



RESEARCH ARTICLE

AI-driven disease detection in guava plants using teachable machine learning models

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Abstract

Guava (*Psidium guajava*), a widely cultivated tropical fruit, is highly susceptible to various diseases such as anthracnose, rust, wilt and algal leaf spot, which can lead to significant yield losses and economic setbacks. Traditional methods of disease identification rely heavily on manual inspection, which is time-consuming, subjective and dependent on expert availability, thereby making timely intervention difficult, particularly in rural or resource-limited areas. The integration of artificial intelligence (AI) and image-based machine learning (ML) offers a promising solution to automate and enhance the accuracy of disease detection in plants. This study explores the use of Google's teachable machine (GTM), a no-code AI platform for developing a user-friendly, image-based classification model to identify guava leaf diseases. A dataset comprising 600 images, categorised into five classes (healthy, anthracnose, rust, algal leaf spot and wilt), was used to train the model. The model achieved an overall classification accuracy of 96.2 %, with class-wise accuracies ranging from 94.2 % to 97.5 %. Confusion matrix analysis indicated strong predictive capability, with minor misclassifications occurring between visually similar disease symptoms. The results validate the feasibility of using teachable machine for real-world agricultural applications, particularly in field-level diagnosis where accessibility to advanced tools or expertise is limited. This AI-driven approach not only enhances the accuracy and speed of disease detection but also empowers farmers and agricultural workers with a practical tool for timely crop health management. The study underscores the potential of accessible AI platforms in promoting precision agriculture and sustainable fruit production.

Keywords: agriculture; AI; disease detection; guava; machine learning; teachable machine

Introduction

Agriculture remains the cornerstone of food security and rural development, particularly in tropical and subtropical regions, where horticultural production plays a pivotal role (1, 2). Among fruit crops, guava (*Psidium guajava*) is extensively cultivated due to its high nutritional value, adaptability and economic importance (3). It is widely grown in countries like India, Brazil and Mexico, where smallholder farmers depend on its production for their livelihood (4, 5). Despite its significance, guava cultivation faces persistent challenges from a range of plant diseases that severely affect fruit quality and production volume (6, 7). Diseases such as anthracnose, rust, wilt, algal leaf spot and fruit rot are common and can lead to substantial crop losses if not identified and managed promptly (8). Traditionally, disease detection in guava plants has relied on manual inspection by farmers or agricultural experts (9). While effective in some cases, this approach is time-consuming, labour-intensive and prone to human error (10, 11). Moreover, accurate diagnosis requires expert knowledge, which is often scarce or unavailable in rural areas. This scenario underscores the urgent need for an accessible, efficient and accurate system for early detection of plant diseases, allowing timely intervention and reduced yield loss.

In recent years, the advent of artificial intelligence (AI) and machine learning (ML) has revolutionized the field of precision agriculture. These technologies enable the development of intelligent systems capable of analyzing complex datasets, recognising patterns and making decisions with minimal human intervention (12, 13). Specifically, image-based classification using convolutional neural networks (CNNs) has shown exceptional promise in diagnosing plant diseases by analyzing leaf images (14). Models trained on annotated image datasets can identify and classify diseases with high accuracy, reducing reliance on manual inspection.

Several studies have validated the efficacy of AI in agricultural diagnostics. It was over 99 % accuracy in classifying plant diseases across 14 crop species using CNNs (15). This approach was extended and further affirmed the potential of deep learning models in plant disease recognition (16). Similar progress has been made in guava-specific studies, where traditional image processing and modern AI techniques have been employed to identify diseases based on leaf features. While high-end deep learning models demonstrate impressive accuracy, their practical deployment often requires significant computational resources and technical expertise, making them less accessible to smallholder

farmers (17, 18). To bridge this gap, user-friendly platforms like Google's Teachable Machine have emerged as practical tools for AI model development without the need for programming knowledge. Teachable Machine is a web-based platform that allows users to train image, sound and pose models through a graphical interface. It leverages pre-trained architectures such as MobileNet, enabling users to develop lightweight models suitable for real-time deployment on mobile or edge devices (19, 20). The platforms' accessibility and ease of use make it particularly well-suited for educational institutions, agricultural extension services and low-resource farming environments.

