Enhancing Transfer Learning for Identifying Tomato Fruit Diseases: Investigating Parameters with Google Teachable Machine

Fernan H. Mendoza

College of Information Technology and Computer Science, University of Cordilleras Baguio City, Philippines, fmendoza@dmmmsu.edu.ph

The use of cutting-edge technologies in agriculture is on the rise to increase efficiency and decrease crop waste. This research emphasizes using machine learning, specifically transfer learning, to enhance the identification of tomato fruit diseases through Google Teachable Machine's Convolutional Neural Networks (CNN). This study investigates how different learning rates, batch sizes, and epoch values affect the classification accuracy of two types of tomato diseases: Blossom End Rot, Spotted Wilt Virus, and determine Healthy Tomato, by utilizing CNNs. The dataset consisted of 1,200 images, which were split into training and testing sets. The findings show that the best parameters for reaching the top accuracy of 98.67% consist of a learning rate of 0.00001, a batch size of 16, and 250 epochs. The results emphasize the importance of adjusting these factors to improve the model's effectiveness, especially in settings with limited resources. This study highlights how transfer learning paired with CNNs can be used in real-world farming situations to identify diseases, providing a reliable method that can be easily accessed by small-scale farmers on any web-enabled device.

Keywords: CNN, disease detection, machine learning, Teachable Machine, transfer learning.

1. Introduction

In recent years, there has been a surge in the application and testing of machine learning-based fruit disease recognition algorithms. Convolutional neural networks (CNNs) have become increasingly popular in recent years because to their effective feature extraction and end-to-end trainable frameworks (Lei et al., 2019; Lv et al., 2019). Since 2012, CNNs have dominated image classification algorithms and affected tasks related to object detection and semantic segmentation in visual recognition (Chen et al., 2021). Convolutional layers, as opposed to all neurons in a standard artificial neural network, allow this to be accomplished by having each neuron in the network receive input from a subset of the neurons in the layer before it (Malahina et al., 2024). Deep learning's uses have spread to many other study domains as a result of its achievements. Convolutional neural networks (CNNs), a leading deep learning technology, are widely used for classifying and detecting various leaf and fruit diseases. When given a large amount of training data, neural networks typically perform well; but, when the training data is limited, they often overfit and perform poorly when they try to generalize (Zhang et al., 2019).

Tomato crops are extremely susceptible to a wide range of diseases during every stage of their growth, which are impacted by environmental and climatic conditions. By identifying these diseases, considerable yield loss can be avoided, and the end product's quality and quantity can be improved. Over the past 20 years, a number of automation systems for disease detection have been developed in response to the labor-intensive and complex nature of manual monitoring (Karthik et al., 2020; Rangarajan et al., 2018; Liang et al., 2019). Image processing is widely utilized in modern agriculture. This technology aids in numerous plant-related activities, such as identifying species, grading fruit, diagnosing diseases, measuring severity, and describing symptoms. Recently, researchers have begun applying deep learning techniques for detection purposes. Umar et al., for instance, successfully identified plant diseases by analyzing images of leaves using deep learning (Umar et al., 2023).

With Teachable Machine, researchers can train machine learning models without having to write any code and achieve 90% to 100% accuracy (Wong et al., 2022). This tool is very helpful for detecting tomato fruit diseases. To help a model identify and categorize different tomato fruits, users can gather and organize images of them. By changing variables like the number of learning rates, batch sizes, and epochs, the process can be made more efficient (Salim et al., 2023; Aldin et al., 2022). Furthermore, the trained model can be included into a mobile web application so that users can use photos to identify plants (Umar et al., 2023).

This study aims to contribute to the advancement of tomato fruit disease detection by optimizing the performance of a machine learning model using Google Teachable Machine. By systematically experimenting with epoch values, learning rate, and batch size, this research seeks to identify the optimal parameter configuration for accurate and efficient disease identification. The findings of this study are expected to provide valuable insights for developing robust and practical disease detection systems, thereby aiding farmers in preventing crop losses and ensuring food security.

