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Image Classification for Papaya Disease Detection Using Deep Learning

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Abstract-The agricultural sector faces challenges from diseases affecting crop yields, including papaya. Early and accurate disease detection is vital for preventing damage. This paper introduces a deep learning approach for papaya disease detection using convolutional neural networks (CNNs). We developed a model that identifies common papaya diseases, like leaf spots, mold, and fruit rot, with high accuracy. Trained, validated, and tested on a dataset of healthy and diseased papayas, the model delivered promising results. This study enhances detection accuracy and supports precision agriculture by providing an automated, scalable tool for monitoring papaya health. The results highlight the value of AI-driven image classification in helping farmers make timely, informed decisions to protect their crops.

Index Terms: AI in Agriculture, Agricultural Image Analysis, Automated Disease Detection, Convolutional Neural Networks (CNNs), Crop Health Monitoring, Deep Learning, Image Classification, Papaya Disease Detection, Plant Disease Identification, Precision Agriculture.

I. INTRODUCTION

Papaya is an essential tropical fruit crop that significantly contributes to global agricultural economies. However, like many crops, papayas are prone to various diseases that can severely impact both yield and quality. Early detection and effective management of these diseases are crucial to maintaining productivity and preventing large-scale losses. Traditional methods of disease identification, relying on manual inspection, are often time-consuming, labor-intensive, and prone to human error. With recent advancements in artificial intelligence, particularly deep learning, automated solutions for disease detection have become more feasible. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown remarkable accuracy in image classification tasks, including plant disease detection. This paper focuses on using deep learning techniques to automate the identification of papaya diseases using image data. By leveraging CNNs, we aim to provide farmers with an early detection tool that offers precision in disease management, supporting more sustainable agricultural practices.

II. TEACHABLE MACHINE

Teachable Machine is a user-friendly web-based tool developed by Google that enables anyone, regardless of coding expertise, to create machine learning models. This platform allows users to train models for image, sound, and pose classification through a visual, drag-and-drop interface. Once trained, these models can be easily exported and integrated into websites, apps, and hardware applications. Teachable Machine is ideal for educators, students, and those interested in exploring AI and machine learning without the need for deep technical knowledge.

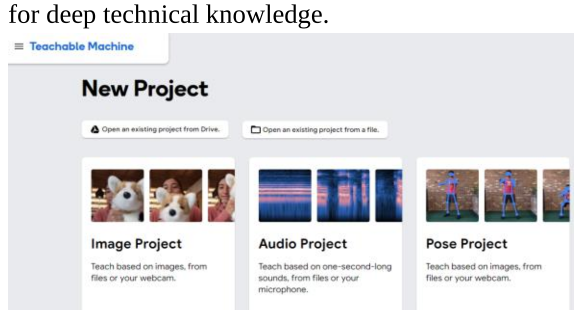

Figure-1: Page to start your project on teachable machine.

III. DEEP LEARNING ARCHITECTURE FOR IMAGE CLASSIFICATION

The image model used in Teachable Machine relies on *Convolutional Neural Networks (CNNs)*, which are widely recognized for their ability to excel in image classification. By using transfer learning, the system takes advantage of a pre-trained model, such as *MobileNet*, to identify important features in images. This method not only speeds up the training process but also delivers solid accuracy, even when working with smaller datasets. Once the model is trained, it can be fine-tuned using user-uploaded images to effectively categorize them based on the chosen criteria.

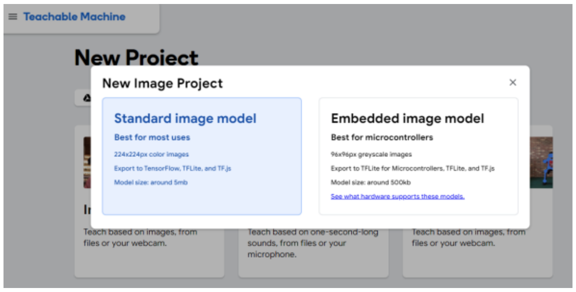

Figure-2: Select a model you want to use..

