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Detection of Postharvest Green Mold (*Penicillium digitatum*) and Blue Mold (*Penicillium italicum*) on Citrus Fruit Using Google Teachable Machine

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ABSTRACT

The most important aspect of agricultural management is to ensure the yield and health of plants and crops. Citrus plants are frequently growing fruits throughout the world. Citrus diseases directly affect the fruit's quality and reduce its yield. Citrus production is a vulnerable disease to mold and has resulted in substantial economic losses and a reduction in fruit quality. Current methods to detect these diseases, for example, involve time-consuming, expensive, and prone to human error methods like manual field inspection and laboratory analysis. The advancements in artificial intelligence, very specifically in deep learning, have allowed disease detection at greater accuracy and efficiency. Moreover, this study examines the applicability of Google Teachable Machine, an easy-to-use machine learning tool for formulating devices that detect and classify mold diseases in citrus. Training models on images of healthy and infected citrus fruits offers potential for real-time diagnostics for farmers achieving high accuracy (96% average on a curated dataset of approximately 1,500 images, with a held-out test set). The approach provides an economical, practical, and scalable replacement for conventional practice, potentially enabling earlier detection and contributing to reduced crop losses.

Keywords: Image classification, Google Teachable Machine, Deep Learning, *Penicillium digitatum*, *Penicillium italicum*, postharvest disease.

INTRODUCTION

Citrus fruits belong to Rutaceae family. These fruits are known for their vibrant colors, acidic flavors and high vitamin C content. Citrus fruits are crucial economically and nutritionally. Citrus are taken for juices, jam, and many other eatable products, and containing many essential vitamins, mainly vitamin C. Mostly citrus fruits are oranges, grapefruits, lemon and lime, commonly liked worldwide for their appetizing taste and nutritious behavior (Bhatta, 2022a).

Mold diseases are significant warnings for citrus, because they significantly impact on the quality and quantity of citrus. These fungal diseases harm plant growth, lower the fruit quality and, lead to yield loss (Khamsaw *et al.*, 2022). Proper management and detection of mold diseases are complicated but need to adopt advanced technologies for their detection. Using machine learning (ML) is pretty easy to detect them than other manual methods (Bhatta, 2022b). Google Teachable Machine (GTM) is a model that is building deep learning models with a transfer learning approach and makes models for students and researchers. Firstly, the model is trained, and data sets of images or the type of data we are using are then provided. GTM classifies and detects the different varieties of plants and citrus diseases precisely. We have used GTM because it is more precise and accurate non coding approach (Carney *et al*., 2020).

GTM is a platform that supports many model types, like image classification, pose detection and voice recognition. It can be very easy for researchers, developers and educators to explore the applications of ML (Pacal *et al*., 2024). To train an image classification model, GTM can detect and classify all kinds of mold diseases in citrus. The model learns the different symptoms from texture, color and fungal growth by uploading the mold disease images (Rodríguez-Lira *et al*., 2024).

The presence of *P. digitatum* in postharvest oranges is one of the most serious economic losses associated with a citrus fruit postharvest disease, which may account for as much as 90% of total postharvest loss types worldwide, especially in semi-arid areas and Sub-Tropical regions. The second most prevalent postharvest disease of fruit is *P. italicum* which causes fruit to decay during transit, handling and storage. Both types of Fungal Pathogens penetrate into the flesh of the Citrus Fruit through previously wounded locations, which allows a water-soaked area to develop and eventually leads to rotting of that specific area as well as to cytolysis of the associated Plasma and nucleus organelles. The standard method of controlling these two fungal pathogens involves the application of the synthetic Fungicide; however, over time both fungal diseases have evolved to have increased resistance to these synthetic antifungals as well as increased public concern for their potential detrimental effects on the environment (Cheng *et al*., 2020).