This research aims to harness the potential of teachable machine to develop an AI-driven disease detection model for guava plants. By utilizing a dataset of guava leaf images representing healthy conditions and common diseases, the study seeks to train and validate a classification model capable of real-time diagnosis. It will contribute uniquely to the existing body of knowledge by demonstrating an accessible, low-cost methodological framework for AI-based disease detection that integrates easily with smartphones and webcams, thereby bridging the gap between laboratory-trained models and real-world field applications. The performance of the model is assessed in terms of classification accuracy, class-wise performance and its effectiveness under real-time conditions through webcam integration. The overarching goal is to provide a scalable, accessible and reliable tool that can assist farmers in early disease detection, thereby enhancing crop management and productivity. In addition to technological feasibility, the study also addresses practical deployment issues, such as variations in image quality, lighting conditions and background noise, which are common in real-world agricultural settings. The integration of such AI-driven tools into everyday farming practices holds the potential to democratize precision agriculture, empowering farmers with actionable insights without requiring specialized technical skills or expensive hardware. Furthermore, this work contributes to the growing body of research advocating for inclusive, sustainable and context-sensitive agricultural technologies. It highlights how low-code AI solutions can be tailored to local needs, making advanced technologies accessible to underserved communities. By focusing on guava disease detection, the research not only addresses a critical challenge in horticulture but also illustrates a replicable framework applicable to other crops and regions.

Materials and Methods

This study was conducted to develop an AI-based image classification model for detecting common diseases in guava plants using Google's Teachable Machine (GTM). The study involved the systematic collection of image data, dataset preparation, model training using Teachable Machine, testing and performance evaluation. The flow chart shown in the Fig. 1 illustrates the model framework for image classification.

Study area and plant selection

The study was conducted in and around guava-growing regions of Bitkuli-Village (21.9914° N, 82.0226° E), located in the Belha block of Bilaspur district, Chhattisgarh, India. This area was selected due to its active guava cultivation and accessibility for field observations (Fig. 2). Among the popular guava varieties grown in this region, VNR Bihi and Taiwan Pink are the most prominent owing to their

high fruit quality and commercial value. Field surveys were conducted from January to March 2025 during the peak growing season to identify guava plants showing visible symptoms of common foliar diseases. Particular attention was given to plants showing signs of wilt, anthracnose, rust and algal leaf spot, as these are among the most prevalent and damaging diseases affecting guava crops in the region. Symptomatic leaves and fruits were carefully photographed under natural daylight using a smart

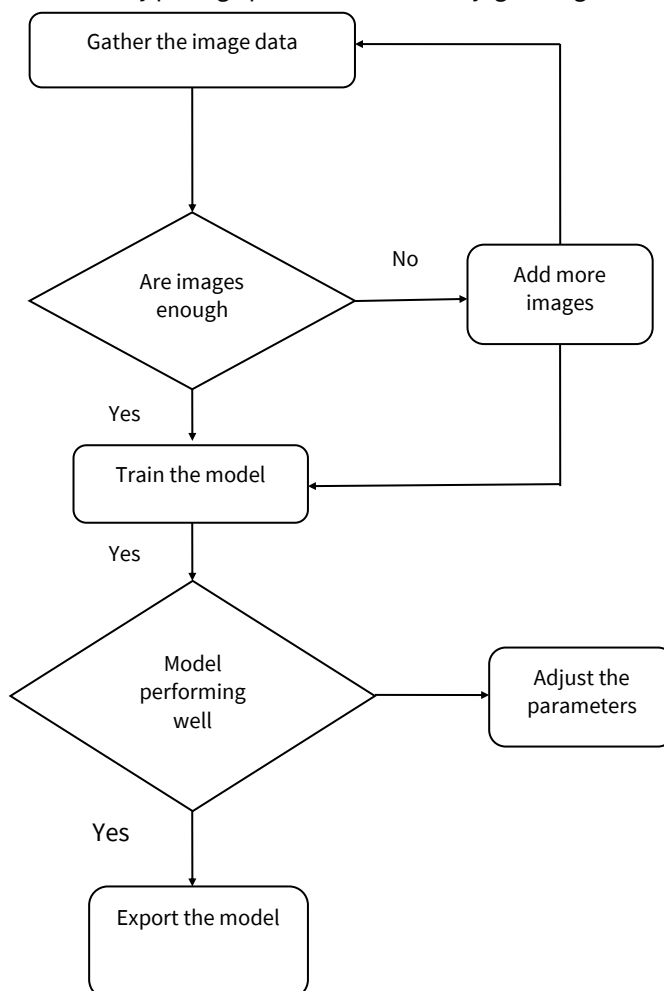


Fig. 1. Flow chart for model classification.