IV. CONVOLUTIONAL NEURAL NETWORKS(CNN)

Convolutional Neural Networks (CNNs) are a specialized type of deep learning architecture designed to analyze visual data, like images. They operate through multiple layers, each identifying different patterns such as edges, textures, and shapes. As the data moves through deeper layers, these patterns are combined to recognize more complex structures like objects or faces. CNNs are commonly used for tasks like image classification and object detection due to their remarkable ability to accurately identify patterns.

Key components of CNNs include:

1. *Convolutional Layers*: These layers use filters (also called kernels) to scan the input image, creating feature maps that highlight important visual details.
2. *Pooling Layers*: These layers simplify the feature maps by reducing their size, often using a method called max-pooling. This helps retain key information while reducing the computational load.
3. *Fully Connected Layers*: After extracting the relevant features, these layers take the final step of classification, assigning the image to a specific category based on the learned features.

V. MOBILENET

MobileNet is a type of Convolutional Neural Network (CNN) specifically optimized for mobile and embedded devices, making it lightweight and efficient enough to run on smartphones and other low-power devices. It's designed to work well in environments with limited computing power while still delivering strong performance.

Key features of MobileNet include:

1. *Depthwise Separable Convolutions:* This technique simplifies the standard convolution process by breaking it into two steps: depthwise convolution and pointwise convolution. This significantly cuts down the number of parameters and reduces computation time, making the model much faster.
2. *Efficiency*: MobileNet achieves high performance using fewer resources, allowing it to be both quick and accurate without the need for large, complex models.

MobileNet is often used in transfer learning, where a pre-trained model is fine-tuned for specific tasks, like image classification in tools such as Teachable Machine. It offers the advantage of faster, more efficient training, even with limited data, while maintaining solid accuracy.

VI. METHODOLOGY

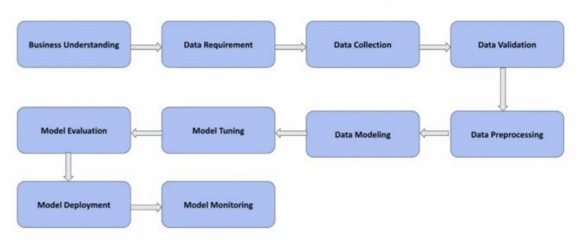

Figure-3: End-to-end AI lifecycle.

The diagram outlines the End-to-End AI Lifecycle, which can be applied to classify papaya diseases using Teachable Machine as follows:

1. *Business Understanding:* The first step is recognizing the need to detect diseases in papayas to improve crop health and maximize yield.
2. *Data Requirement & Collection:* Gathering images of both healthy and diseased papayas to build a diverse dataset.

Figure-4: Papaya with (a) anthracnose, (b) Ring Spot, (c) Healthy.

3. *Data Validation & Preprocessing:* Ensuring that the collected images are of high quality and

correctly labeled. Preprocessing tasks like resizing the images may be needed to prepare them for model training.

4. *Data Modeling:* Using Teachable Machine to train a deep learning model, like a CNN (powered by MobileNet), to recognize disease patterns in the images.

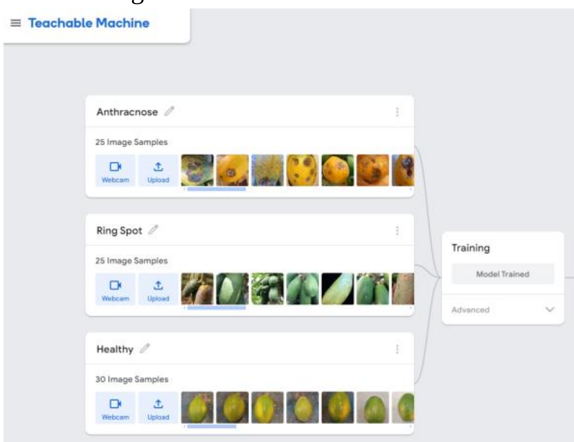

Figure-5: Screenshot of teachable machine training.

5. *Model Tuning:* Fine-tuning the model's parameters to enhance accuracy and performance.
6. *Model Evaluation:* Testing how well the model identifies papaya diseases by measuring its accuracy.