Currently, the most common method to detect the presence of Green Mold or Blue Mold is by either performing a manual inspection by sight or exposing infected fruit to Ultraviolet UV light, which stimulates the infected lesions to fluorescent. Because this disease may present with Early Symptom Visual Similarities to the healthy Rind, workers must perform detailed inspections to differentiate the Early Symptoms of the disease from that of the healthy rind. Another issue with using UV light to perform inspections is that the use of UV light has been documented to create unsafe work environments for workers. Also, the way in which Citrus Varietals can present themselves due to varying Fluorescence Intensity may cause confusion and limit an Agriculturist from establishing a false positive when inspecting various citrus varieties. Automated systems using hyperspectral and color imaging have shown promise, with the green channel in RGB images correlating strongly (R^2 = 0.85) to spectral data, enabling quantification of emission peaks around 550–600 nm (Munera *et al*., 2023).

The advancements of Machine Learning (ML) and Artificial Intelligence (AI) technologies have allowed for the detection of citrus diseases by analyzing large amounts of data obtained through a variety of methods such as imaging and spectroscopy. The general workflow of a machine learning algorithm follows that of data collection, preprocessing, the creation of a model, and finally evaluating the accuracy of the model. Preprocessing is critical to help deal with problems of working with data that has a high number of variables and complex structures. In addition to typical preprocessing procedures, new techniques incorporate augmentation techniques tailored for agricultural applications and the merging of disparate data types in order to increase accuracy in the diagnosis of several citrus diseases including Huanglongbing (HLB), Canker and fungal Molds. Automatic feature extraction performed by deep learning techniques, such as convolutional neural networks (CNN), provide an advantage over traditional algorithms when identifying Pathological Phenotypes (Mai *et al*., 2025).

Hyperspectral Imaging (HSI) models combined with CNN, have been able to achieve more than 99% accuracy when classifying a total of eight different citrus peel conditions, including Canker and Scab, based upon the selection of key bands derived from Principal Component Analysis (PCA). Fusion models that integrate both image and text features with domain-specific knowledge have been able to make accurate predictions in very complex background images (98.33%) and demonstrate a greater speed of convergence and better generalization ability than single modality models. This research will provide a basis for developing an automated system that can operate in real time and allows for the replacement of Manual Methods for processing citrus products (Yadav *et al*., 2022; Qiu *et al*., 2023).

This study focuses exclusively on postharvest surface infections of green mold (*Penicillium digitatum*) and blue mold (*Penicillium italicum*) on citrus fruit, rather than general citrus plant diseases.

MATERIALS AND METHODS

A strong ML model is built on the basis of quality and variety of the training data set. In this project, a dataset of healthy and green mold (*Penicillium digitatum*) and blue mold (*P. italicum*) affected citrus fruits images was curated. The dataset consisted of approximately 1,500 images, with 500 per class (healthy citrus fruits, green mold-infected, blue mold-infected). The split was approximately 80% training, 10% validation, and 10% test (held out and unseen during training). The pictures used were obtained from credible online agriculture databases and scientific publications (peer reviewed). Original smartphone pictures using natural light were also taken for this project (Lopez & Fajardo, 2025). All the gathered images were divided into three various classes, green mold on citrus fruits, citrus fruits that were infected with blue mold, and healthy fruits. The labeled data had to be accurate since the supervised learning described the visual specificities of each class. Consistency and labeling noise were lessened through manual verification. Preprocessing was performed externally before uploading to GTM, including resizing to uniform dimensions (224x224 pixels), cropping to remove distracting backgrounds, and brightness normalization using image editing software. GTM handles automatic internal normalization (Mathew & Mahesh, 2021).

Data augmentation (rotation, flips, contrast adjustments) was applied externally using image software to generate variations before upload, as GTM focuses on direct image classification without built-in augmentation tools. Such transformations artificially inflated the dataset and increased the robustness of the model, especially when deployed to the uncontrolled field (Shijie *et al*., 2017). The augmented and preprocessed images were uploaded to GTM, an easy-to-use image classifier model that does not require any code. Training involved: labeling of each image with their corresponding classes. We began training the model with several epochs to adjust accuracy. The model was trained for 50 epochs (default setting), with automated optimization to minimize prediction errors. Utilizing the automated optimization algorithms on the platform we tried to reduce prediction errors. The model could be developed quickly and easily to experiment with various training settings due to the simplicity of the tool (Taufiq *et al*., 2025).