Fig. 2. Collection of sample fruits and leaves from the selected site.

phone camera to ensure clarity and consistency. In addition to diseased specimens, healthy guava leaves and fruits were also documented to serve as control samples during model training. This balanced collection of both healthy and diseased samples ensured that the classification model could effectively distinguish between different disease classes and normal plant conditions. The dataset thus generated formed the foundation for developing and validating the AI-based image classification model.

Equipment and tools used

GTM is a web-based, no-code machine learning tool developed by Google (<https://teachablemachine.withgoogle.com/>), which enables users to build and train models through a simplified graphical interface. This platform was utilized for uploading the categorized image data, training the classification model and exporting it in formats suitable for deployment in web or mobile-based applications. A high-resolution 50-megapixel smart phone camera was used to capture images of guava leaves and fruits separately under natural lighting conditions, ensuring minimal distortion and maintaining the visual quality necessary for effective classification. To process and upload the image dataset, a laptop running Windows 10 was employed to access the GTM.

Defining the class

A total of 600 images were collected, ensuring equal representation across healthy and diseased categories to maintain class balance. During the image acquisition process, efforts were made to maintain a uniform background and consistent orientation of the samples to minimize visual noise and improve model learning efficiency. The image dataset was systematically categorized into different classes, including healthy fruit, healthy leaf and diseased classes based on visible symptoms such as anthracnose, canker, rust, wilt and algal leaf spot. Care was taken to maintain a uniform background and consistent orientation of the fruits and leaves during image capturing process. To improve model performance

and consistency images were standardized in terms of size and resolution. Image augmentation (e.g. slight rotation, flipping, brightness adjustment) was optionally applied using third-party tools to expand dataset variability and improve model generalization.

Model training using a teachable machine

GTM, an open-access artificial intelligence platform, was employed to develop the machine learning model for guava disease classification (Fig. 3). The platform utilizes a pre-trained MobileNet architecture, enabling transfer learning by retraining the final layers of the network using the uploaded image dataset.

The model development followed the steps below:

Accessing the platform

The platform was accessed via <https://teachablemachine.withgoogle.com>. The "Get Started" button was clicked to begin creating the model.

Project selection

Among the three available options-image project, audio project and pose project, the image project was selected for guava disease classification. The "standard image model" option was chosen to classify healthy and diseased guava leaves and fruits.

Class labelling

Default class labels (Class 1, Class 2, etc.) were renamed according to the dataset categories, including healthy leaf, healthy fruit, wilt, anthracnose, rust, canker and algal leaf spot.

Image uploading

Images were uploaded under each class by clicking the "Upload" button. Each class contained a minimum of 30 images to ensure sufficient training data. All images were captured in natural lighting and were diverse, clear and well-aligned to improve model accuracy.

