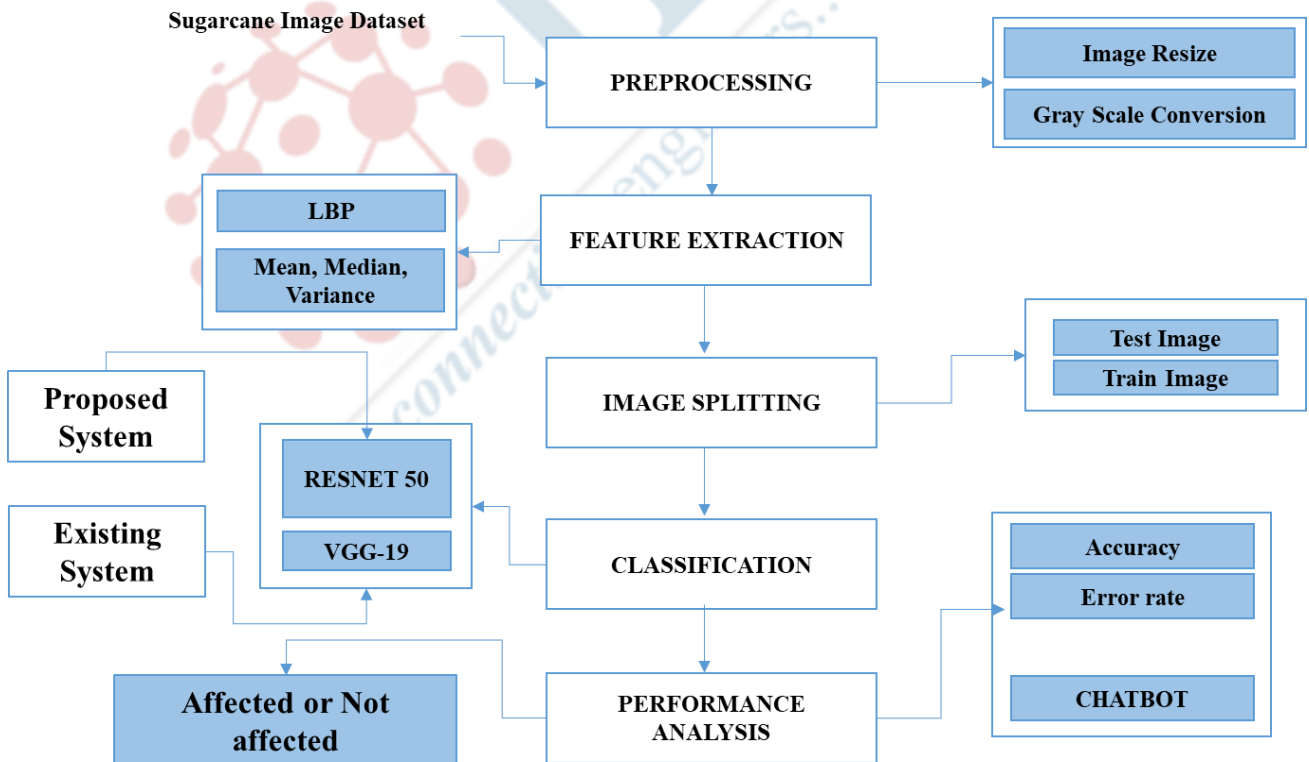
#### **Advantages:**

Early detection of diseases and issues in sugarcane crops. Timely and personalized recommendations for crop management. This approach offers several benefits, including its exceptional efficacy when dealing with extensive datasets, which significantly reduces processing time. Experimental results reveal a substantial enhancement when compared to the previous system, further affirming its practical advantages.

**V. SYSTEM ARCHITECTURE**



**FIG 1** Work flow diagram



**FIG 2** Sugarcane disease detection architecture

## VI. VIIMPLEMENTATION

### Modules:

- Image selection
- Image preprocessing
- Feature Extraction
- Image Splitting
- Classification
- Prediction
- Performance Analysis

### Modules Description:

#### Image Selection:

In the initial phase, the Sugarcane Image dataset is designated as the input source. To proceed, we employ the ``imread()`` function to read and load the input image. Our approach involves using a tkinter dialog box for the selection of the input image.