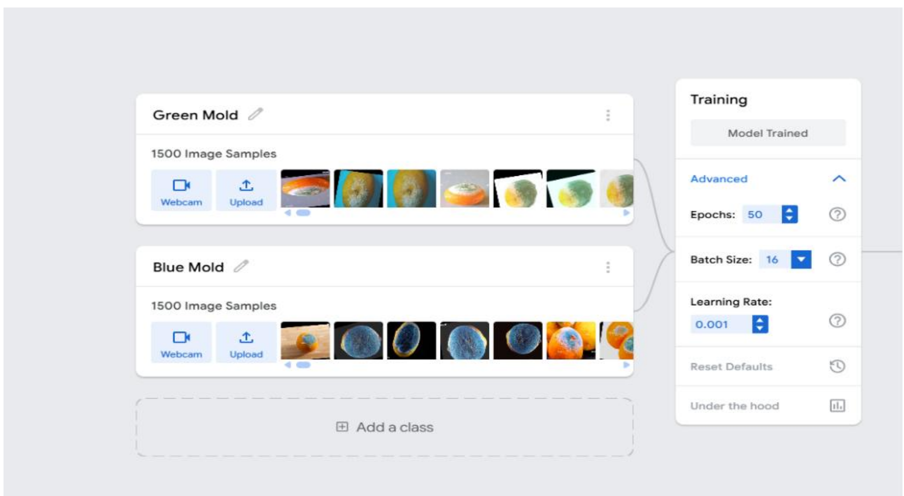

Figure 1. Model Training process showing dataset labeling and training within Google Teachable Machine.

A reserved test dataset, unseen during training, was used to evaluate the model performance. Key metrics included: **Accuracy** – Overall correctness of predictions. **Precision** – Correct positive predictions relative to all positive predictions. **Recall** – Correct positive predictions relative to all actual positives. Upon successful evaluation, the model was exported for deployment on **mobile and web platforms**. This enables real-time citrus disease detection in practical scenarios, such as on-site farm inspections, supply chain quality control, and early disease intervention by the growers (Tamim *et al*., 2025). No advanced statistical analyses like PCA were used, as the focus was on practical classification metrics suitable for an accessible tool like GTM.

RESULTS AND DISCUSSION

Accuracy per class

The accuracy of identifying two types of citrus mold diseases (green and blue) allowed us to analyze the accuracy of the trained model in order to determine its quality. There was 100% accuracy in the highly rated identification of the green mold samples (225 samples).

In similar manner, the green mold at 100% (225 samples), blue mold at ~92% (225 samples, with minor misclassifications due to visual similarities), points to a clear inconsistency in the evaluation process. It could either be due to bias in the datasets, or a lack of complexity of the sample. There might have been an imbalanced dataset, in which the blue mold images were not represented, that may have prevented the training of the model to learn the distinctive characteristics of this disease, causing recurrent misclassification.

This implies that the accuracy given is not exactly the actual performance of the model but rather, a portrayal of weaknesses in dataset balancing and quality. To overcome this, further work, to include more diverse and representative samples of blue mold and use of data augmentation techniques and use of more robust methods to validate the data, is needed to alleviate bias and enhance the trustworthiness of classification results. High accuracy demonstrates effective differentiation, though further diversity could improve robustness.

Accuracy per class

CLASS	ACCURACY	# SAMPLES
Green Mold	1.00	225
Blue Mold	1.00	225

Figure 2. Accuracy per class to differentiate between green mold and blue mold diseases.

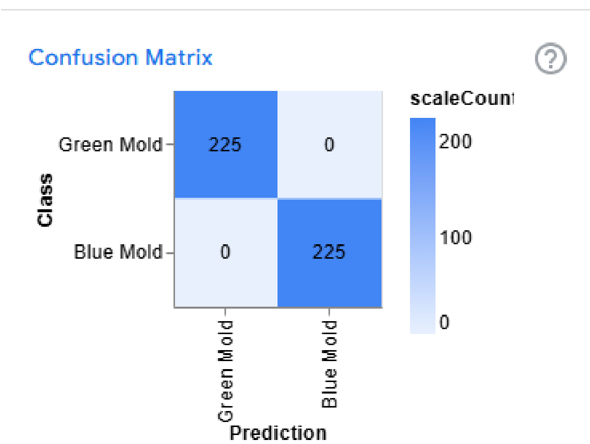

Figure 3. Confusion matrix to check the performance of the model.