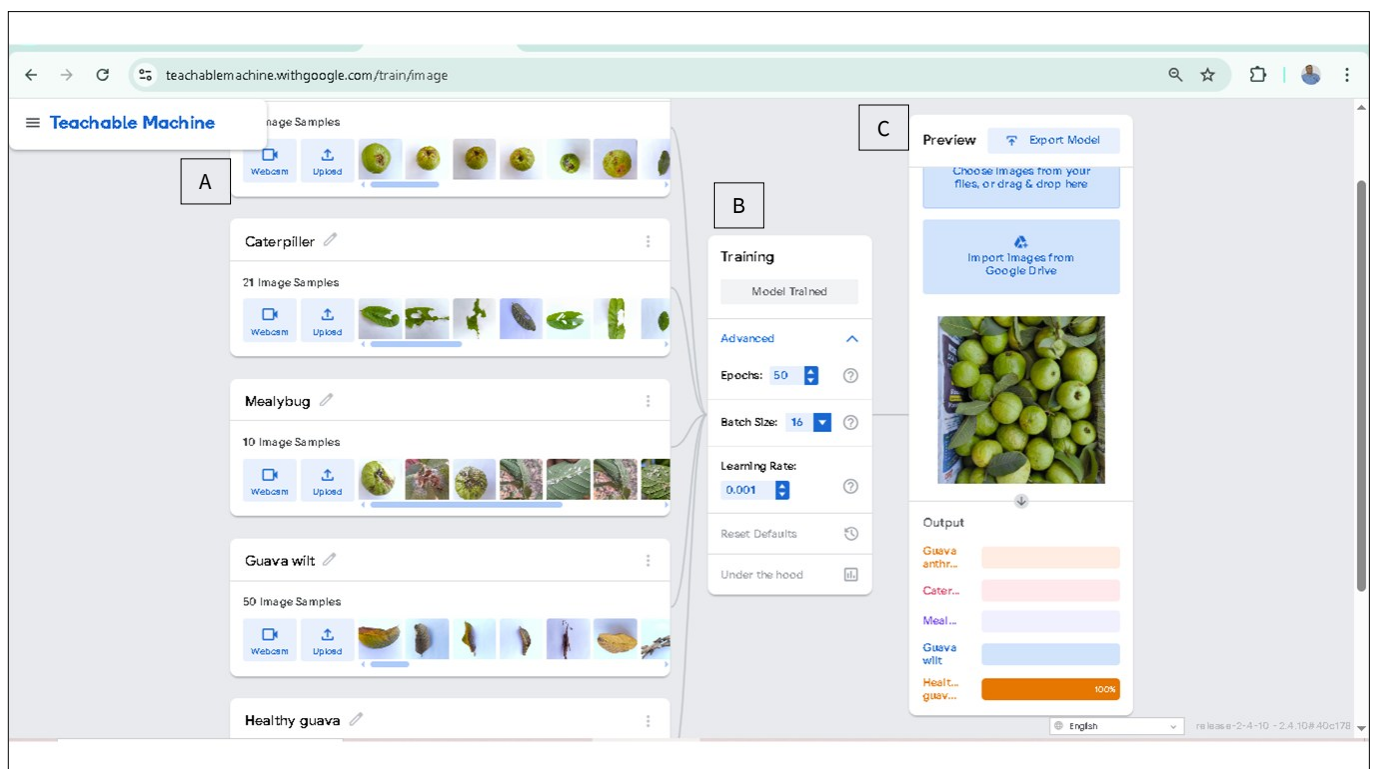


Fig. 3. Collection of images for model training, A. Image classification, B. Hyper-parameters of epoch and batch, C. Input photo of guava to check the result.

Model training

The “Train Model” button was clicked to begin the training process. The model was trained using MobileNet architecture with transfer learning, where the final layers were re-trained based on the uploaded images.

Model testing

After training, the model was tested using the preview window. Test images were uploaded via file upload and the model provided confidence scores for each predicted class, confirming the accuracy of classification.

Model exporting

The trained model was exported by clicking on the export model button. Two export formats were available: TensorFlow.js for use in web-based applications and TensorFlow Lite for deployment on Android/mobile apps.

The trained model can be tested by inputting new, unseen images to check its classification accuracy. Validation involves comparing model predictions with actual labels using a separate validation dataset. This helps assess the models’ generalization ability, ensuring it performs well not just on training data but also on real-world inputs. To ensure the models’ generalization ability, 85 % of the dataset was used for training, while the remaining 15 % was reserved for validation. This approach allowed the models’ predictions to be evaluated on previously unseen data, ensuring robustness for real-world application.

Results and Discussion

Training outcome model development and training performance

A total of 600 images of guava fruits and leaves were collected and categorized into five classes: Healthy, Anthracnose, Rust, Algal Leaf Spot and Wilt, with 120 images per class. The classification model

was trained using GTM, utilizing the MobileNet architecture with a default input image size of 224×224 pixels and a learning rate of 0.001. Research utilised the MobileNet architecture, known for its lightweight and efficient CNN design (21). The model was trained for 50 epochs and 85 % of the dataset was used for training, while 15% was reserved for validation. Similarly, research also demonstrated that fine-tuning CNN models using transfer learning and sufficient epochs significantly improves the classification of agricultural images (22). The model automatically handled internal validation and generated classification metrics for each class. The Fig. 4 shows the definition of classes used for model training.