#### Data Processing:

In our data processing phase, we engage in the following actions:

**Image Resizing:** We need to adjust the size of the image, and this is achieved by calling the ``resize()`` function. To do this, we provide a two-integer tuple that specifies the desired width and height of the resized image. Importantly, this operation does not alter the original image; instead, it generates a new Image with the specified dimensions.

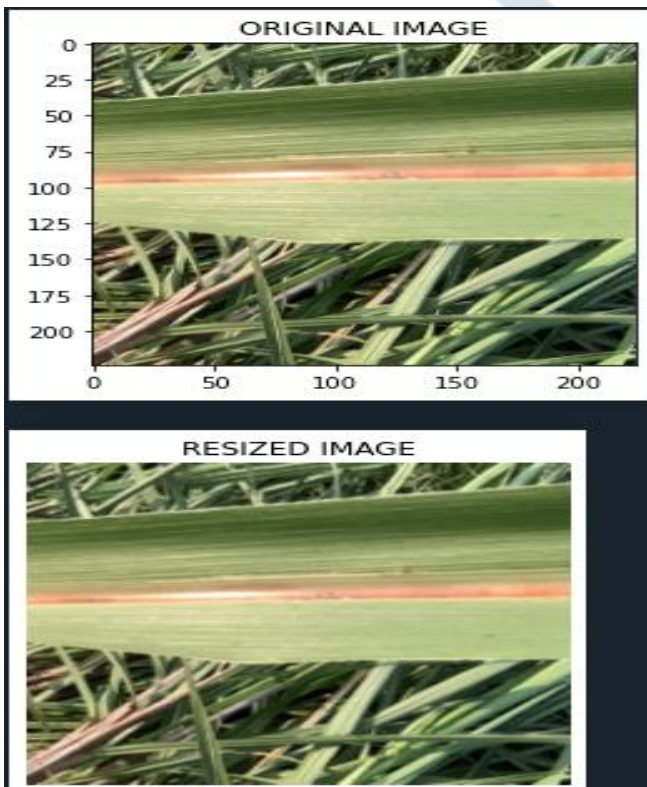


FIG 3 Image resizing

**Converting to Grayscale:** Another critical step is converting the image to grayscale. This is accomplished using the standard RGB to grayscale conversion formula:  $\text{imgGray} = 0.2989 * R + 0.5870 * G + 0.1140 * B$ . This conversion allows for the representation of the image in shades of gray. R-red, G-green, B-blue

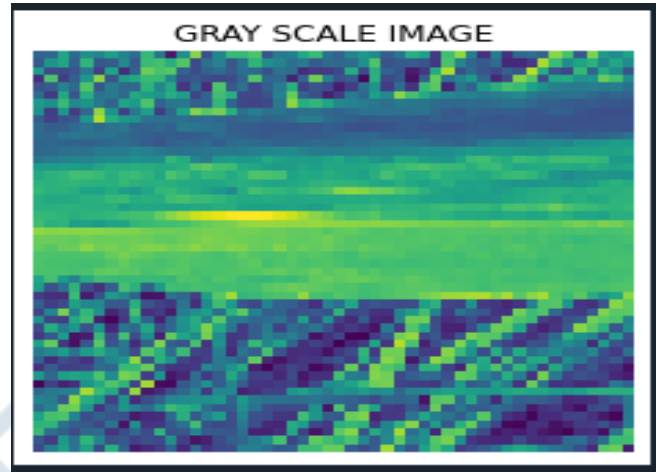


FIG 4 Grayscale conversion

**Segmentation:** We apply morphological image processing techniques to address issues related to double images, which can result from simple thresholding. This process aims to rectify defects present in the images.