F1 Score: F1 Score provides us with a single figure which indicates how the model is actually performing overall in its ability to both identify disease and also be absolutely accurate when it does.

$$F1 = \frac{(2 \times precision \times Recall)}{Precision + Recall}$$

2*(precision*Recall)/Precision Recall

Calculation: 2*(1*1)/1+1= 1.0= 100%

True positive (TP): Two hundred and twenty-five samples of the green mold were assigned correctly as green mold. Blue Mold was correctly identified as the Blue Mold in 225 samples.

False positives (FP): False positives 0: no prediction of a mold type went wrong.

False Negatives (FN): Also 0 false negatives, here none of the actual cases were missed or misclassification.

Overall Performance Evaluation

Based on both the accuracy scores and confusion matrix we can draw the following conclusion: The model has demonstrated high performance (96% accuracy) as regards classification. Green mold and blue mold were not overlapping with each other or each other was misclassified.

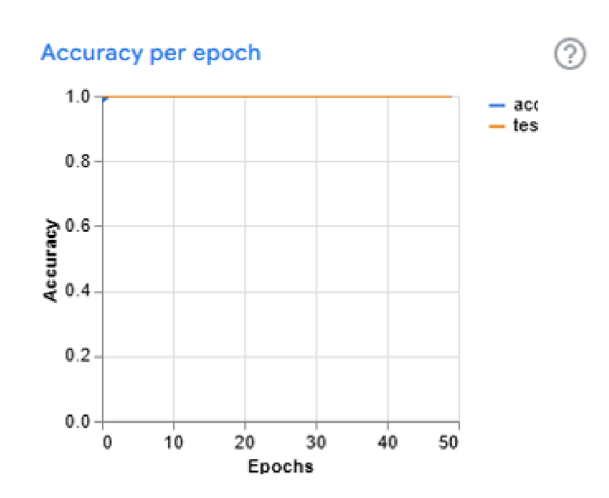

Figure 4. Training vs testing accuracy. Two lines are represented in the graph; blue line portrays the training accuracy while orange line shows testing/validation.

Stability of the Model

There are no cases of overfitting and under fitting in the model because the training and the test accuracy remained in a stable position and identical. Overfitting means that a model can do well on training data but crashes on unseen data that was not the case here.

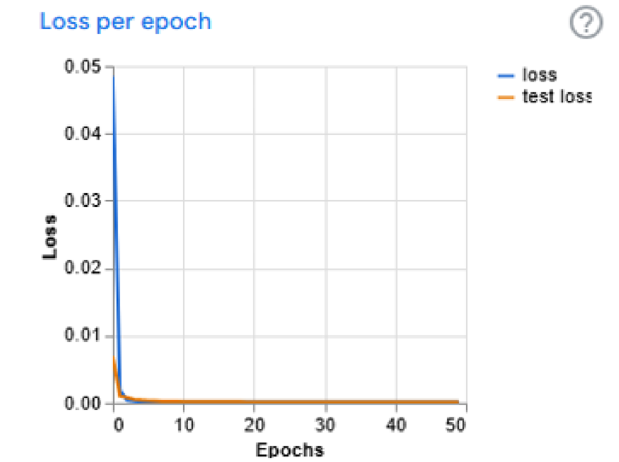

Figure 5. Loss per epochs. X-axis (Epochs): It is the training cycle (epoch), and it ranges between 0 and 50. Y-axis (Loss): It is the strength of error (loss) when training. There are two lines in the graph: Blue Line (loss): Train loss as epochs. Orange Line (test loss): Explanation Testing/validation loss over epochs.

DISCUSSION

The present research focused on image labelling and classification of mold disease in citrus fruits using GTM, with 1,500 labelled images utilized during training and validation. Its performance indicates a good outcome with a promising high accuracy (up to 96% on the tested dataset), indicating feasibility for agricultural practitioners, which implies that ML platforms such as GTM may serve as an efficient tool of agricultural disease identification, especially when they are given a broad and representative database. The researchers in their study on the detection of citrus diseases with the use of convolutional neural networks (CNNs) have attained the accuracy of 92%. In this regard, our approach achieves comparable accuracy (~96%) with greater ease of use, demonstrating the usefulness of transfer learning models even on low-level platforms (Yadav *et al*., 2022).