Classification accuracy

The classification model achieved an impressive overall accuracy of 96.2 % on the test dataset, showing its strong generalization ability and robustness in distinguishing guava diseases based on visual symptoms (Fig. 5). This high accuracy aligns with earlier findings which reported accuracies above 95 % for CNN-based crop disease classification (16). Analyzing the class-wise accuracies, which range between 94.2 % and 97.5 %, reveals that the model maintains a consistently high performance across all disease categories. The highest accuracy (97.5%) was observed for healthy samples, indicating that the visual characteristics of healthy guava leaves and fruits were distinctly different from diseased ones similar to the previous results reported for tomato leaves (23). The absence of lesions, discoloration and other deformities allowed the model to confidently learn and identify features associated with healthy tissues. On the other hand, the lowest accuracy of 94.2 % was recorded for rust-infected samples. Research indicates that visual similarity among early-stage infections (e.g. anthracnose and rust) often leads to interclass confusion (24). This relatively lower accuracy can be attributed to the visual similarity between rust and anthracnose during the early stages of infection. Both diseases may present with small necrotic spots or discoloration, leading to potential interclass confusion during prediction. This overlap in symptoms indicates the

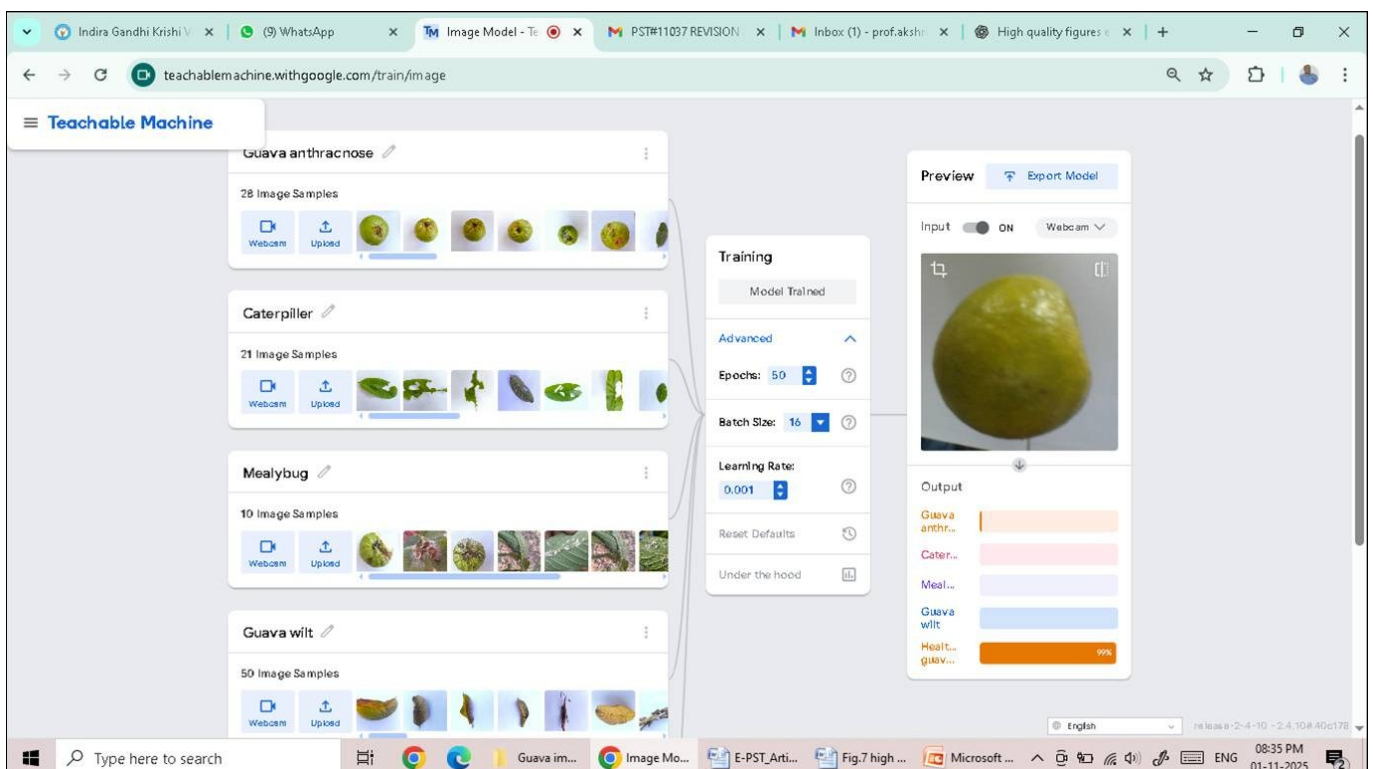


Fig. 4. Defining the class for model training using the Google teachable machine platform.