2. Literature Review

Fruit recognition techniques based on machine learning, particularly deep learning, have been used and tested more frequently in recent years. Machine learning is a superior answer to conventional methods for problems since it is more dependable and accurate. Siddiquee et al.'s research demonstrates this. They tested a system that identifies ripe tomatoes by combining more conventional image processing techniques like "color transformation," "color segmentation," and "circular Hough transformation" with a machine learning technique called cascaded object detector. According to research, machine learning approaches increase accuracy by 95% when compared to traditional methods (Siddiquee et al., 2022).

A machine learning technique called transfer learning makes use of information from one task to improve performance on another. For example, in image classification, truck identification can benefit from the same knowledge as vehicle identification (Farahani et al., 2020). The Teachable Machine service is a prime example of this approach; it uses pre-trained models to reduce the amount of new data that is needed, speeding up the training process by concentrating just on the last few layers of the model ("TensorFlow.js: Make your own 'Teachable Machine' using transfer learning with TensorFlow.js,", 2024).

In order to identify three tomato diseases—leaf mold, early blight, and late blight—by comparing them with healthy leaves, this study employed a transfer learning model called DenseNet201. After training, testing, and validation, the model achieved a high accuracy of 99.688% (Hemalatha et al., 2021).

Choudhary et al., (2023) conducted a study that explores using deep learning models to classify various stress factors in tomato plants using microscopic images. Images were collected from tomato-growing regions in Florida and Georgia and categorized into different classes. Various non-coding deep learning (NCDL) platforms were used to train and test these images. Notably, Google Teachable Machine, while not the top performer, still achieved a respectable F1 score of 91.6, indicating its potential usefulness (Choudhary et al., 2023).

Teachable Machine is an online application that makes machine learning model building easier for developers, educators, artists, and students. It doesn't require any prior knowledge of machine learning. Models can be trained by users to identify images, sounds, and poses. These models can then be used in a variety of projects, websites, and applications [18] (Siddiquee et al., 2022).

A related study shows that Teachable Machine from Google is a useful and easy-to-use technology for image-based plant disease detection. It accurately and successfully detects a variety of plant diseases, including potato plant early and late blight. The tool is helpful for farmers and non-technical users because it may be used even by those without programming experience. This aids in the early detection of disease, enabling prompt action to increase agricultural productivity (Mathew et al., 2021).

An Android app that employs deep learning to identify plant diseases is presented in another research. It provides two ways to detect images: snapping one with the camera or uploading an already-taken image. Among other crops, the software can reliably diagnose infections in tomatoes, potatoes, and apples. In comparison to conventional procedures, it is incredibly accurate, efficient, and economical (Saif et al., 2023).

In order to identify three different illness types and healthy tomatoes, the study of Nyarko et al. (2023) suggests using a 15-layer convolutional neural network (CNN) as the foundation for a single shot detector (SSD). The suggested CNN-SSD model outperformed these cutting-edge models, with a higher detection accuracy of 98.87% when compared to ResNet-

50, AlexNet, VGG 16, and VGG 19 (Nyarko et al., 2023).

One major area of unmet research need is the predominance of research on tomato leaf disease detection. Researchers can directly target the vital stage of tomato production where economic losses occur by turning the attention to images of fruit. Since that fruit symptoms could be more noticeable in the early stages, this method may help diagnose the disease earlier.

3. Case and Methodology

When using the machine learning technique of transfer learning, one task's knowledge can be applied to another task to increase performance. For instance, truck recognition can benefit from knowledge gained from a car recognition in image classification (Farahani et al., 2020). Teachable Machine facilitates the identification of new objects with fewer instances and faster training periods by applying pre-trained models to use transfer learning ("TensorFlow.js: Make your own 'Teachable Machine' using transfer learning with TensorFlow.js,", 2024). This method works especially well in online contexts that vary in resource availability. It builds models without any prior knowledge by utilizing the JavaScript-based machine learning framework TensorFlow.js (Malahina et al., 2024). A wide range of users can utilize Teachable Machine, which facilitates training models for sounds, images, and poses (Toivonen et al., 2020). This approach relies heavily on Convolutional Neural Networks (CNNs), which convert unprocessed images into meaningful representations (Gu et al., 2018).

