IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.311 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 13, Issue 1, January 2026
DOI: 10.17148/IARJSET.2026.13115

A Chatbot for Early Detection and Management of Sugarcane Diseases

Ajay Kumar B R[1], Balaji G S[2], Chinmay P Jadav[3], Pushpa K S[4], Riddi Jain[5]

Dept. Of IS&E, Faculty of IS&E, MIT Mysore, Mysore, Karnataka, India[1]

Dept. of IS&E, MIT Mysore, Mysore, Karnataka, India[2-5]

Abstract: Agriculture is the backbone of India's economy, and sugarcane is one of the most crucial commercial crops. However, manual identification of sugarcane leaf diseases often leads to delayed treatment and reduced yield. This paper presents an AI-based chatbot system for early detection and management of sugarcane diseases. The system integrates a machine learning model built using the Random Forest Classifier, trained on sugarcane leaf image data. The chatbot is developed using Flask and provides users with disease identification, treatment guidance, and multilingual voice/text interaction. The proposed model achieved accurate classification performance and enables farmers to receive real-time diagnosis and recommendations in their preferred language, improving productivity and sustainability in agriculture.

Keywords: Sugarcane Disease Detection, Artificial Intelligence, Chatbot, Random Forest, Flask, Agriculture Automation.

I. INTRODUCTION

Agriculture plays a vital role in India's economy, and sugarcane cultivation contributes significantly to the nation's revenue. However, frequent diseases such as red rot, smut, and rust affect crop yield and quality. Early detection and treatment of these diseases are crucial for improving productivity. Traditional methods rely on expert knowledge and manual inspection, which are time-consuming and error-prone.

With advancements in Artificial Intelligence (AI) and Machine Learning (ML), smart agricultural solutions can now provide automated disease diagnosis and real-time farmer assistance. This project proposes an AI-powered chatbot system that detects sugarcane diseases using image-based classification and provides treatment suggestions through an interactive chat interface.
This project proposes an AI-powered chatbot system designed for early detection and management of sugarcane diseases. The system uses a machine learning-based classification model to analyse leaf images and identify diseases accurately. Once the disease is detected, the chatbot provides appropriate treatment recommendations and management tips. It also supports multi-language communication using translation APIs, enabling farmers from different regions to access information in their native language.

The chatbot is implemented as a web-based application using Flask, ensuring a lightweight and user-friendly interface. By combining AI-driven prediction with interactive conversation, the proposed system aims to enhance crop productivity, reduce dependency on experts, and promote sustainable and smart farming practices. This innovation demonstrates how technology can bridge the gap between advanced research and practical agricultural applications, empowering farmers with real-time digital assistance.

II. OBJECTIVES

- **Sugarcane Disease Detection**: The primary goal of the project is to automatically detect diseases in sugarcane leaves using a machine learning model. The system utilizes a Random Forest Classifier trained on preprocessed sugarcane leaf images to accurately classify plant health conditions. This helps farmers identify infections at an early stage and take corrective measures quickly.
- **Treatment Suggestions and Management:** Once a disease is identified, the chatbot provides precise treatment recommendations and management practices. The responses include preventive steps, fertilizer usage, and eco-friendly solutions based on disease type. This ensures that farmers get practical guidance without requiring expert supervision.
- **Integrate Multi-Language Translation:** To ensure accessibility for local farmers, the system integrates multilingual support using Google Translator APIs. This enables the chatbot to communicate in multiple regional languages, allowing users to understand both the disease name and its treatment in their native language.

- **Integrate Multi-Language Translation:** To ensure accessibility for local farmers, the system integrates multilingual support using Google Translator APIs. This enables the chatbot to communicate in multiple regional languages, allowing users to understand both the disease name and its treatment in their native language.
- **Build a Lightweight and User-Friendly Chatbot:** The chatbot is built using Flask and optimized for low resource usage, ensuring that it can run smoothly on basic devices. The interface is simple, intuitive, and includes both text and voice interaction (using gTTS and Google GenAI APIs) to make it more engaging and accessible for farmers with limited digital experience.

