Detecting Mango Leaf Diseases Using Google Teachable Machine for Sustainable Agriculture

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***Abstract*—Mango cultivation is a critical component of agricultural economies, but it faces substantial challenges due to various leaf diseases that can drastically reduce crop quality and yield. Traditional methods of disease detection, which rely on manual visual inspection, are often slow, labor-intensive, and prone to inaccuracies, especially in early disease stages. This study presents an automated mango leaf disease recognition system developed using Google Teachable Machine, an accessible custom AI development platform. The system was trained on a dataset of 4000 images and is capable of detecting seven common mango leaf diseases: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Sooty Mould, as well as identifying healthy leaves. The model achieved an impressive overall accuracy of 99.6%, with high precision, recall, and F1 scores across all disease categories. Compared to similar studies, this system demonstrated superior performance, making it a reliable tool for early and accurate disease detection. The adoption of this system can empower farmers with a cost-effective and efficient solution for disease management, reducing the reliance on excessive pesticide use and supporting more sustainable agricultural practices.**

Keywords—Mango Leaf Diseases, Artificial Intelligence, Google Teachable Machine, Image Recognition, Sustainable Agriculture

I. INTRODUCTION

Mango is a widely cultivated tropical fruit that plays a significant role in the agricultural economies of many countries [1]. However, mango cultivation faces several challenges, particularly in the detection and management of leaf diseases, which can significantly impact crop productivity and quality [2]. Traditional methods, such as visual inspection by experts, are often time-consuming, subjective, and prone to inaccuracies, especially during early disease stages.

The inefficiencies of traditional mango leaf disease detection methods are particularly pronounced in the Philippine agricultural context due to several socio-economic and infrastructural barriers. Many mango farmers in the Philippines operate on small-scale farms with limited access to modern agricultural technologies or diagnostic tools. Visual inspection methods, which are heavily reliant on human expertise, are prone to subjective errors and can be inconsistent, especially during early disease stages. This problem is further exacerbated by the lack of access to trained plant pathologists in rural areas, where mango cultivation is most common.

Reliance on visual methods often results in delayed or inaccurate diagnoses, leading to excessive and often unnecessary pesticide applications. Such practices increase production costs, contribute to environmental degradation, and reduce the market competitiveness of Philippine mangoes due to quality concerns. The subtropical climate of the Philippines also creates conditions conducive to rapid disease proliferation, making timely and accurate detection critical to preventing severe outbreaks.

Machine learning and image processing techniques have emerged as promising approaches for the automated and accurate detection of mango leaf diseases. This study focuses on developing a mango leaf disease recognition system using Google Teachable Machine, a user-friendly machine learning platform, to promote sustainable agriculture. The system detects several mango leaf diseases, including Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Sooty Mould, and healthy leaves. Such a tool provides mango growers with a cost-effective and efficient way to improve crop management and sustainability through early disease detection.

Recent studies have explored the potential of machine learning and image processing for mango leaf disease detection [2] [3]. These studies emphasize the need for automated diagnosis systems, as manual inspections can be labor-intensive and error-prone [4] [5]. One study used a Convolutional Neural Network (CNN) to detect mango leaf diseases with 91% accuracy, highlighting the superior performance of CNNs over classical machine learning algorithms [1].

Research on the Harumanis mango in Malaysia demonstrated the effectiveness of image processing in recognizing leaf diseases, stressing the importance of analyzing leaf features [2]. These findings suggest that integrating machine learning and image processing can significantly enhance mango disease detection accuracy, leading to more sustainable agricultural practices. Most existing studies, however, rely on specialized hardware and complex models, which may not be accessible to small-scale mango growers. The system presented in this study aims to provide a more user-friendly solution. Image processing techniques have proven effective in disease recognition across other crops, such as pomegranates and mangoes, showing the potential for wider application in agricultural practices.