The brains underlying Google Teachable Machine, convolutional neural networks, provide a simple-to-use, yet remarkably powerful tool for item categorization tasks (Shafi et al., 2023). Convolution layers are a type of Generalized Linear Model (GLM) for an image (Lin et al., 2023). Convolution layers are employed to transform raw input images into representations that are easier for the network to understand. Because photo recognition performance can be fairly good depending on several contributing factors, many researchers still utilize the classic CNN today.

Batch size, learning rate, and epoch are important training model parameters. The number of epochs indicates the number of times the complete dataset is processed; overfitting may result from using too many epochs. Smaller learning rates avoid overfitting but slow down training. The learning rate regulates how frequently the network's knowledge is updated. The amount of samples processed in each iteration is influenced by batch size, which balances training speed and accuracy (Salim et al., 2023; Nurfita et al, 2018; Sari et al., 2022). Since the values of these parameters affect the effectiveness and precision of training, experimenting with them is necessary to maximize model performance.

This study investigates the effects of batch size, learning rate, and epoch value on tomato fruit disease detection accuracy. Both the researcher's personal collection and the internet were used to gather the images (Kaggle, Mendeley and Google Dataset Search). After being cleaned, the photos were divided into three groups: healthy tomatoes, spotted wilt virus, and blossom end rot. Images from the internet were altered by cropping, resizing and adjusting their rotations and positions in order to expand the dataset. Due to the limited data, this was done to provide diversity. A total of 1,200 photos were utilized, 400 of which were in each category. The dataset was divided into 85% training and 15% testing sets. To properly train the model for classifying data into the specified classes, training dataset are used. Test datasets are not included in the model's training process; instead, they are used to create a confusion matrix that measures how well the model performs when applied to fresh, unidentified data. The dataset samples of tomato fruit classes are shown in Figure 1.

Figure 1. Some samples images from blossom end rot, spotted wilt virus and healthy tomato fruit datasets.

blossom end rot | spotted wilt diseases | healthy tomato

To determine tomato fruit diseases, Google Teachable Machine was employed. The model utilized for categorization is CNNs. The tested epoch value, learning rate, and batch size are as follows:

Table 1. Training parameters with epoch value, batch size and learning rate

Epoch	10	50	100	250
Batch size	16	32	64	128
Learning rate	0.00001	0.0001	0.001	

The parameters in table 1 were used to determine the accuracy of percentage value of the tomato disease detection rate. Each learning rate (0.00001, 0.0001 and 0.001) were tested against the epoch values (10, 50, 100 and 250) and batch size (16, 32, 64 and 128) which are fixed in Teachable Machine.

4. Results and Discussions

The following table presents testing results to find the most optimal and ideal values from the tomato fruit datasets manually tested, identifying the best percentage from the sample data and the amount of training data in the Teachable Machine service.

Using the Teachable Machine, 48 data points were tested and tabulated to determine the optimal value of parameters in the detection of tomato fruit diseases. Tests included three categories for learning rate (0.00001, 0.0001 and 0.001) based on the epoch values (10, 50, 100, and 250) and batch size (16, 32, 64, and 128). However, this research considers the average of the accuracy per class in each test to identify the best detection accuracy. To provide a simple assessment of the model’s performance, the average of the accuracy of each class were calculated. A model with high accuracy per class denotes that it is most likely have a good precision and recall.