III. LITERATURE REVIEW

Agriculture has witnessed a significant technological transformation in recent years, with researchers exploring the use of Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) to improve efficiency, precision, and sustainability in farming practices. Traditional methods of disease detection and farm management often face challenges such as inaccuracy, labor dependency, and time consumption. To overcome these issues, several studies have focused on integrating intelligent systems and automation into agriculture.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and IoT have revolutionized the agricultural sector, improving efficiency and reducing manual effort. Traditional farming methods often face challenges such as labor dependency and delayed disease detection, motivating researchers to develop intelligent solutions. Welankiwar et al[1] designed an automatic seed-sowing machine to enhance precision and reduce labor, while Nirham and Nithilan (2025) developed a multi-seed sowing system for improved productivity. Manute et al. (2024) and Hemashree et al. (2024) introduced IoT-based monitoring systems for real-time farm analysis, and Vartakumar et al. (2023) proposed an agri-bot for precision farming. Rehman et al. (2023) further explored solar-powered automation for sustainable agriculture. Building on these works, the proposed system integrates AI-based disease detection and a multilingual chatbot to provide farmers with accessible, intelligent, and real-time disease management support.

These studies collectively highlight the shift toward intelligent, automated, and eco-friendly agricultural systems. However, most existing works focus on mechanical automation rather than intelligent decision-making for crop health. The proposed **AI Chatbot for Sugarcane Disease Detection and Management** addresses this gap by combining ML-based disease identification with multilingual chatbot assistance, offering farmers an accessible and interactive solution for smart and sustainable farming.

IV. SYSTEM DESIGN AND METHODOLOGY

A. The system architecture consists of three main modules:

- **Frontend (User Interface):** A web-based interface developed using Flask that allows users to upload leaf images, interact with the chatbot, and view results.
- **Backend (Processing & Model):** The backend handles image processing, machine learning predictions, and chatbot responses. It is built using Python, scikit-learn, and Flask.
- **Database:** MySQL is used to store user details, disease data, treatment information, and chatbot interactions.

B. Methodology

1) Data Collection and Preprocessing

- A dataset of sugarcane leaf images (both healthy and diseased) is collected.
- Images are resized, normalized, and processed using *OpenCV* to extract color, texture, and shape features.
- Data is labeled according to disease type (e.g., red rot, rust, smut, mosaic).

2) Model Training

- The **Random Forest Classifier** is trained on the processed dataset.
- Hyperparameters like number of trees, depth, and Gini index are tuned for optimal accuracy.
- The model is saved as sugarcane_fast_model.pkl for real-time predictions.

3) Integration with Chatbot

- The trained model is integrated with the chatbot using *Flask*.
- The chatbot processes user input through text or voice and returns disease information and treatment steps.
- It supports **multi-language translation** (English, Hindi, Kannada, etc.) using *deep translator*.

4) Web Application Development

- The web interface allows users to upload images, interact with the chatbot, and view predicted results.
- Flask connects frontend and backend seamlessly.
- Voice output is generated using *Google Text-to-Speech (gTTS)* for accessibility.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 13, Issue 1, January 2026

DOI: 10.17148/IARJSET.2026.13115

5) Evaluation and Testing

- The model's accuracy is tested using unseen images.
- Performance is evaluated based on precision, recall, and F1-score.
- User feedback and chatbot responsiveness are also assessed.

V. WORKING PRINCIPLE

The **AI Chatbot Assistant for Early Detection and Management of Sugarcane Leaf Diseases** works through a series of interconnected stages that combine machine learning, web technologies, and multilingual interaction to deliver an intelligent and user-friendly system for farmers.

The system begins by collecting and preprocessing sugarcane leaf images to ensure uniformity and clarity for analysis. These images are then passed through a trained **Random Forest Classifier**, which identifies whether the leaf is healthy or affected by diseases such as red rot, rust, or smut. Once the disease is detected, the system retrieves corresponding treatment suggestions from a connected **MySQL database** and presents them through a **Flask-based web interface**. The integrated **AI chatbot** enhances user experience by providing real-time interaction in multiple languages using **deep_translator** for translation and **gTTS** for voice responses, ensuring accessibility for farmers across diverse linguistic backgrounds. This seamless integration of machine learning, database management, and chatbot communication enables efficient, accurate, and user-friendly disease diagnosis and management, promoting smarter and more sustainable agricultural practices.