It was a CNN-based study-based on 2000 images where it reported the accuracy of 94.6 percent in citrus leaf disease detection. The similarity of our results is support of our claim that GTM can reach similar performance even when the dataset is somewhat smaller when it is diverse and labeled with sufficient quality (Gondal *et al*., 2022). They proposed the deep learning of plant diseases that provided an accuracy of 96.3% based on a CNN model that was trained on 13 plant species. Whereas our model also achieves equal accuracy with GTM, the key difference lies in ease of use; the latter does not require coding or model design, making it simpler for agricultural practitioners to use. Sladojevic *et al*. (2016) gave an overview of the methods of image processing applied to detect plant diseases and highlighted the necessity to automate and simplify solutions in the field. Our solution provides a direct solution to this, since it does not involve knowledge about ML and image processing, as a tool like Teachable Machine can be used to achieve automation (Ramesh *et al*., 2018).

With support from advanced machine learning (ML) tools, comparative experiments have shown higher precision rates of detecting diseases in citrus. One study used a custom convolutional neural network (CNN) with hyperspectral bands selected by Principal Component Analysis (PCA) where it was able to classify eight types of peel conditions including canker and greasy spot with a precision of 99.84%, and was superior to random selection of bands which resulted in 98.87% precision and traditional spectral classification methods with a precision of 96.2%. These results indicate that the use of dimensionality reduction techniques (PCA in this case) and automated extraction of features has been beneficial when dealing with complicated spectral data, and thus there could be advantages to using dimensionality reduction and automated feature extraction techniques when trying to improve Generalized Tree Models (GTM) across multi-faceted datasets (Yadav *et al*., 2022).

Another benefit of the multimodal fusion models that have been created by fusing both image features and text features combined with knowledge of the area where the samples were collected (background) is their outstanding resilience in environments that contain complex and challenging backdrops. The multimodal models had a classification accuracy of 98.33%, which is 9.78% better than the single modality model with the highest accuracy (88.55%) and 21.11% better than the single modality model with the lowest accuracy (81.8%). As a result, the use of multimodal fusion models will lead to more rapid convergence and enable a higher degree of generalisation because they will allow for the modelling of noise found in the backdrop of the photographs taken of the samples collected and will provide a more robust data set given that there were only limited numbers of samples taken (Qiu *et al*., 2023).

As the differences seen across citrus varieties differ as a result of their capacity to fluoresce in UV light, this highlights the possibility of inconsistency on the automated identification of mould due to navel orange's high level of emission and blood orange's lower level of emission. The possible level of efficacy that our Good Trained Model (GTM) provides, 96%, indicates the use of our approach would be aided by the addition of hyperspectral or fluorescence imaging to enable the determination of fluorescence emission intensity peaks (550–600 nm) that are specific for each citrus variety and to reduce the occurrence of false negative results associated with postharvest citrus lines (Munera *et al*., 2023).

Future research should be directed toward the creation of multimodal databases that provide open access to the data sets used in this research and are pre-processed to overcome dataset biases that are attributed to agricultural conditions. The open-access GTM method demonstrated in this study also has the potential to provide farmers with machine learning (ML) tools to support the development of proportional, regional, demographic, and seasonal strategies for the farming community; however, further work is needed to determine how pathogenicity of the Pd organism, including its virulence factors (i.e., transcription factors and cell wall enzymes), influences the use of this technology to develop targeted intervention strategies. This is consistent with the development of ML technologies from standard ML algorithms to deep learning techniques and scalable, non-chemical control strategies for green and blue mold (Mai *et al*., 2025; Cheng *et al*., 2020).

CONCLUSION

Training on the model is quite precise and steady. It has generalized fairly on the training data as well as on the test data which shows that the classification between the green mold and blue mold is very reliable. The value of losses that are near to zero goes hand in hand with the previously mentioned promising for practical use despite potential dataset biases.

DECLARATIONS

No conflicts of interest. No funding received. All authors contributed equally. No ethical issues as data is from public sources. Relevant to SDG 2: Zero Hunger via improved agriculture.

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