Table 2. The results of the best accuracy level selection testing on Teachable Machine

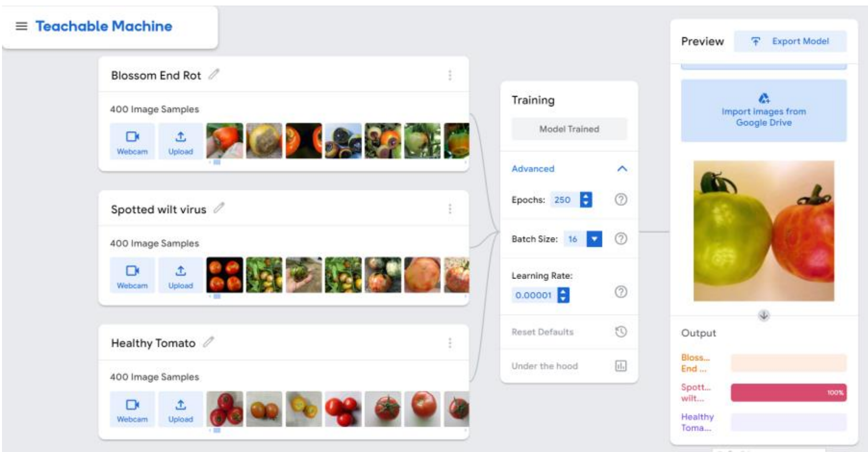
Dataset	Learning Rate	Batch Size	Epoch	Accuracy per Class			Average
				Blossom End Rot	Spotted wilt virus	Healthy Tomato	
1200	0.00001	16.00	10.00	0.87	0.78	0.98	87.67%
1200	0.00001	16.00	50.00	0.93	0.93	0.98	94.67%
1200	0.00001	16.00	100.00	0.92	0.92	1.00	94.67%
1200	0.00001	16.00	250.00	0.98	0.98	1.00	98.67%
1200	0.00001	32.00	10.00	0.92	0.82	0.98	90.67%
1200	0.00001	32.00	50.00	0.90	0.85	1.00	91.67%
1200	0.00001	32.00	100.00	0.97	0.98	1.00	98.33%
1200	0.00001	32.00	250.00	0.97	0.92	1.00	96.33%
1200	0.00001	64.00	10.00	0.82	0.50	0.90	74.00%
1200	0.00001	64.00	50.00	0.97	0.88	0.98	94.33%
1200	0.00001	64.00	100.00	0.93	0.88	1.00	93.67%
1200	0.00001	64.00	250.00	0.92	0.98	1.00	96.67%
1200	0.00001	128.00	10.00	0.65	0.72	0.75	70.67%
1200	0.00001	128.00	50.00	0.97	0.88	1.00	95.00%
1200	0.00001	128.00	100.00	0.93	0.90	1.00	94.33%
1200	0.00001	128.00	250.00	0.97	0.98	1.00	98.33%
1200	0.0001	16.00	10.00	1.00	0.95	1.00	98.33%
1200	0.0001	16.00	50.00	0.95	0.98	1.00	97.67%
1200	0.0001	16.00	100.00	0.92	0.98	1.00	96.67%
1200	0.0001	16.00	250.00	0.97	0.95	1.00	97.33%
1200	0.0001	32.00	10.00	0.95	0.97	1.00	97.33%
1200	0.0001	32.00	50.00	0.95	0.95	1.00	96.67%
1200	0.0001	32.00	100.00	0.93	0.95	1.00	96.00%
1200	0.0001	32.00	250.00	0.90	0.98	1.00	96.00%
1200	0.0001	64.00	10.00	0.90	0.93	1.00	94.33%
1200	0.0001	64.00	50.00	0.98	0.97	1.00	98.33%
1200	0.0001	64.00	100.00	0.93	1.00	1.00	97.67%
1200	0.0001	64.00	250.00	0.98	0.95	1.00	97.67%
1200	0.0001	128.00	10.00	0.92	0.92	1.00	94.67%
1200	0.0001	128.00	50.00	0.93	0.95	1.00	96.00%
1200	0.0001	128.00	100.00	0.92	0.98	1.00	96.67%
1200	0.0001	128.00	250.00	0.88	0.95	1.00	94.33%
1200	0.001	16.00	10.00	0.98	0.92	0.98	96.00%
1200	0.001	16.00	50.00	0.95	0.92	1.00	95.67%
1200	0.001	16.00	100.00	0.98	0.97	0.97	97.33%
1200	0.001	16.00	250.00	0.95	0.98	1.00	97.67%
1200	0.001	32.00	10.00	0.90	0.95	1.00	95.00%
1200	0.001	32.00	50.00	0.93	0.93	1.00	95.33%
1200	0.001	32.00	100.00	0.97	0.98	1.00	98.33%
1200	0.001	32.00	250.00	0.93	1.00	1.00	97.67%
1200	0.001	64.00	10.00	0.97	0.97	1.00	98.00%
1200	0.001	64.00	50.00	1.00	0.92	1.00	97.33%
1200	0.001	64.00	100.00	0.95	0.98	1.00	97.67%
1200	0.001	64.00	250.00	0.93	0.98	1.00	97.00%
1200	0.001	128.00	10.00	0.97	0.95	0.98	96.67%
1200	0.001	128.00	50.00	0.93	0.97	1.00	96.67%
1200	0.001	128.00	100.00	0.93	0.93	1.00	95.33%

