A Deep Learning Approach for Papaya Disease, Pest and Maturity Identification via Mobile Imaging

Peiris M.M.A.E
Dept of Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it21161056@my.sliit.lk

Perakum K.K.P
Dept of Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it21160066@my.sliit.lk

Mangchanayaka M.V.V
Dept of Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it21161810@my.sliit.lk

Senevirathne U.W.H.N
Dept of Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it21386022@my.sliit.lk

Hansi De Silva
Dept of Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
hansi.d@sliit.lk

Thilini Jayalath
Dept of Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
thilini.d@sliit.lk

***Abstract*— Papaya cultivation plays a crucial role in the agricultural sector but faces numerous challenges from diseases, pests, and improper maturity classification, which affect both yield and quality. Early detection of diseases and accurate maturity classification are essential for improving crop management. This research presents a deep learning solution aimed at helping farmers detect diseases and pests on papaya fruits while classifying the maturity level at an early stage. The proposed mobile app integrates advanced models such as EfficientNetV2B0, ViTs, Custom CNN, DenseNet121, and MobileNetV2 to provide real-time disease diagnosis and recommend prevention strategies to reduce crop damage. Additionally, the app helps farmers identify mature, unripe, partially ripe, and rotten papayas. Data for this study was collected using smartphones from selected farms. The model's performance was evaluated on these images, showing an excellent rate of disease and pest detection, and maturity classification. Overall, the results highlight the effectiveness of deep learning models in enhancing pest and disease control and maturity identification, offering farmers an affordable and reliable tool for early intervention and reducing post-harvest losses, ultimately leading to better crop yields and quality.**

***Keywords*—Deep Learning (DL), EfficientNetV2B0, Vision Transformers (ViT), Convolutional Neural Network (CNN), DenseNet121, MobileNetV2, Fruit Research and Development Institute (FRID), You Look Only Once version 5 (YOLOv5)**

I. INTRODUCTION

Papaya (Carica papaya) is a vital fruit crop in Sri Lanka with significant nutritional and economic value. It thrives in the country's tropical climate, with key production regions including Anuradhapura, Hambantota, Puttalam, Kurunegala, Monaragala, Polonnaruwa, and Ampara. Rich in vitamins A and C, papaya is widely used in food and pharmaceutical products such as jams, juices, chewing gum, and cosmetics. However, its cultivation faces challenges like plant diseases, pest attacks, and difficulty in determining fruit maturity, all of which impact productivity and profitability.

One of the major threats to papaya farming is plant diseases like Papaya mosaic virus and Cercospora leaf spot. The Papaya mosaic virus causes leaf mottling, reduced photosynthesis, and stunted plant growth, ultimately lowering fruit yields. Cercospora leaf spot leads to yellow lesions on leaves, causing significant damage. Many farmers lack the skills and resources to detect and treat these diseases early. To address this, our project proposes a DL based mobile application for disease identification. The system will use EfficientNetV2B0 for binary classification to identify fruit or leaves, along with a comprehensive database of remedies and suggestions for disease protection and maturity prediction.

Another, significant obstacle in papaya cultivation is the occurrence of diseases like Papaya Ringspot Virus (PRSV) causes ring like lesions and mosaic on leaves, while Powdery Mildew produces white powdery spots that discourage photosynthesis. For the early detection, our system will utilize a custom CNN model to classify papaya fruits as healthy or infected.

Apart from diseases, pest infestations by Mites and Mealy Bugs are a major concern. These pests damage crops by sucking plant tissues and promoting the growth of sooty mold, which disrupts photosynthesis. The Papaya Mealy Bug is particularly difficult to identify due to its resemblance to other pests. To improve pest management, our system will integrate DL techniques, specifically using DenseNet121, for detecting and predicting infestations.