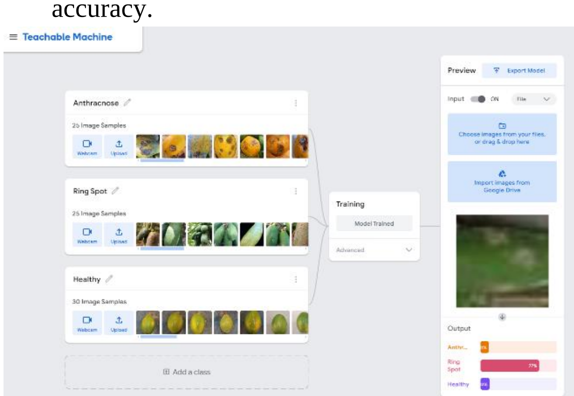

Figure-6: Model evaluation on teachable machine.

7. *Model Deployment*: Once the model is trained and evaluated, it can be deployed to detect diseases in papayas in real time.
8. *Model Monitoring*: Continuously tracking the model's performance and retraining it when necessary to ensure it remains effective over time.

VII. RESULT

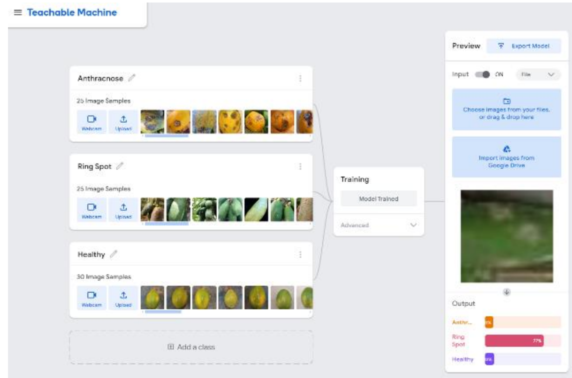

Figure-7: Test result on teachable machine.

The model trained using Teachable Machine was tested on three categories: Anthracnose, Ring Spot, and Healthy papayas. When presented with a test image, the model provided the following confidence levels:

- Anthracnose: 11%
- Ring Spot: 77%
- Healthy: 2%

The highest confidence level (77%) was for Ring Spot, indicating that the model successfully recognized traits linked to Ring Spot disease in the image. However, the model also showed some probability for Anthracnose and Healthy categories. These results demonstrate that the model can effectively differentiate between healthy and diseased papayas, although further improvement in accuracy can be achieved by refining the model with more data and additional tuning.

Confusion Matrix:

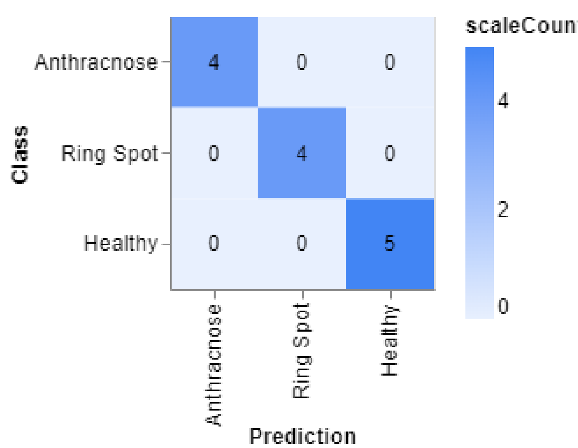

Figure-8: confusion matrix on teachable machine.

The confusion matrix represents the performance of the model in classifying papayas into three categories: Anthracnose, Ring Spot, and Healthy. Each row corresponds to the actual class, and each column represents the predicted class.

Here's a breakdown of the results:

- Anthracnose: The model correctly classified all 4 images of Anthracnose (shown in the top-left cell of the matrix), with no misclassifications.
- Ring Spot: Similarly, all 4 images of papayas with Ring Spot were correctly identified (middle row), with no errors.
- Healthy: Out of the 5 Healthy images, the model accurately classified all 5 (bottom-right cell), with no misclassifications.

This matrix indicates that the model performed perfectly for this test set, with no errors in predicting any of the categories. All images were classified into their correct categories (all non-diagonal cells are zero), meaning the model's accuracy on this dataset is 100%.