1200	0.001	128.00	250.00	0.95	0.95	1.00	96.67%

Table 2 shows how critical it is to adjust parameters like epochs, learning rate, and batch size when improving the accuracy of a model designed to detect diseases in tomato fruits. The peak accuracy of the model was reached by training it with 250 epochs, a low learning rate of 0.00001, and a small batch size of 16. This mix enabled accurate updates through multiple rounds, leading to almost flawless classification in every category. On the other hand, the poorest performance was seen with just 10 epochs, showing that the model wasn't trained enough, resulting in underfitting, particularly in the more difficult Spotted Wilt Virus category. The fluctuation in class performance underscores the significance of factoring in the average accuracy per class for evaluating overall model performance.

After determining the best parameters for the tomato fruit disease detection, it was fed to Google Teachable Machine for training and testing. There are 400 tomato fruit images for each class namely Blossom End Rot, Spotted Wilt Virus and Healthy Tomato as seen in Figure 2.

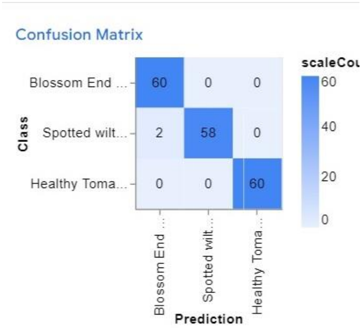
Figure 2. Uploaded tomato fruit datasets in Google Teachable Machine.



The confusion matrix shown in Figure 3 reveals a high level of accuracy in the model's performance across all three classes: Blossom End Rot, Spotted Wilt, and Healthy Tomato. Specifically, the precision, recall, and F1 scores for the Blossom End Rot and Healthy Tomato classes are all perfect (1.00), indicating that the model is both highly accurate in predicting these classes and consistent in doing so without any false positives or false negatives. This suggests that the model has effectively learned the features associated with these conditions, leading to reliable classification.

However, for the Spotted Wilt class, while the recall remains perfect (1.00), indicating that the model correctly identifies all instances of Spotted Wilt, the precision drops slightly to 0.967. This minor decline in precision reflects the presence of a few false positives, where the model incorrectly predicted Spotted Wilt in some cases. Despite this, the F1 score for Spotted Wilt remains high at 0.983, indicating a robust overall performance. The near-perfect performance across all metrics underscores the effectiveness of the model in distinguishing between the different classes of tomato conditions. Nonetheless, the slight reduction in precision for Spotted Wilt could suggest that the model might benefit from further fine-tuning to eliminate the small number of false positive predictions in this class.

Figure 3. Confusion Matrix of the Tomato Fruit Disease Detection Model.



On the other hand, Figure 4 depicts the performance of a machine learning model over 250 training epochs. The blue line (accuracy) represents how well the model learns to classify data within the training set, while the orange line (test accuracy) represents how well the model generalizes to unseen data.

Both accuracy and test accuracy improve significantly during the initial training, but the rate of improvement slows down after around 100 epochs. This suggests that the model is starting to overfit to the training data, meaning it's memorizing the training examples rather than learning generalizable patterns.