Another critical challenge in papaya farming is determining the optimal maturity stage for harvesting. Harvesting too early or too late leads to economic losses and food waste. Farmers currently rely on visual inspection, which is prone to errors. Our approach uses DL to classify papayas into four maturity stages: not ripe (all green), partially ripe (green with yellow patches), ripe (mostly yellow with green patches), and rotten (fully yellow with bruising). MobileNetV2, architecture designed for mobile deployment, will process fruit images and provide accurate maturity classification.

By integrating disease detection, pest detection, and maturity assessment into a single mobile application, this project aims to revolutionize papaya farming in Sri Lanka. The app will feature a simple interface where farmers can take or upload images for analysis, with reminders to encourage regular use. Leveraging advanced DL algorithms, the system will provide real-time, data-driven insights, boosting productivity, minimizing losses, and promoting sustainable agricultural practices.

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II. Literature Review

Papaya is an economically significant tropical fruit crop that faces several challenges, particularly from diseases such as Cercospora, Mosaic Virus Mite Disease, Mealy Bug Disease, Papaya Ring Spot Virus, and Powdery Mildew. These diseases severely affect the yield and quality of papaya, resulting in significant losses. Early identification of these diseases is crucial for effective disease management and minimizing the adverse impact on papaya cultivation. Additionally, accurate classification of the maturity levels of papaya fruits is important for determining the optimal time for harvesting, which can help reduce post-harvest losses and ensure high-quality produce. Traditionally, these processes have relied on manual inspection, which is time-consuming and prone to errors. However, with the advancement of machine learning and DLtechniques, there has been a significant shift towards automating disease detection and fruit maturity classification using computer vision and image processing.

The significance of automating disease detection and maturity classification lies in the potential to increase accuracy, efficiency, and scalability. Automated systems for disease identification can assist farmers in detecting diseases at an early stage, preventing widespread damage, and reducing the reliance on chemical treatments. Similarly, automated maturity classification systems can help determine the ideal harvesting time for papayas, leading to better quality control and reduced losses during the post-harvest stage. These innovations are crucial for improving the sustainability and profitability of papaya farming, particularly in regions where manual labor and expertise may be limited.

Several studies have explored the application of DL for papaya disease detection and maturity classification. T. A. Mir et al. (2024) [1] proposed a hybridized model combining CNNs with Random Forest, which demonstrated improved accuracy in papaya leaf disease classification. This hybrid approach leverages the strengths of CNNs for feature extraction and Random Forest for classification, providing a robust model for detecting papaya diseases. The research highlights the effectiveness of hybrid models in improving the performance of disease detection systems, making them more reliable and suitable for real-world agricultural applications. This is particularly relevant for detecting diseases like Cercospora and Papaya Ring Spot Virus, which are often difficult to identify using traditional methods.

Another important area of research has been the classification of papaya fruit maturity using machine learning techniques. S. Gayathri et al. (2021) [5] applied DL to detect the ripeness of papaya fruits, showing the potential of CNNs to recognize ripeness stages based on visual characteristics such as color and texture. This approach contributes to reducing post-harvest losses and ensuring that papayas are harvested at the optimal stage for quality. Similarly, M. K. R. Asif et al. (2022) [3] developed a machine vision system to recognize papaya maturity, highlighting the effectiveness of visual features in classifying papayas as unripe, ripe, or partially ripe. Their research underlines the importance of image-based systems in streamlining harvest decisions and enhancing the overall quality of the fruit.

In the field of disease detection, Hossen et al. (2020) [6] used DL models to identify papaya diseases, emphasizing the role of CNNs in classifying various diseases, including Powdery Mildew and Mosaic Virus Mite Disease. Their study demonstrated that CNNs offer high accuracy in detecting diseases based on image data, making them a valuable tool for farmers. Similarly, Nagaraj et al. (2022) [7] employed CNNs for papaya disease classification, showing that these models can outperform traditional methods in terms of accuracy and efficiency. These findings are critical for the development of real-time disease detection systems that can help farmers manage disease outbreaks more effectively.