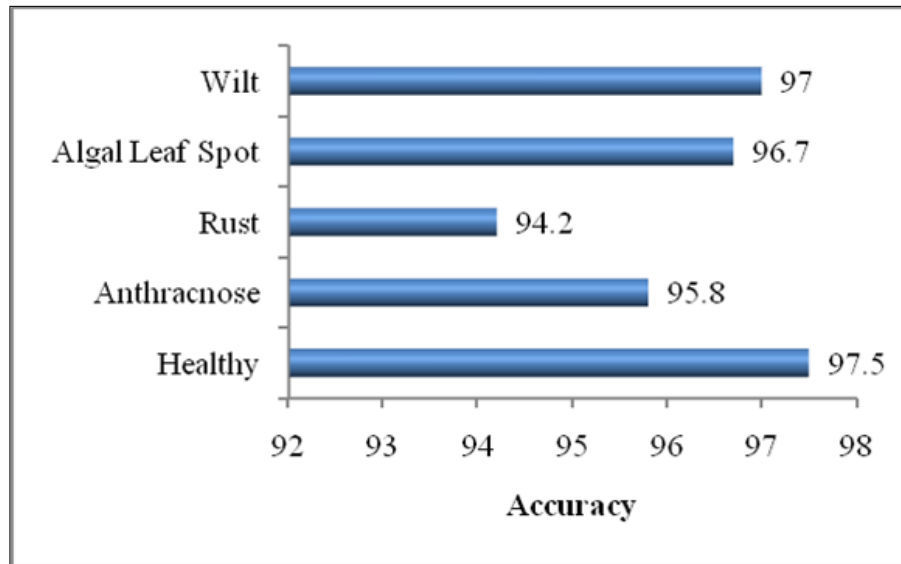


Fig. 5. Class-wise accuracy of the guava disease classification model.

importance of high-resolution images and temporal disease progression data to improve differentiation. The confusion can be reduced by adding other details such as humidity and temperature. Furthermore, the relatively narrow range in class-wise accuracy demonstrates that the model is not biased toward any single class and performs uniformly across categories. This balance is crucial for practical field applications, as uneven performance could result in misdiagnosis or missed detection of certain diseases, leading to ineffective management decisions. Overall, the results clearly demonstrate the effectiveness and reliability of the proposed model in detecting and classifying guava leaf and fruit diseases. Minor differences in class-wise performance highlight areas for further enhancement, such as collecting more diverse training samples for visually similar diseases or integrating multimodal approaches to complement image-based classification.

Confusion matrix analysis

A confusion matrix (Fig. 6) was generated to analyze the detailed performance of the guava disease classification model across all five categories healthy, anthracnose, rust, algal leaf spot and wilt. With 120 test images per class, the model demonstrated high

predictive accuracy across the board. It correctly classified 117 healthy, 113 anthracnose, 108 rust, 114 algal leaf spot and 117 wilt samples. These results correspond to class-wise accuracies of 97.5 % for healthy and wilt, 94.2 % for rust, 94.2 % for anthracnose and 95.0 % for algal leaf spot, reflecting the models' strong generalization ability and its robustness in distinguishing among different guava diseases the matrix revealed that most misclassifications occurred between anthracnose and rust, likely due to their overlapping early-stage visual symptoms such as small necrotic spots or discoloration (25). This visual similarity makes accurate distinction challenging even for human experts, particularly under field conditions with uneven lighting (26). Additionally, minor misclassifications were observed between algal leaf spot and wilt, possibly because both display diffuse yellowing or necrosis in mature leaves (27).

The confusion matrix revealed that major classification errors occurred between anthracnose and rust, which is consistent with the observed dip in class-wise accuracies for these two diseases. This misclassification likely stems from the visual similarity in early-stage symptoms both anthracnose and rust