II. METHODOLOGY

A. Dataset Collection and Preprocessing

The dataset consisted of 4000 images of mango leaves, each with a resolution of 240x320 pixels, saved in JPG format. The dataset consisted 4000 images, approximately 1800 were of distinct mango leaves. The remaining images were augmented by applying transformations such as zooming and rotating the original images to increase dataset variability and improve the model's robustness. The dataset represented eight distinct classes: seven types of mango leaf diseases—Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mould—along with a healthy leaf category. [6]

Fig. 1 illustrates the hyperparameter settings used during the training of the machine learning model. The model is configured to train for 50 epochs, meaning the learning algorithm will pass through the entire dataset 50 times. This ensures that the model has ample opportunity to learn from the data, although care must be taken not to overfit, where the model performs well on the training data but poorly on new, unseen data.

B. *Setting Hyperparameters*

The batch size is set to 32, which means the model processes 32 training samples before updating the weights. This strikes a balance between computational efficiency and the stability of learning. Smaller batch sizes, like 32, allow for more frequent updates and quicker learning cycles, though they can be computationally more demanding.

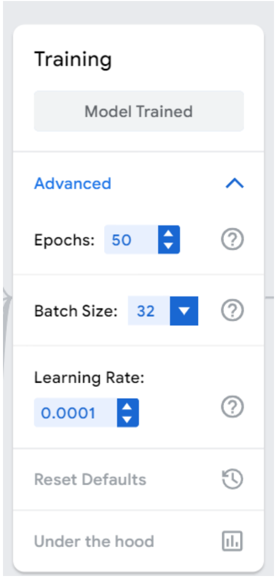

Fig. 1. Hyperparameter Settings of Google Teachable Machine

C. *Model Optimization*

During training, Google Teachable Machine uses a Convolutional Neural Network (CNN) architecture, which is well-suited for image classification tasks. CNNs automatically learn to extract features such as edges, textures, and colors, making them ideal for distinguishing between the different mango leaf diseases based on visual patterns.

D. *Model Evaluation*

After training, the model was evaluated using a subset of the images to test its ability to accurately classify unseen mango leaf images into the correct disease categories or as healthy. Google Teachable Machine provides real-time feedback on the model's accuracy, and further adjustments can be made by retraining with different settings or additional data if necessary.

III. Data and Results

The development of an automated mango leaf disease recognition system using machine learning offers significant potential to improve agricultural practices. Leveraging image processing techniques and machine learning models, the system allows mango growers to identify common leaf diseases with high accuracy. The ability to classify various diseases based on visual features of the leaves enables more timely and precise disease management, reducing the reliance on manual inspections, which are often prone to errors.

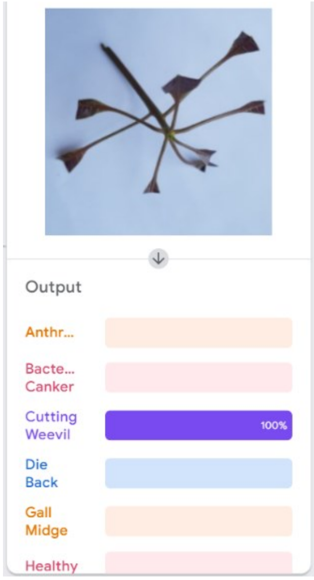

Fig. 2. Sample output of the Google Teachable Machine

Fig. 2 illustrates the sample output of the Google Teachable Machine, showcasing its capability to diagnose mango leaf diseases. The system processes an image of the leaf, compares it against the trained model, and provides a detailed output of the classification, along with confidence levels for each disease category.