Furthermore, de Moraes et al. (2023) [9] introduced Yolo-Papaya, a CNN-based model integrated with Convolutional Block Attention Modules (CBAMs) for papaya fruit disease detection. This model is designed to improve the detection of papaya diseases by focusing on the most relevant features of the images. The use of attention mechanisms enhances the accuracy of disease detection systems, particularly in real-time applications, making them more suitable for field use. This approach has the potential to revolutionize the way diseases such as Papaya Ring Spot Virus are detected and managed in the field.

In addition to these advancements, recent research has explored more sophisticated models like ViT. R. Jahangir et al. (2023) [2] conducted a comparative study of Big Transfer (BiT) and ViT models for plant disease classification. Their findings indicated that both models performed well, with ViT showing strong promise in plant disease detection tasks. While their study focused on potato leaf disease, the implications for papaya disease detection are clear, as ViT could offer improved generalization and robustness when applied to papaya diseases.

Despite these promising advancements, there are still several challenges and gaps in the existing literature. Many of the current models are trained on limited datasets, which may hinder their ability to generalize across different environmental conditions or geographic regions. Moreover, the development of real-time disease detection systems remains an area of ongoing research. Most existing models focus on detecting diseases or classifying maturity levels in isolation, without addressing the challenge of simultaneously detecting multiple diseases or integrating both disease detection and maturity classification within a single system. Furthermore, hybrid models combining CNNs with other machine learning algorithms, are not widely explored, despite their potential to enhance model performance.

The primary objective of this research is to develop an integrated system that can simultaneously explore the use of DL models, particularly CNNs, to classify papaya diseases and determine the maturity of fruits. Additionally, the research will investigate hybrid models to improve the accuracy and reliability of disease and maturity detection.

In summary, the existing literature demonstrates the potential of DL techniques, particularly CNNs, for papaya disease detection and maturity classification. However, gaps remain, particularly in terms of dataset limitations, real-time detection, and the integration of disease detection with maturity classification. This research aims to address these gaps, contributing to the development of more accurate and efficient systems for managing papaya cultivation.

III. METHODOLOGY

\ff The proposed solution intends to provide a smart approach for stakeholders, fruit researchers, agriculture students, and papaya growers for real-time pest and disease identification allow with the remedy suggestion. Papaya Buddy is an AI-powered mobile application designed to automate the identification of papaya diseases and pests using deep neural networks. The system employs a two-stage classification approach. First EfficientV2B0 is used to binary classification determine whether the captured image is a fruit or a leaf. If classified as a leaf or fruit, the image is further processed using, ViTs for Cercospora and Mosaic virus identification of Papaya leaf, Custom CNN for Ringspot Virus and Powdery Mildew identification of Papaya fruit, DenseNet121 for Mite and Mealy bug Detection and MobileNetV2 for Papaya fruit Maturity identification. Identified prediction details are stored in AWS Cloud. Based on the classification results, Papaya Buddy suggests optimal remedies, helping farmers take timely actions to protect their crops, by leveraging DL and cloud base storage. As shown in Fig. 1, the system streamlines the process of diagnosis and the treatments, making it accessible to a broader audience in the agriculture sector.

