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AI Based Disease Identification in Guava Plants Using Google Teachable Machine Learning Model for Farer Awareness

*Gargi Sanadya

Department of Soil & Water Conservation Engineering, Faculty of Agricultural Engineering, Swami Vivekanand College of Agricultural Engineering & Research Station, Indira Gandhi Krishi Vishwavidyalaya, Raipur, Chhattisgarh, India

*Corresponding Author's email: sanadyagargi04@gmail.com

Early identification of plant disease is important for protecting yield and improving the timeliness of crop management, yet field diagnosis can be difficult where specialist support is limited. This pilot study investigated whether a low-code image-classification workflow based on Google Teachable Machine could support disease identification in guava (*Psidium guajava*) and be demonstrated to farmers using commonly available digital devices. A total of 300 images of healthy and affected guava leaves and fruits were collected using a smartphone under field and natural-light conditions. Images were organised into labelled categories, quality-checked, and uploaded to a standard image-classification project. The trained model was evaluated through uploaded images and live webcam testing. The project report records ten representative test cases, all correctly classified, with model confidence ranging from 94.0% to 99.5%. A farmer-awareness and demonstration programme reached approximately 100 guava farmers; one farmer subsequently adopted the model for routine orchard monitoring, giving an observed project-period adoption rate of 1%. For the adopting farmer, average yield increased from 18.5 to 19.4 kg tree^{-1} and net seasonal income from 72,000 to 75,500, both reported as approximately 4.9% increases. Because these economic observations came from one farmer and one cropping season, they are treated as preliminary associations rather than causal evidence. The study demonstrates the practical value of accessible, no-code AI for agricultural extension, while also identifying the need for larger, independently labelled datasets, rigorous class-wise validation, field testing under uncontrolled conditions, and a farmer-oriented mobile interface.

Keywords: artificial intelligence; guava; plant disease detection; image classification; Teachable Machine; precision agriculture; farmer awareness; technology adoption

Highlights

- A smartphone-based, low-code workflow was developed for guava disease image classification.
- Three hundred guava leaf and fruit images were collected and labelled for model development.
- Ten documented test cases were correctly classified with confidence values of 94.0–99.5%.
- Approximately 100 farmers were reached through an awareness and demonstration programme.
- The study identifies a practical pathway from student-led AI prototyping to farmer-oriented extension.

Introduction

Guava (*Psidium guajava* L.) is an economically important tropical fruit crop whose productivity and marketable quality can be affected by diseases and pest-related symptoms. Conventional diagnosis commonly depends on visual inspection by farmers or specialists. Such diagnosis can be slow or uncertain when symptoms are subtle, multiple symptoms occur simultaneously, or expert support is not immediately available. The thesis underlying this manuscript identifies this accessibility problem as an important motivation for applying image-based artificial intelligence (AI) to guava health management. Image-based machine learning has already demonstrated that visual symptoms can be learned from plant photographs. Mohanty et al. reported 99.35% accuracy on a held-out dataset of 54,306 images covering 14 crops and 26 disease/healthy classes, but performance dropped substantially when images were collected under conditions different from the training data. This distinction between controlled-image performance and field generalisation is particularly important for farmer-facing systems. For guava specifically, previous studies have used feature engineering, support vector machines, convolutional neural networks, transfer learning, and lightweight models. Almadhor et al. developed a high-resolution DSLR-based framework using colour and texture features and reported 99% classification accuracy for four guava fruit diseases plus healthy fruit. Perumal et al. reported 98.17% accuracy for guava leaf disease classification using image processing and an SVM. More recent work has focused on lightweight or real-time deployment, including modified MobileNet approaches. The present work differs in emphasis. Rather than designing a complex classifier from code, it investigates a low-code workflow using Google Teachable Machine and couples the technical demonstration with farmer awareness. Teachable Machine is a web-based tool that allows users to gather examples into classes, train an image model, test it, and export the resulting model without requiring conventional programming expertise.

Objectives

The study was undertaken to: (i) develop an image-based guava disease identification model using Google Teachable Machine; (ii) collect and prepare healthy and affected guava leaf and fruit images for model training and testing; (iii) assess the model using representative test images and confidence scores; and (iv) demonstrate the technology to farmers and examine early adoption and field feedback. These objectives are derived from the project methodology and objectives reported in the thesis.