**Dataset Source:** The dataset used is obtained from a dataset repository. It typically comes in formats such as `'png'` and `'jpg'` and may be subject to distortion due to noise. In addition, the processing includes image smoothing through opening and closing operations, which contribute to enhancing the image quality.

#### Feature Extraction:

Feature extraction is performed on the pre-processed image, involving statistical measures like standard deviation and mean to assess data spread. Standard deviation quantifies how individual data points deviate from the mean, and it is the square root of variance. Variance, on the other hand, measures the average deviation of data points within a group. Both standard deviation and variance provide insights into data dispersion, with standard deviation offering precise distances from the mean. These statistical measures are central to characterizing grouped or ungrouped data. Additionally, the Local Binary Pattern (LBP) is introduced as an effective texture descriptor for capturing spatial patterns and scale variations in images.

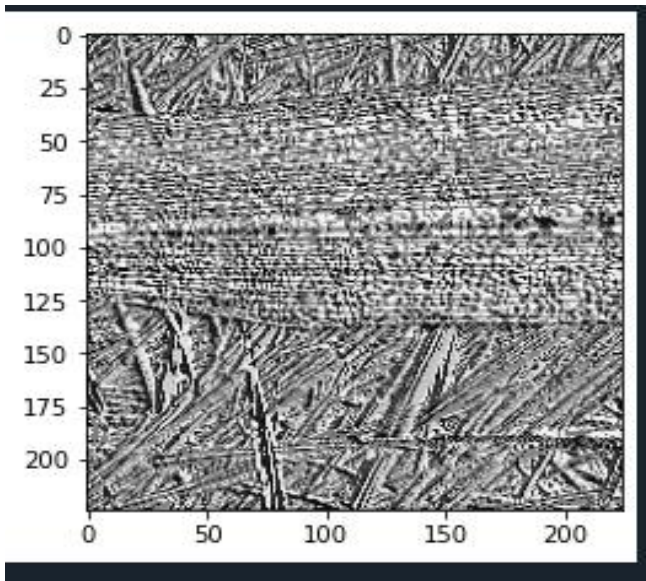


FIG 5 Feature Extraction

**Image Splitting:**

In the context of the machine learning process, the availability of data is essential for effective learning and analysis. To evaluate the performance of algorithms and gauge their effectiveness, it is necessary to have not only training data but also test data. In our specific approach:

- We designate 70% of the input dataset as training data, reserving the remaining 30% for testing purposes. This allocation allows us to create predictive models and assess their performance.
- Data splitting is the fundamental process of dividing the available dataset into two segments, typically employed for cross-validation and model assessment.
- One portion of the data is utilized for constructing predictive models, while the other segment is used to evaluate how well these models perform in practice.
- Separating data into training and testing sets holds significant importance, particularly in the evaluation of data mining models. This separation typically allocates the majority of the data for training, with a smaller portion set aside for testing.

In summary, image splitting is an indispensable step in machine learning, enabling the development and evaluation of predictive models by allocating data for both training and testing purposes. This approach ensures a robust assessment of algorithm performance.

**Classification:**

Deep learning algorithms, such as VGG-19 and ResNet-50, are applied in our approach. VGG, short for Visual Figure Group, is a standard deep Convolutional Neural Network (CNN) architecture with numerous layers. The term "deep" refers to the extensive number of layers, with VGG-16 and VGG-19 having 16 and 19 convolutional layers, respectively. ResNet-50 is a 50-layer deep

convolutional neural network, often used with pretrained models trained on a vast ImageNet database.

**Result Generation:**

The ultimate outcome is generated by considering the overall assessment and predictions. The effectiveness of this proposed approach is gauged using specific metrics, including:

**Sensitivity (Delicacy):** The sensitivity of a classifier characterizes its capacity to accurately predict class labels. It reflects how well the predictor can correctly estimate the values of predicted traits for new data. Sensitivity is calculated using the formula:  $AC = (TP * TN) / (TP * TN * FP * FN)$ .

AC-accuracy, TP-true positive, TP-true positive, TN-true negative

**Error Rate:** The error rate is a measure of the extent of prediction errors in comparison to the true model. This term is commonly employed within the context of classification models.