Figure 4. Accuracy per epoch of the model

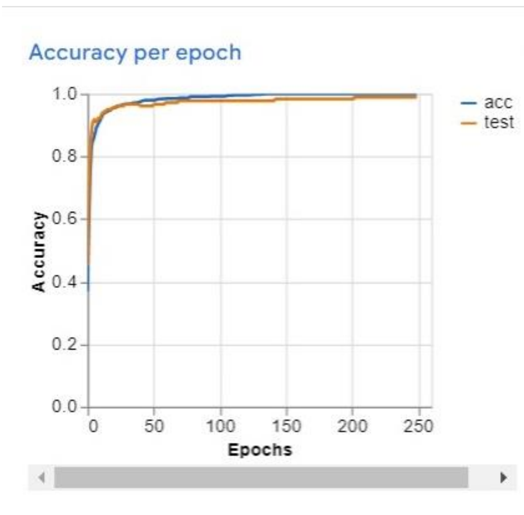
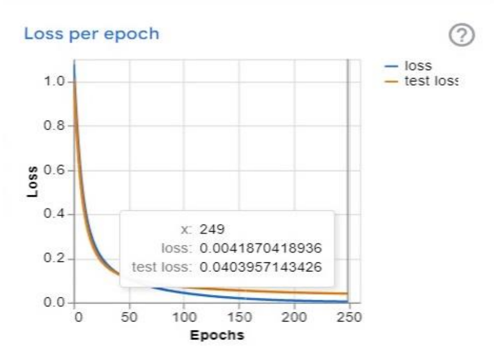


Figure 5. Loss per epoch of the model



Consequently, Figure 5 presents a line chart illustrating the loss per epoch during the training of the tomato fruit disease detection model. The horizontal axis represents the amount of epochs (training iterations) and the vertical axis shows the loss value, reflecting the model's error in predicting the right output. The blue line indicates the training loss, which assesses the model's performance on the training data, while the orange line shows the validation loss, which evaluates the model's performance on a different validation dataset. The training and validation loss both decrease quickly in the first epochs, indicating effective learning by the model. The training loss continues to decrease steadily, approaching zero. The validation loss also decreases initially but plateaus and starts to increase slightly after around 150 epochs.

After the model is trained, the link for this trained tomato fruit disease detection model can be exported. This is done by clicking on the export button in the preview pane of Teachable Machine as shown in Figure 6. Then, there is an option for uploading the trained model to the cloud as seen in Figure 7. This link can be copied, shared and sent to emails, SMS, Messenger or any messaging apps or software. The Tomato Fruit Disease Detection System can be used by anybody who has the link. Thus, any electronic device such as mobile phone, tablet, laptop desktop computer or any device that is capable of web browsing can access the system. Figure 8 illustrates these capabilities of the Tomato Fruit Disease Detection Model.