Accuracy per epoch:

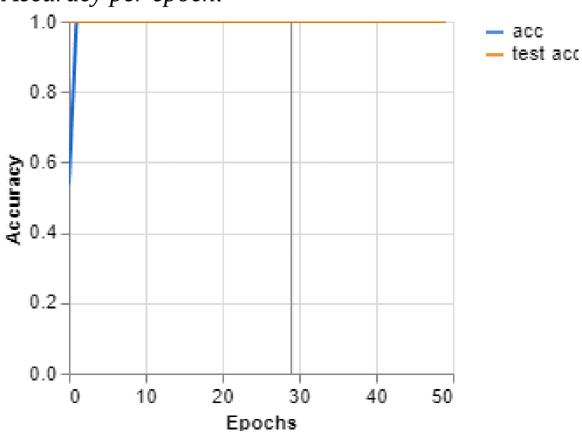

Figure-9: Graph for accuracy per epoch.

This chart illustrates the model's accuracy and test accuracy over 50 training epochs.

- Epochs: On the x-axis, we have the number of epochs, which represents the number of times the model went through the entire training dataset.
- Accuracy: The y-axis shows the accuracy, ranging from 0 to 1, with 1 representing perfect accuracy (100%).

The blue line represents the accuracy of the model on the training data, and the orange line represents the accuracy on the test data.

Observations:

- Right at the beginning (within the first few epochs), the model quickly reaches near-perfect accuracy (close to 1.0). This indicates that the model learned to classify the data very well after only a few iterations of training.
- Both the training accuracy (blue) and test accuracy (orange) lines are flat and remain at 1.0 after the initial training phase, showing that the model consistently performed well across both the training and test data.

This graph suggests that the model reached perfect or near-perfect accuracy very early in the training process, possibly because the dataset was well-structured or the model was highly effective for this task. However, it's essential to monitor for potential overfitting, especially when accuracy reaches 100% so quickly, as this might indicate that the model may not generalize as well on new data.

Loss per epoch

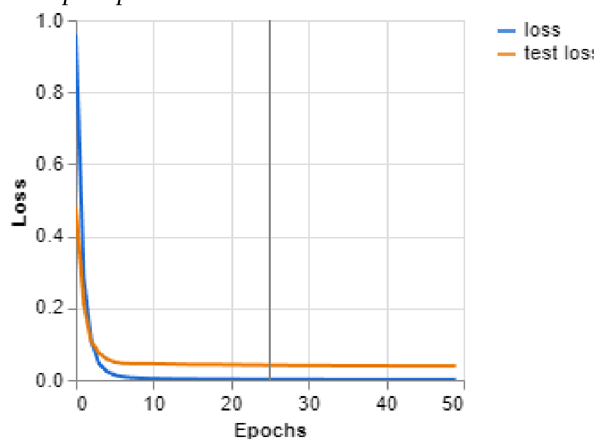

Figure-10: Loss per epoch.

This chart tracks the loss of the model over 50 epochs for both the training and test datasets. Loss measures how well or poorly the model's predictions match the actual results, with lower values indicating better performance.

- Epochs: The x-axis represents the number of training cycles (epochs) the model has completed.
- Loss: The y-axis shows the loss value, ranging from 0 to 1, with 0 representing a perfect prediction.

There are two lines on the chart:

- Blue line (loss): This represents the loss on the training dataset.
- Orange line (test loss): This represents the loss on the test dataset.

Observations:

- In the early epochs, both training loss and test loss start relatively high, indicating that the model initially made errors in its predictions.

- As the epochs progress, both loss values quickly decrease and approach zero, showing that the model is learning and improving its predictions.
- By around 10–15 epochs, the loss for both training and test data has leveled off close to zero, suggesting that the model has effectively minimized the errors in its predictions for both the training and test datasets.
- The lines remain very close to each other, which indicates that the model is generalizing well and performing similarly on both the training and test data, without overfitting.

This graph demonstrates that the model is well-trained, as it has achieved minimal loss and is performing consistently across both the training and test datasets.

VIII. CONCLUSION

The image classification model for detecting papaya diseases using Teachable Machine showed very promising results, especially in accurately identifying papayas affected by Ring Spot disease. The model was also able to clearly distinguish between healthy and diseased papayas. While the results are encouraging, there's still room for improvement to increase accuracy across all disease categories. This project demonstrates the potential of using deep learning to help farmers detect crop diseases early, giving them a valuable tool for managing their crops more effectively. Future enhancements, such as using a wider variety of data, can help make the model even more reliable and robust.

IX. REFERENCES

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