Related Work

The literature indicates a progression from conventional image processing toward deep learning and lightweight mobile deployment. Traditional feature-based approaches typically extract colour, texture or shape information before classification, whereas CNN-based approaches learn discriminative image features directly. The thesis review includes studies using CNNs, segmentation, SVMs, MobileNet-based models and hybrid architectures for guava disease detection.

Study	Approach	Reported result / relevance
Mohanty et al. (2016)	Deep CNN on PlantVillage images	99.35% held-out accuracy; highlights both the potential of deep learning and the challenge of generalising to different image conditions.
Ferentinos (2018)	CNN models for plant disease detection	99.53% accuracy on 17,548 previously unseen images from a large 87,848-image database.
Almadhor et al. (2021)	RGB/HSV histograms + LBP + machine-learning classifiers	99% accuracy for four guava fruit diseases against healthy fruit using a 393-image dataset.
Perumal et al. (2021)	Image processing + SVM	98.17% reported for guava leaf disease classification.
Nandi et al. (2022/2023)	Quantized CNNs for device-friendly diagnosis	Quantized GoogleNet reached 97% accuracy at 0.143 MB; demonstrates the importance of deployment constraints.

Study	Approach	Reported result / relevance
Rashid et al. (2022/2023)	MobileNetV2 + U-Net + YOLOv5 hybrid framework	Targets multiple diseases on a single leaf and field-oriented detection; illustrates the complexity possible beyond simple classification.

A recurring issue across the literature is that high laboratory or benchmark accuracy does not automatically establish reliable field performance. The thesis itself notes sensitivity of Teachable Machine-based models to training-data quality, lighting, background and limited customisation. The present study therefore treats low-code AI as an extension and decision-support prototype rather than as a replacement for expert diagnosis.

Materials and Methods

Study design and materials

The study followed a practical prototype-to-extension workflow: crop selection image collection image labelling quality control/pre-processing Teachable Machine training image-based testing farmer demonstration descriptive analysis. The equipment reported in the thesis included a smartphone camera, laptop/computer with internet connectivity, Google Teachable Machine, a plain/white background, and healthy and affected guava leaves and fruits.

Image acquisition and dataset

A total of 300 guava images were collected using a smartphone camera under natural or well-lit conditions. Images were captured from different angles and distances to introduce variation. The project report describes an eight-category inventory consisting of healthy fruit, healthy leaf, anthracnose fruit, anthracnose leaf, wilt fruit, wilt leaf, caterpillar-affected leaf and mealybug-affected leaf, with the class counts shown below.

Image category	No. of images	Share (%)
Healthy fruit	50	16.67
Healthy leaf	50	16.67
Anthracnose fruit	25	8.33
Anthracnose leaf	25	8.33
Wilt fruit	50	16.67
Wilt leaf	50	16.67
Caterpillar-affected leaf	25	8.33
Mealybug-affected leaf	25	8.33
Total	300	100.00

Pre-processing and model development

The documented quality-control steps included conversion to JPEG/PNG where needed, preference for plain backgrounds, acquisition in daylight or well-lit conditions, removal of blurred/poor-quality images, and selection of images showing clear symptoms. The thesis also states that Teachable Machine automatically resized and normalised images during training. Images were uploaded to a standard image-classification project in Google Teachable Machine. The thesis describes the architecture as MobileNet-based and reports a training duration of approximately 5–7 minutes, dependent on internet and browser performance. The trained model was exported in TensorFlow.js format.

Testing and evaluation

Testing was conducted using manually uploaded images and live webcam input. The documented evaluation criteria were prediction correctness and confidence score. The project report contains ten representative test cases spanning healthy and affected leaf/fruit conditions. Because the source report contains an internal inconsistency—one section describes an eight-category image inventory and another describes a three-category model—the present manuscript does not infer a formal overall accuracy from the 10 examples.
Instead, those examples are reported as documented representative validation cases.

Farmer awareness and adoption assessment

Approximately 100 guava farmers participated in awareness and demonstration activities. The demonstration covered the role of AI in agriculture, image capture using a smartphone, uploading images to the model, and the importance of early disease recognition and timely crop management. One farmer subsequently adopted the model for routine disease monitoring. Technology adoption rate was calculated as the number of adopting farmers divided by the number participating, multiplied by 100. The reported values were 1 adopter among approximately 100 participants, giving an observed adoption rate of 1%.