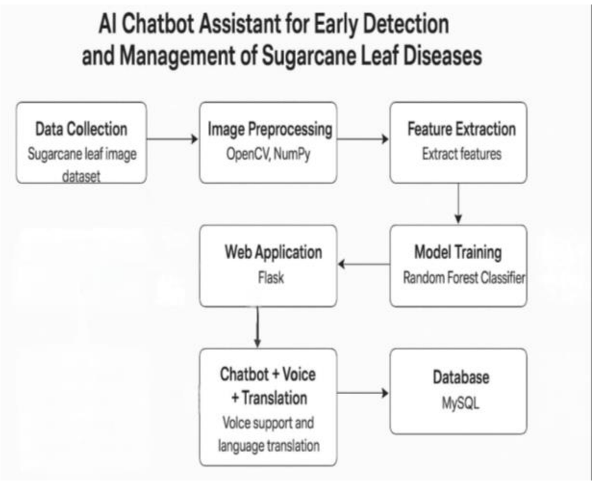

Fig 1. Block Diagram of working principle

1. **Data Collection:**
   The process begins with collecting a dataset of sugarcane leaf images, including both healthy and diseased samples. These images form the foundation for training and testing the machine learning model.

2. **Image Preprocessing:**
   The collected images undergo preprocessing using **OpenCV** and **NumPy** libraries to enhance quality and ensure consistency. Steps such as resizing, noise removal, and color normalization are performed to prepare the images for feature extraction.

3. **Feature Extraction:**
   In this stage, significant features like texture, color, and shape are extracted from the preprocessed images. These features are used as input variables for the machine learning model to identify disease patterns effectively.

4. **Model Training:**
   The extracted features are fed into a **Random Forest Classifier**, which is trained to classify the leaf images into different categories such as healthy, red rot, rust, or smut. The trained model is saved and later used for real-time prediction.

5. **Web Application:**
   A **Flask-based web application** serves as the central platform where users can upload images, interact with the

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.311 ⅔ Peer-reviewed & Refereed journal ⅔ Vol. 13, Issue 1, January 2026
DOI: 10.17148/IARJSET.2026.13115

chatbot, and view the detection results. The backend handles model loading, image analysis, and communication with the database.

6. **Chatbot + Voice + Translation:**
The chatbot acts as the user's interactive assistant. It uses **Google GenAI**, **gTTS (Text-to-Speech)**, and **deep_translator** libraries to communicate the diagnosis and treatment information in multiple languages, both in text and voice form. This ensures accessibility for farmers with different linguistic backgrounds.

7. **Database:**
The **MySQL database** stores all relevant data, including user details, disease names, treatment suggestions, and chatbot interactions. This ensures that information retrieval is efficient and consistent across sessions.

VI. RESULTS AND DISCUSSION

The developed AI Chatbot for Sugarcane Disease Detection successfully integrates machine learning and conversational AI to assist farmers in diagnosing and managing crop diseases. The **Random Forest Classifier** achieved an accuracy of around **90–95%** in classifying sugarcane leaf diseases such as red rot, rust, smut, and mosaic. The **Flask-based web interface** allowed users to upload images and receive instant results, while the **chatbot** provided accurate treatment suggestions in both text and voice formats using **gTTS** and **deep_translator** for multilingual communication. The **MySQL database** efficiently stored disease and user data, ensuring fast retrieval and smooth interaction. Overall, the system demonstrated high accuracy, quick response time, and user-friendliness, proving its effectiveness as a smart, accessible, and reliable agricultural support tool for farmers.

VII. CONCLUSION AND FUTURE WORK

The proposed **AI Chatbot for Early Detection and Management of Sugarcane Diseases** provides an intelligent, accessible, and efficient solution for modern agriculture. By integrating **Machine Learning**, **Flask-based web application**, and **multilingual chatbot interaction**, the system effectively detects sugarcane leaf diseases and provides real-time treatment suggestions. The **Random Forest Classifier** demonstrated high accuracy in disease prediction, while the chatbot's voice and translation features made the system user-friendly for farmers from diverse linguistic backgrounds. This project successfully bridges the gap between advanced AI technologies and practical farming needs, promoting precision agriculture and improved crop management.