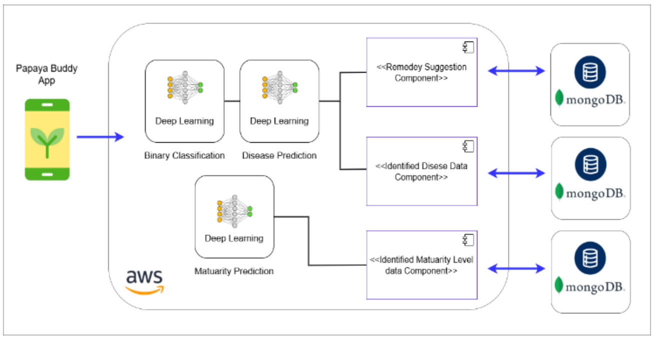

Fig. 1 Overall System Diagram of the proposed solution

A. *Identification of Cercospora Virus, Mosaic Virus, and Healthy Papaya Leaves*

1) Data Collection Preprocessing

To build a DL model for Cercospora Virus, Mosaic Virus, and healthy papaya leaf detection, image data were collected manually by mobile phones. Data collection has been done under varying light sources and conditions of environment at both Diwulapitiya Papaya Farm and the Horana Fruit Research Centre, using images of disease-infected papaya leaves as well as normal papaya leaves. Research officers from Horana Fruit Research Centre facilitated the verification of diseases occurring in the leaves to make the dataset authentic. The dataset was based on 1,018 images classified into three categories: 339 healthy leaf images, 429 images of Cercospora-infected leaves, and 250 images of Mosaic Virus-infected leaves.

In an effort to optimize model performance while minimizing overfitting, certain data augmentation and preprocessing strategies were employed. Such strategies involved applying random resized crops to emphasize relevant regions of the leaf, applying horizontal flip probability of 50%, and incorporating small rotations (+/-5°) to help introduce variations. Color jitter was also applied by modifying brightness, contrast, and hue, followed by normalization involving standard mean and standard deviation for normalization. All the images were resized to 224×224 pixels in order to ensure consistency. The dataset was then split into 80% training data and 20% test data to facilitate model training and testing.

2) Train the detection model

A hybrid DL approach was used to classify papaya leaf diseases accurately. EfficientNet-B0 was used as a binary classifier to identify whether the leaf was healthy or not. If the leaf was detected as unhealthy, the ViT model (Google/Vit-Base-Patch16-224) was used to classify the disease as Cercospora Virus or Mosaic Virus.

The EfficientnetV2B0 model was trained for more than 14 epochs using the Adam optimizer and learning rate of 0.001 and the cross-entropy loss as the loss function. The Vision Transformer model was trained for more than 5 epochs with the AdamW optimizer.

B. *Identification of Ringspot Virus, Powdery Mildew and Healthy of Papaya Fruit*

1) Data Collection and Pre-processing

Papaya fruit photos infected with Ringspot virus and Powdery Mildew were captured with mobile phones from the selected farms in Diwulapitiya and Fruit Research center Horana. Three datasets curation of comparing about 1500 images were created or Ringspot Virus, Powdery Mildew and Healthy Papaya Fruits identification. The data set contains 500 images in each of three classes, ensuring balance.

Three sets of the dataset were created: 70% for training, 20% for validation and 10% for testing. To get the good model performance, pre-processing entailed downsizing the photos to 256×256 pixels. The photos were shrunk by dividing their pixel values by 255 in order to keep the data between 0 and 1 and make them normal. Normalization is required because the model can better understand inputs in this range, which enhances training effectiveness and model performance.

2) Training the detection model

Initially, a custom CNN model and YOLOv5 model were trained to determine which performed best in the given scenario. The custom CNN model was chosen based on performance criteria. To differentiate between frit and leaves, an EfficentNetV2B0 model for binary classification was used initially. After the model recognized the object as a fruit, the custom CNN model was used for further classify the Papaya fruit as either Healthy or diseased with Ringspot Virus or Powdery Mildew. To achieve the best performance for accurate classification results, the model was trained across 30 epochs. After 30 training epochs, the Custom CNN model achieved impressive accuracy and demonstrating its optimized performance in multi-class identification.

C. *Identification of Mite and Mealy bug and Healthiness of the fruit and leaf*

1) Data Collection Preprocessing

To assess the health of fruits and leaves and identify Mite and Mealy bug infestations, image classification was performed using DL algorithms. Images of Mite-Infected, Mealy bug infected, and healthy fruits and leaves were captured using smartphone cameras. Data was collected from the Horana Fruit Research center and the Duwlapitiya Papaya fruit estate. The dataset consists of approximately 900 images of healthy leaves and fruits, while around 1000 images were collected of Mite and Mealy bug-infected fruits and leaves. The compiled dataset of Mite and Mealy bug infestations in shown Fig 2.