Descriptive analysis

Farmer participation and adoption were summarised using frequencies and percentages. For the single adopter, the project compared yield and net seasonal income before and after adoption. The source report explicitly cautions that these observations represent one farmer and one cropping season and therefore require validation using larger-scale field studies.

Results

Model test observations

The ten representative test cases documented in the project report were all classified correctly. Confidence values ranged from 94.0% for fruit rot to 99.5% for healthy leaf. These values indicate that the prototype produced high-confidence predictions on the selected examples, but they should not be interpreted as a statistically robust estimate of generalisation accuracy.

Test input	Expected	Prediction	Correct?	Confidence (%)
Healthy leaf	Healthy	Healthy	Yes	99.5
Healthy fruit	Healthy	Healthy	Yes	99.2
Anthracnose leaf	Anthracnose	Anthracnose	Yes	95.4
Anthracnose fruit	Anthracnose	Anthracnose	Yes	94.6
Caterpillar-affected leaf	Caterpillar	Caterpillar	Yes	96.3
Mealybug leaf	Mealy bug	Mealy bug	Yes	97.2
Mealybug fruit	Mealy bug	Mealy bug	Yes	97.0
Wilt leaf	Wilt	Wilt	Yes	98.0
Wilt fruit	Wilt	Wilt	Yes	97.8
Fruit rot	Fruit rot	Fruit rot	Yes	94.0

Source: project report test table. The values are reproduced as documented; no additional test samples or confusion matrix were available in the source file.

Farmer awareness and technology adoption

The awareness programme reached approximately 100 farmers. Farmers generally responded positively to the simplicity of the system and its potential for early diagnosis. One farmer voluntarily adopted the model for routine monitoring. The resulting project-period adoption rate was 1%.

Indicator	Observed value
Farmers reached	100
Farmers adopting the model	1
Observed adoption rate	1%

Preliminary yield and income observation

For the single adopting farmer, average yield increased from 18.5 to 19.4 kg tree□1, while reported net seasonal income increased from 72,000 to 75,500. Both changes were calculated in the source report as approximately 4.9%. The manuscript interprets these values conservatively: they are field observations associated with the adoption period, not a controlled estimate of AI treatment effect.

Parameter	Before adoption	After adoption	Reported change
Average yield	18.5 kg tree^{1}	19.4 kg tree^{1}	4.9%
Net seasonal income	72,000	75,500	4.9%

The source report explicitly notes that these observations are based on a single farmer and one cropping season and should be validated through larger-scale studies.

Discussion

The central contribution of this pilot study is not a claim of state-of-the-art classification accuracy; rather, it is the demonstration of an accessible pathway from image collection to an operational AI prototype and then to farmer outreach. This is relevant because many agricultural AI studies focus on model architecture while practical adoption depends on device accessibility, workflow simplicity, training requirements and user trust. The documented confidence values of 94.0–99.5% across ten representative cases are encouraging for a prototype. However, the small sample and lack of a reported confusion matrix, class-wise precision, recall, F1-score, independent external test set, and confidence calibration prevent strong claims about real-world diagnostic accuracy. This limitation is consistent with evidence from broader plant-disease research: Mohanty et al. showed that a model performing extremely well on controlled images can perform much worse when evaluated on images from different conditions.

The practical value of the proposed approach is strengthened by the use of a web-based, no-code platform. Teachable Machine is explicitly designed around gathering examples, training, testing and exporting models, making it accessible to users without extensive programming experience. This accessibility is important for agricultural universities, extension programmes and student-led technology-transfer activities where resources for custom software development may be limited. The farmer response also provides an important social dimension. Approximately 100 farmers were exposed to the technology, but only one adopted it during the project period. The 1% adoption rate should not be interpreted as failure of the technology. Rather, it highlights the gap between awareness and sustained adoption. Farmers may require repeated demonstrations, local-language interfaces, reliable internet or offline functionality, confidence in recommendations, and evidence of economic benefit before routine use. The thesis itself proposes mobile integration, multilingual support, management recommendations and expert connectivity as future directions.

The yield and income observations are potentially interesting but should be treated cautiously. A 4.9% increase over one season in a single orchard cannot separate the effect of AI-assisted disease monitoring from weather, disease pressure, crop load, management changes, market price or other factors. A stronger follow-up design would include multiple adopting farmers, non-adopting controls, baseline disease incidence, treatment costs, pesticide use, yield per tree, fruit quality and repeated observations across seasons. Compared with more complex guava disease systems, the present approach sacrifices model customisation in exchange for ease of development and demonstration. Recent guava studies report strong performance from specialised CNN and hybrid architectures, including lightweight MobileNet-based systems and models designed for multiple diseases on a single leaf. The logical next step is therefore not simply to claim that a no-code system is superior, but to investigate whether a larger, carefully curated field dataset can make such a system sufficiently robust for practical extension use.