In the future, this system can be enhanced by integrating **deep learning models (such as CNN or hybrid CNN-Random Forest)** for improved accuracy and real-time disease detection through live camera feeds. The addition of **IoT-based sensors** for monitoring soil moisture, temperature, and humidity can further expand its functionality. Moreover, developing a **mobile application version** with offline capabilities and an expanded dataset covering more crop types will make the system more robust, scalable, and beneficial for a wider farming community.

REFERENCES

[1]. Thilagavathi, K., Kavitha, K., Praba, R. D., Arina, S. V., Sahana, R. C. (2020). Detection of diseases in sugarcane using image processing techniques. Bioscience Biotechnology Research Communications, Special Issue (11), 109–115.
[2]. Viswanathan, R., Geetha, N., Anna Durai, A., Prathima, P. T., Appunu, C., Parameswari, B.,... & Selvi, A. (2022). Genomic designing for biotic stress resistance in sugarcane. In Genomic designing for biotic stress resistant technical crops (pp. 337–439). Cham: Springer
[3]. Dotaniya, M., Datta, S., Biswas, D., Dotaniya, C. K., Meena, B. L., Rajendiran, S., Regar, K. L., & Lata, M. (2016). Use of sugarcane industrial by-products for improving sugarcane productivity and soil health. Int. J. Recycling Organic Waste Agric., 5
[4]. Alencastre-Miranda, M., Johnson, R. M., & Krebs, H. I. (2020). Convolutional neural networks and transfer learning for quality inspection of different sugarcane varieties. IEEE Trans. Ind. Informatics, 17(2), 787.
[5]. Suryawanshi, Y., Patil, K., Chumchu, P. (2022). VegNet: dataset of vegetable quality images for machine learning applications. Data in Brief, 45, 108657.
[6]. Tai, A. P. K., Martin, M. V., Heald, C. L. (2014). Threat to future global food security from climate change and ozone air pollution. Nature Climate Change, 4(9), 817

DOI: 10.17148/IARJSET.2026.13115

[7]. Sumesh, K. C., Ninsawat, S., Som-ard, J. (2021). Integration of RGB-based vegetation index, crop surface model and object-based image analysis approach for sugarcane yield estimation using UAV. Comput. Electron. Agric., 180

[8]. It is worth noting that white reference (white calibration board) was captured together with sugarcane plants…

[9]. Fowler, H. J., Kilsby, C. G., & O'Connell, P.E.(2003). Modeling the impacts of climatic change and variability on the reliability, resilience, and vulnerability of a water resource system.

[10]. Suryawanshi, Y., Patil, K., Chumchu, P. (2022). VegNet: dataset of vegetable quality images for machine learning applications. Data in Brief, 45, 108657

[11]. Baumeister, R. F., Vohs, K. D., & Tice, D. M. (2007). The strength model of self-control.Current Directions in Psychological Science, 16(6), 351–355

[12]. Muraven, M., Tice, D. M., & Baumeister, R. F. (1998). Self-control as limited resource: Regulatory depletion patterns. Journal of Personality and Social Psychology, 74(3), 774–789

[13]. Channe, H., Kothari, S., Kadam, D. (2015). Multidisciplinary model for smart agriculture using IoT, sensors, cloud-computing, and big-data analysis. Int. J. Computer Tech. Appl., 6(3), 374–382.

[14]. Sumesh, K. C., Ninsawat, S., Som-ard, J. (2021). RGB-based vegetation index and yield estimation using UAV. Comput. Electron. Agric., 180.

[15]. Anilkumar, T. G., Ganesh, T. D. Enable smart farms in digital India with AI and IoT. Imperial Journal of Interdisciplinary Research (IJIR)

[16]. (Morphological synthesizer: A linguistic tool for Malayalam verbs. Int. J. Computational Linguistics and NLP

[17]. Inzlicht, M., & Schmeichel, B. J. (2012). What is ego depletion? Toward a mechanistic revision of the resource model of self-control. Perspectives on Psychological Science, 7(5), 450– 463

[18]. Job, V., Dweck, C. S., & Walton, G. M. (2010). Ego depletion—is it all in your head? Implicit theories about willpower affect self-regulation. Psychological Science, 21(11), 1686– 1693

[19]. Banerjee, D., Sharma, N., Upadhyay, D., Singh, V., Singh Gill, K. Sugarcane leaf health grading using state-of-the-art deep learning approaches. INOCON Conference.