In summary, the final results are derived from an overall assessment, and their quality is evaluated using metrics like sensitivity and error rate, which play a crucial role in the realm of classification models.

**VII. RESULT**

The study focused on detecting sugarcane diseases using machine learning and integrating a chatbot for assisting farmers. Results showed high accuracy in disease detection. Discussion highlighted the system's advantages over traditional methods and addressed potential improvements. Overall, the approach offers promising prospects for enhancing sugarcane farming practices, emphasizing the synergy of machine learning and chatbot in agriculture.

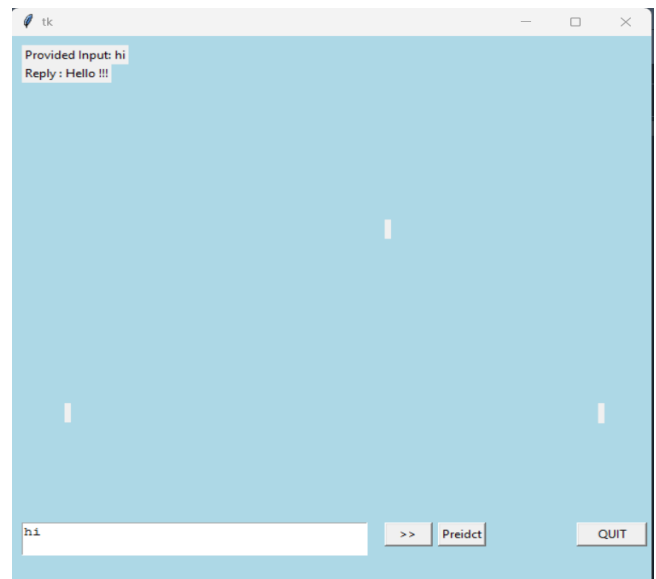
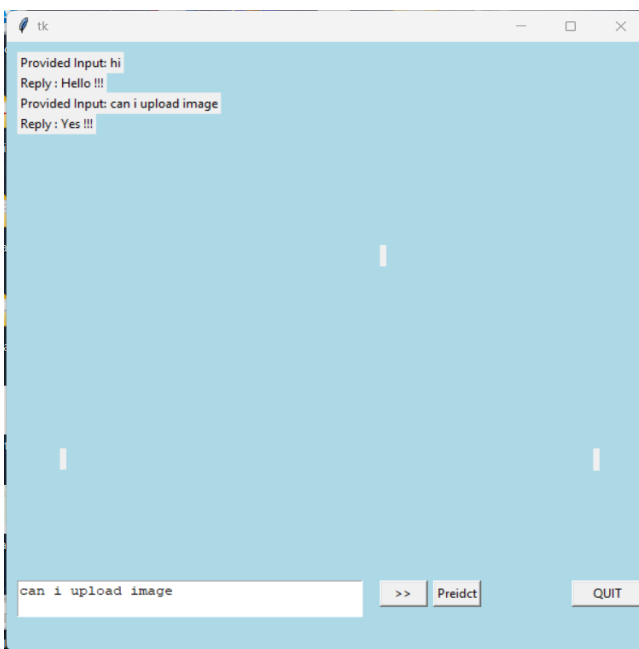