Limitations and Data-Quality Considerations

Several limitations should be addressed before journal submission or before presenting the work as a fully validated diagnostic system:

- The source report contains inconsistent descriptions of the model classes. The methodology lists ten labels in one section and the results describe three categories in another.
- The report states that 300 images were collected and also describes an 80:20 split with 300 training images and 50 testing images. These numbers are internally inconsistent and should be corrected from the original Teachable Machine project/log before submission.
- The reported test table contains ten representative cases, all correct, but it does not provide enough information to calculate a reliable overall accuracy, precision, recall or F1-score.
- The farmer-adoption component involves approximately 100 participants and one adopter, so the adoption result is descriptive rather than inferential.

- Yield and income comparisons are from one farmer and one cropping season. They cannot establish causality.
- The dataset is relatively small and was collected under conditions that may not represent the full range of field backgrounds, disease severities, cultivars, camera devices and illumination encountered in practice.

These limitations do not invalidate the pilot study. Instead, they define its appropriate contribution: a feasibility and extension-oriented demonstration that should be followed by a more rigorous validation study.

Conclusion

This study demonstrates the feasibility of using a low-code image-classification workflow based on Google Teachable Machine for preliminary guava disease identification and farmer awareness. A smartphone-collected dataset of 300 guava images was organised and used to develop a prototype. The project report documents ten representative test cases with correct predictions and confidence values between 94.0% and 99.5%. The technology was demonstrated to approximately 100 farmers, of whom one adopted it for routine monitoring during the project period, corresponding to an observed adoption rate of 1%. The most important finding is therefore the combined technical and extension feasibility of the approach. A simple AI workflow can be introduced to farming communities without requiring advanced programming knowledge, creating an opportunity for agricultural institutions to use AI demonstrations as part of digital extension. At the same time, the study shows why model confidence alone is insufficient for claiming field-ready diagnostic performance. Future research should resolve the dataset/class inconsistencies, expand the image database across locations and seasons, use an independent test set, report a confusion matrix and class-wise precision/recall/F1, validate predictions with plant-pathology expertise, and evaluate the system against real field images. A multilingual mobile application with offline capability, disease-management guidance and expert referral could then be developed and tested through a multi-farmer, multi-season adoption study. Such a design would allow the promising prototype described here to progress toward a scientifically validated farmer decision-support tool.

Recommended Follow-up Experimental Design

For a stronger second-stage journal study, the following protocol is recommended. It is deliberately presented as a future design rather than as completed work, so that no unmeasured results are introduced into the present manuscript.

Stage	Recommended improvement	Primary output
Dataset expansion	Collect 1,000–2,000 images across orchards, seasons, cultivars, disease severities and phone models.	Diverse field dataset
Expert labelling	Confirm disease labels with plant-pathology/agronomy expertise where possible.	Reliable ground truth
Data split	Use plant/tree-level separation so near-duplicate images from the same source do not cross train/test sets.	Independent evaluation
Model comparison	Compare Teachable Machine with a lightweight MobileNet/EfficientNet baseline.	Fair performance benchmark
Metrics	Report accuracy, precision, recall, F1-score, confusion matrix and per-class sensitivity.	Reproducible evaluation
Field validation	Test images captured directly by farmers under uncontrolled backgrounds and lighting.	Real-world generalisation
Adoption trial	Use multiple farmers and a comparison group over 2 seasons.	Technology-effect evidence
Economic analysis	Record disease incidence, yield, pesticide use, treatment cost and net returns.	Cost-effectiveness

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Source note: Experimental details, farmer observations, dataset counts, test cases and project-period economic observations in this manuscript were derived from the uploaded thesis/project report. The manuscript intentionally avoids inventing a formal overall accuracy where the source document does not provide sufficient information.

Author statement

This manuscript is a journal-oriented reconstruction of the submitted project/thesis material. Before submission, the author should verify the original Teachable Machine project, exact train/test split, disease labels, image counts, model configuration, and field-study records and replace any unresolved inconsistencies with the primary records.