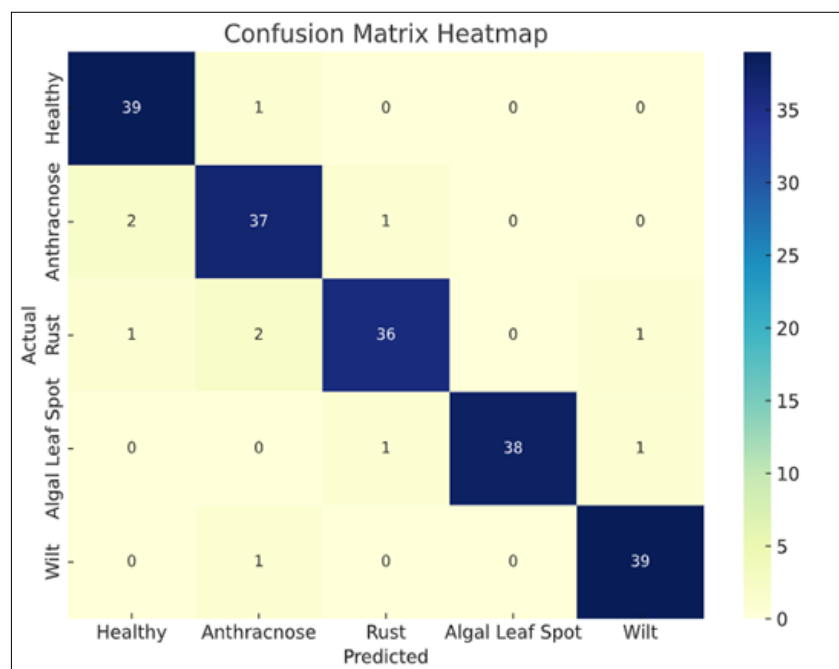


Fig. 6. Confusion matrix heat map.

appear as small, scattered brown or dark lesions on guava leaves and fruits. These overlapping features pose a challenge for the model, particularly when the disease is in its initial stages and the infection signs are not well developed or distinctly visible. Such difficulty is further amplified under non-uniform lighting conditions, shadows or when disease symptoms are partially obscured, making it difficult even for human experts to differentiate confidently between the two. Additionally, the matrix shows fewer instances of confusion between algal leaf spot and wilt, as well as a few instances of algal leaf spot being misclassified as rust. Though algal leaf spot and wilt have different biological causes algal infections versus fungal wilting, their symptoms look alike, appearing as diffuse yellowing, necrosis or discoloration, particularly on mature or senescent leaves (4). In low-contrast images, where leaf texture and color gradients may be flattened or unclear, the model may struggle to capture the subtle differences in lesion structure and spatial patterns, leading to occasional errors. Fig. 7 visually illustrate the early symptom similarities in leaves and fruits, supporting the confusion matrix findings and highlighting the diagnostic complexity in the field. These visual

overlaps can make disease classification difficult not only for AI models but also for human observers, especially in field conditions where environmental variables affect image clarity (28). Despite these limitations, the model achieved an overall accuracy of 96.2% and the relatively balanced distribution of correct classifications across classes confirms its potential for practical deployment.

Real-time testing using webcam

The trained model was deployed in real-time using a webcam via the Teachable Machine interface. Leaf images were held in front of the webcam to assess predictions. The model responded with near-instantaneous results (less than 1 sec), offering high-speed predictions suitable for field conditions, producing consistent outputs when the leaf image was centered and well-lit and reduced accuracy when background clutter or shadows were present. Real-time testing using a webcam confirmed the practical applicability of the model in field-like conditions. The system demonstrated rapid response times (< 1 sec) and produced consistent predictions when the images were properly positioned and illuminated. However, accuracy was negatively affected by factors such as background