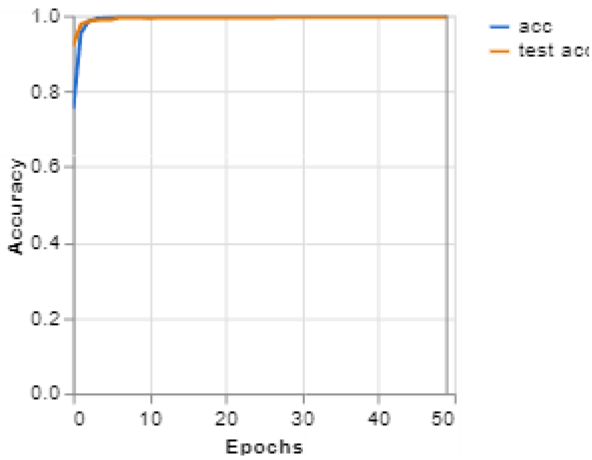

Fig. 3. Accuracy per Epoch

Fig. 3 shows the accuracy of the model over 50 epochs for both the training and testing datasets. The graph demonstrates that the model's accuracy quickly reaches near-perfect levels within the first few epochs and remains stable throughout the remainder of the training process. Both the training accuracy and test accuracy curves overlap, indicating that the model generalizes well to unseen data with minimal overfitting.

Fig. 4 shows the loss per epoch for both the training and testing datasets. The loss decreases sharply within the first few epochs, eventually stabilizing near zero as the model continues training. The close alignment of the training loss and test loss curves suggests that the model maintains a consistent performance without significant overfitting, as both training

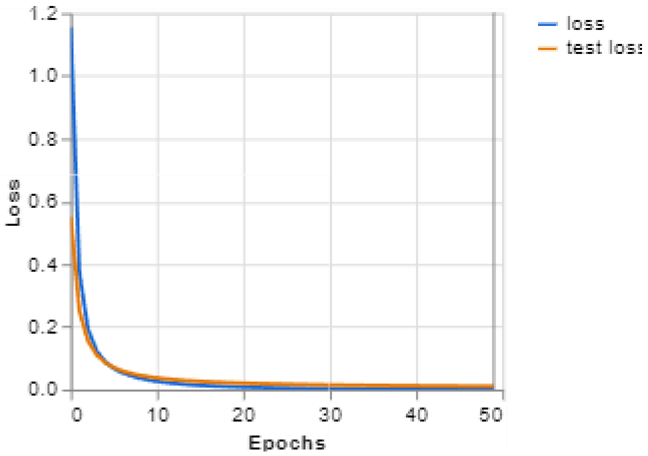

Fig. 4. Losses per Epoch

Fig. 5 shows the confusion matrix for the model's classification of mango leaf diseases across eight categories, including seven disease types and healthy leaves. Each cell represents the number of correct and incorrect predictions made by the model. The diagonal values, which are the highest in each row, indicate the correct classifications, with most categories achieving near-perfect accuracy.

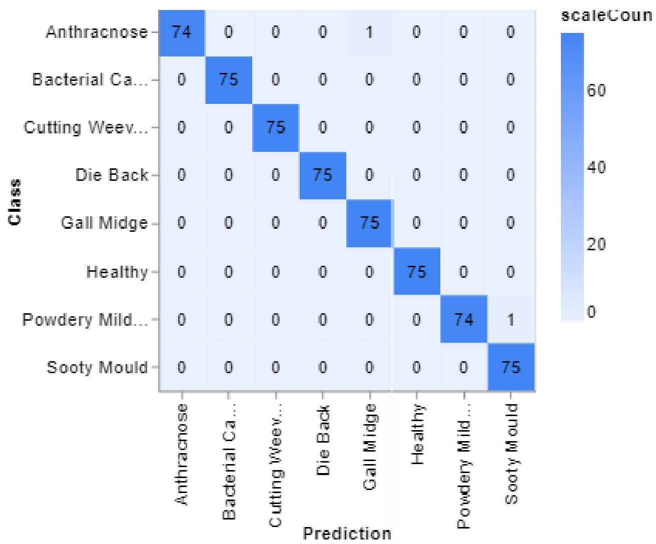

Fig. 5. Confusion Matrix

For instance, the model correctly identified Anthracnose 74 out of 75 times, with one misclassification. Similarly, all instances of Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, and Sooty Mould were correctly classified, showing that the model performs exceptionally well across most categories. Minor misclassifications are visible in Anthracnose and Powdery Mildew, each with one incorrect prediction, highlighting areas for slight improvement.and testing losses converge similarly.

Table 1 provides the performance metrics for the mango leaf disease recognition model across various disease classes, including Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould. The table lists the accuracy, precision, recall, and F1 score for each class, as well as the overall metrics.