Figure 6. Exporting the Tomato Fruit Disease Detection Model

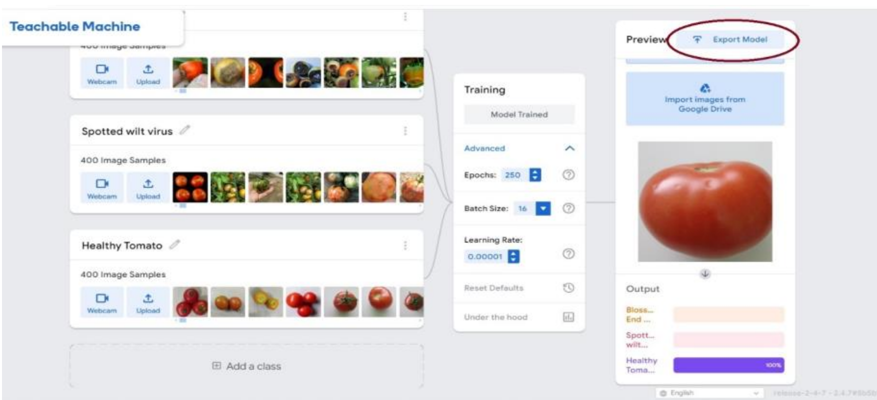


Figure 7. Options for exporting the Tomato Fruit Disease Detection model

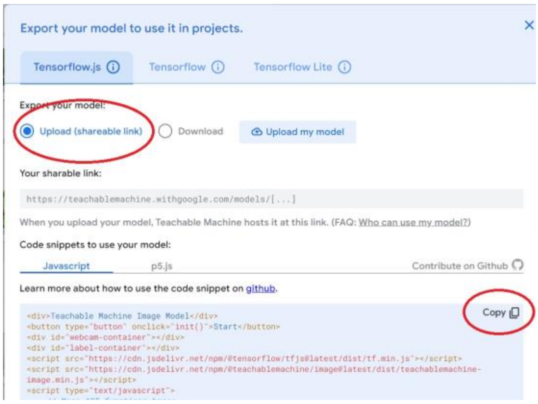
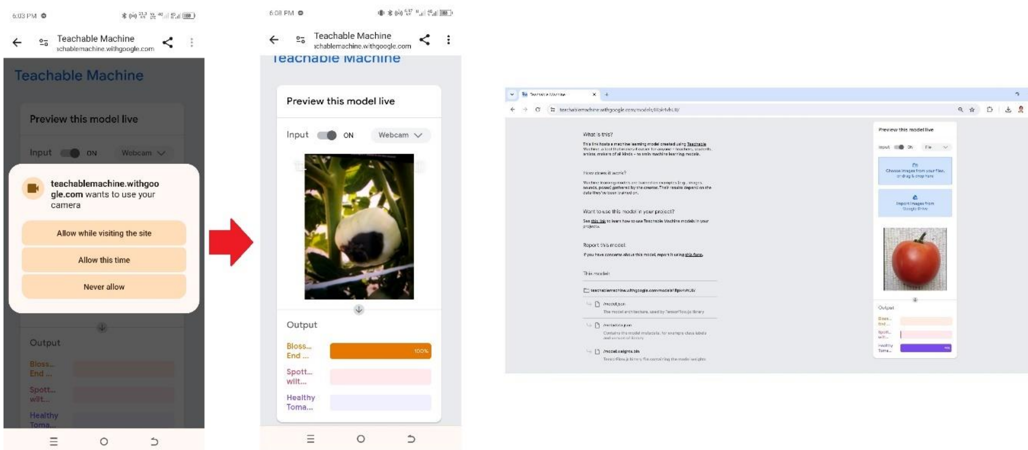


Figure 8. Screenshots of running the Tomato Fruit Disease Detection System in (a) Mobile device and (b) laptop computer.



(a) Mobile device (b) laptop computer

5. Conclusions and Recommendations

The experiments done in the study focused on identifying the optimal parameters for a model that detects tomato fruit diseases using the Teachable Machine. The tests involve varying three primary hyperparameters namely learning rate, batch size, and the number of epochs. The evaluation criterion is the average accuracy per class across three categories: Blossom End Rot, Spotted Wilt Virus, and Healthy Tomato.

The results of the test show that decreasing learning rates, increasing training periods, and using smaller batch sizes result in the best accuracy for identifying tomato diseases. More precisely, the optimal performance was achieved with a learning rate of 0.00001, a batch size of 16, and 250 epochs, resulting in an accuracy rate close to perfection at 98.67%.

On the other hand, fewer epoch counts (such as 10 epochs) led to notably lower accuracy, especially with lower learning rates, indicating that underfitting occurred due to inadequate training.

After the training is complete, the model can be quickly exported and shared through a link that is accessible on any web-enabled device, making the Tomato Fruit Disease Detection System very accessible and easy to use.

Additional adjustments might be needed to improve precision for the Spotted Wilt Virus class, such as modifying learning rates or using data augmentation techniques. Ultimately, the model must undergo validation using a wider range of data to confirm its ability to be applied in different practical situations.

Lastly, it is important to take advantage of the simplicity in exporting and sharing the trained model to encourage its widespread usage. This ensures that the system can be accessed on any device capable of web browsing, making it easier for adoption and practical use in various agricultural situations.

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