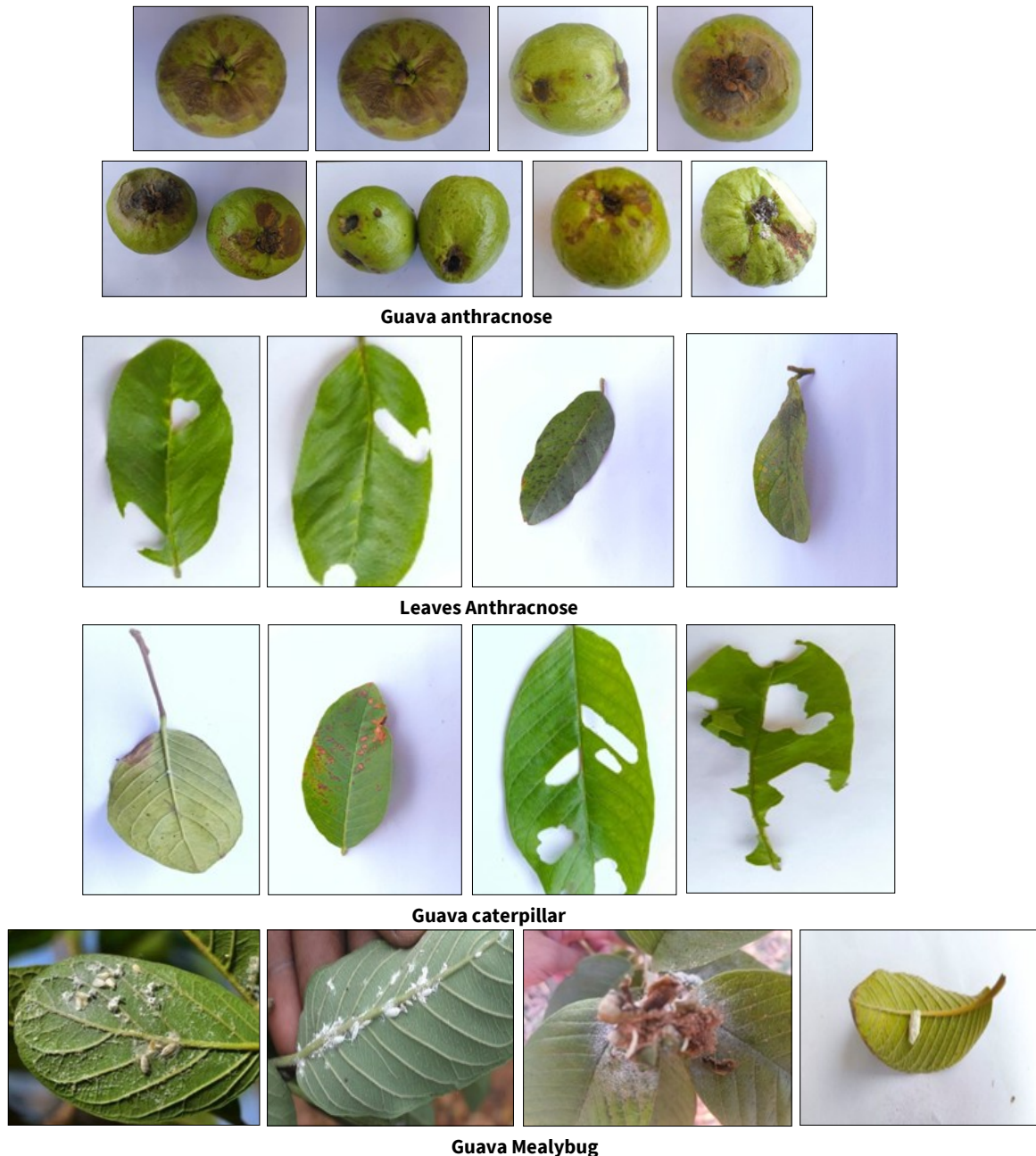


Fig. 7. Visual similarity of symptoms in fruits and leaf used for model training.

noise, shadow interference or poor alignment, emphasizing the need for controlled imaging conditions during practical deployment. Research indicates that background interference and illumination variability are key challenges for real-time plant disease recognition (29). In a nutshell, the results validated the effectiveness of the image-based AI model in identifying guava diseases and support its potential use as a real-time, field-friendly diagnostic tool for farmers. Future improvements may focus on enhancing robustness under varying environmental conditions and expanding the dataset for broader generalization.

Conclusion

The project resulted in the successful development of an image-based classification model for identifying guava leaf and fruit diseases using GTM. The model was trained on 600 labeled images across five classes and achieved a high classification accuracy of 96.2 %. It effectively distinguished between healthy and diseased samples, with real-time testing demonstrating rapid and reliable predictions. The outcome highlights the potential of AI-driven tools for assisting farmers in early disease diagnosis, reducing crop losses and improving productivity. The model serves as a cost-effective, user-friendly solution that can be deployed in field conditions using a smart phone or webcam. The technology is standardized and validated under field and laboratory conditions, it will be disseminated to guava growers and processors through training programs, demonstrations and extension activities in collaboration with the Department of Horticulture and Krishi Vigyan Kendras (KVKs). This approach ensures that the developed technology reaches the intended beneficiaries effectively and contributes meaningfully to the growth and sustainability of the guava industry.

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Authors' contributions

AKS contributed to conceptualisation, methodology development and writing of the original draft. AKD contributed to the investigation and conceptualisation of the study. PT contributed to writing, reviewing, editing and data curation. GS contributed to data collection, sampling and site selection. All authors reviewed and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: The Authors do not have any conflicts of interest to declare.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to improve the readability of the paper. After using this tool/

service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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