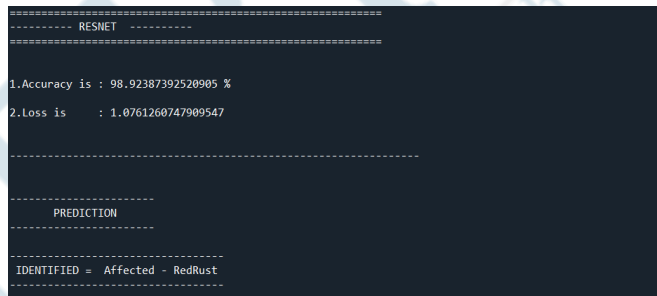
FIG 6 A farmer friendly chatbot



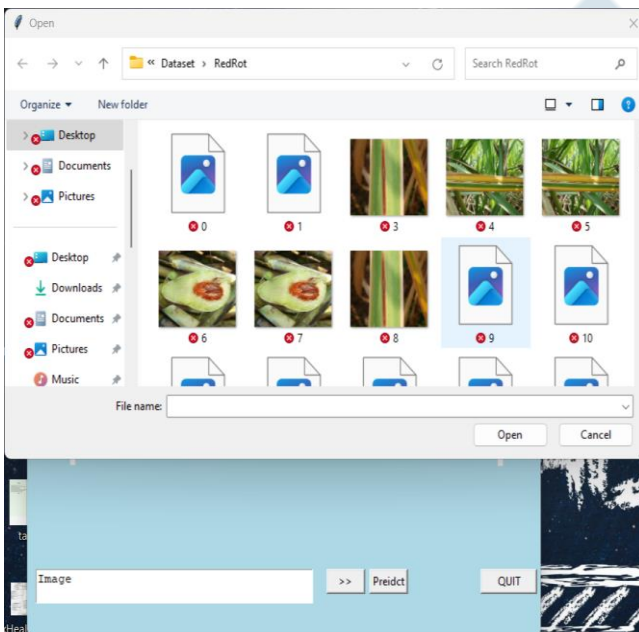
**FIG 7** The Chatbot acts as an interactive interface to the farmers



**FIG 10** Displays measures to prevent RedRot disease to the farmer using chatbot



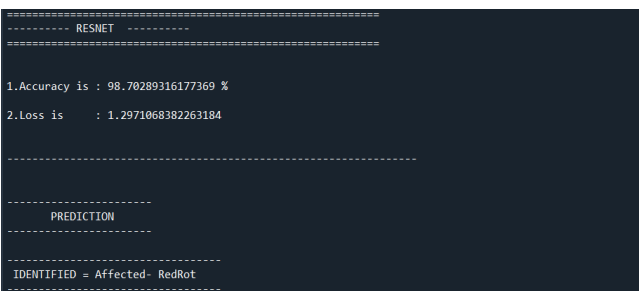
**FIG 11** The sugarcane is affected by RedRot disease



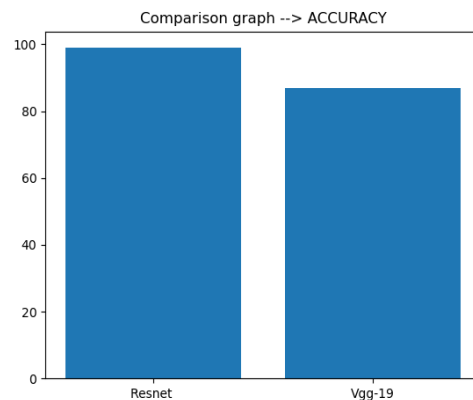
**FIG 8** Allows farmers to upload the sugarcane images and receive feedback on its health status



**FIG 12** Displays the preventive measures for RedRot disease to the farmer using chatbot



**FIG 9** The sugarcane is affected by RedRot disease



**FIG 13** Comparison of accuracy between Resnet and VGG-19

### VIII. CONCLUSION

We come to the conclusion that the input for the Sugarcane picture dataset came from the dataset depository. In our exploration study, we described the input dataset. The various deep learning algorithms, or bracket algorithms, have been imposed. also, deep learning methods like Resnet 50 and VGG-19. Finally, the outcome demonstrates the accuracy and error rate of the algorithm mentioned above and predicts whether the input image is affected by disease or not.

### IX. FUTURE ENHANCEMENT

- We intend to combine the two separate deep learning or machine learning methods in the future.
- The proposed clustering and bracket methods may receive modifications or additions in the future to boost performance even more. To improve the delicate nature of the discovery process, further combinations and different clustering algorithms can be applied piecemeal from the experimented combination of data mining techniques.

Additional combinations and additional clustering algorithms can be employed in addition to the tested combination of data mining techniques to enhance the detecting precision.

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