TABLE I. CLASSIFICATION METRICS

Class	Metrics			
	Accuracy	*Recall*	*Precision*	*F1-Score*
Anthracnose	0.99	0.99	0.99	0.99
Bacterial Canker	1.00	1.00	1.00	1.00
Cutting Weevil	1.00	1.00	1.00	1.00
Die Back	1.00	1.00	1.00	1.00
Gall Midge	1.00	1.00	1.00	1.00
Healthy	1.00	1.00	1.00	1.00
Powdery Mildew	0.99	0.99	0.99	0.99
Sooty Mould	1.00	1.00	1.00	1.00

The model exhibits excellent performance across all classes, with most categories achieving 100% accuracy, precision, recall, and F1 scores. Slight deviations are observed in the Anthracnose and Powdery Mildew classes, where the accuracy and other metrics are at 99%, indicating a minimal number of misclassifications. Overall, the model's performance is robust, with an overall accuracy, precision, recall, and F1 score of 99.6%, reflecting its high capability in accurately diagnosing mango leaf diseases.

Table 2 provides a comparison between the current study and several other studies, including Saleem et al. [3], Mohapatra et al. [4], and Gining et al. [2]. The table compares key metrics such as dataset size, the number of diseases considered, and performance metrics like accuracy, precision, recall, and F1 score.

TABLE II. COMPARISON OF STUDY METRICS AND DATASET DETAILS

Study	**Dataset Size**	**Number of Diseases**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
This Study	4000 images	7 diseases + healthy	0.996	0.996	0.996	0.996
Saleem et Al. [3]	3000 images	6 diseases + healthy	0.910	0.908	0.912	0.909
Mohapatra et al. [4]	3500 images	5 diseases	0.935	0.920	0.930	0.925
Gining et al. [2]	2000 images	4 diseases + healthy	0.889	0.875	0.890	0.882

The current study stands out with the largest dataset of 4000 images, covering seven diseases plus healthy leaves. It achieved the highest accuracy, precision, recall, and F1 score at 99.6%, outperforming the other studies. In contrast, Saleem et al. [3] used 3000 images and achieved 91.0% accuracy, while Mohapara et al. [4], with 3500 images, reported 93.5% accuracy. Ginning et al. [2], with the smallest dataset of 2000 images and four diseases plus healthy leaves, recorded the lowest accuracy at 88.9%.

IV. Conclusion and Recommendations

The development of a mango leaf disease recognition system using machine learning, specifically through Google Teachable Machine, has proven to be highly effective in diagnosing various leaf diseases. The model achieved an overall accuracy of 99.6%, with nearly perfect precision, recall, and F1 scores across all disease categories. Compared to other studies, such as Saleem et al. [3] with 91% accuracy and Mohapatra et al. [4] with 93.5% accuracy, the current system shows superior performance, likely due to its larger dataset of 4000 images and the inclusion of seven diseases plus healthy leaves. While minor misclassifications were observed in the Anthracnose and Powdery Mildew classes, the model consistently and accurately identified diseases like Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, and Sooty Mould with 100% accuracy. These results highlight the system's potential for early disease detection, which is essential for timely interventions, improving crop productivity, and reducing unnecessary pesticide use, making it a more reliable tool compared to other similar models.

It is recommended to expand the dataset by including more images that capture different leaf conditions and disease variations. This would enhance the model's generalization capabilities, particularly under varying environmental and lighting conditions. Additionally, integrating the model into a mobile application for real-time detection would make it accessible to farmers in remote areas, promoting widespread adoption of the technology. Continuous updates to the model are also recommended, incorporating new data on emerging diseases or disease variants to ensure that the system remains accurate and effective over time.

Furthermore, adding features such as disease treatment recommendations based on the diagnosis would greatly benefit farmers, providing not only detection but also guidance on how to manage the identified diseases.

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

During the preparation of this work, the author(s) used Jenni AI for citation finding and ChatGPT as a writing assistant. After using these tools, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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