2) Training the detection model

To improve model performance and generalization, images were collected in diverse natural conditions. The dataset was divided into three subsets 70% for training, 20% for validation, and 10% for testing to ensure an effective learning process. Preprocessing techniques were used to enhance accuracy and ability to perform well on unseen data. Since images were taken using different smartphone models, variations in size and color formats were present. To address this all images were resized into 224x224 pixels and pixel values were normalized to a range of 0 to 1 for consistent model training.

D. Papaya Maturity level detection

1) Data Collection Preprocessing

A dataset of 2,000 images was compiled, evenly distributed across four categories: not mature (all green), partially mature (predominantly green with some yellow), mature (mainly yellow with some green), and rotten (entirely yellow with visible damage), with 500 images per category. These images were captured under natural lighting conditions using standard smartphone cameras to reflect real-world scenarios. To ensure consistency and enhance model performance, several preprocessing steps were applied to the collected images. Each image was resized to 224x224 pixels, aligning with the input requirements of MobileNetV2 architecture. Pixel values were normalized to a [0, 1] range by scaling them by 1/255. Data augmentation techniques, including random rotations, flips, and zooms, were employed to increase dataset variability and improve the model's generalization capabilities.

2) Training the detection model

The MobileNetV2 architecture, optimized for mobile and embedded vision applications, was selected for its balance between accuracy and computational efficiency. Leveraging transfer learning, MobileNetV2 was initialized with pre-trained weights from ImageNet, excluding the top classification layer. A global average pooling layer and a dense layer with a softmax activation functions were added to classify the images into the four defined categories. The model's layers were fine-tuned using the preprocessed dataset, employing the Adam optimizer and categorical cross-entropy loss function. Training was conducted over multiple epochs, with early stopping implemented to prevent overfitting.

IV. RESULTS AND DISCUSSION

1) Identification of Cercospora Virus, Mosaic Virus, and Healthy Papaya Leaves

The Hybrid DL approach gave satisfactory classification performance in papaya leaf disease detection. EfficientNetV2B0 model was precise to 99.34% to differentiate between healthy and unhealthy leaves, while Vision Transformer model was precise to 95.77% in classifying specific diseases.

Overfitting and insufficient data for certain classes were challenges that were encountered during model training. Data augmentation techniques were employed to minimize overfitting, and regularization techniques were utilized

The below Fig. 2 represents the fluctuation in training accuracy and validation accuracy with epochs. The model had achieved a training accuracy of 99.25% and validation accuracy of 97.76% in identifying Cercospora and Mosaic Virus using ViT at Epoch 5, which was satisfactory performance with minimal overfitting.

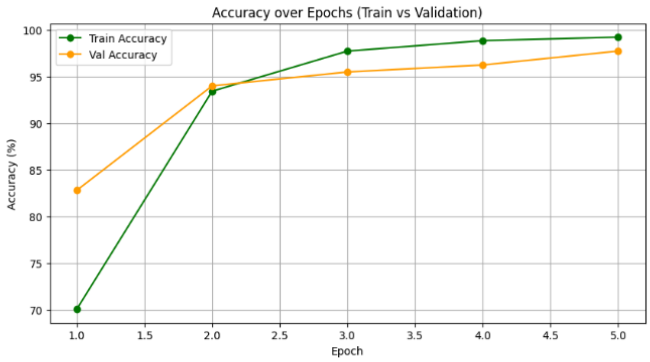

Fig. 2 Model Training Accuracy of Identification of Cercospora Virus, Mosaic Virus, and Healthy Papaya Leaves

2) Identification of Ringspot Virus, Powdery Mildew and Healthy Papaya Fruit

The Custom CNN model was extensively developed to identify Ringspot Virus, Powdery Mildew and Healthy Papaya Fruits, with 256×256 resized images of rigorous training. The Fig. 3 shows the training and validation accuracy of the custom CNN model. The model was trained to 30 epochs with the highest training accuracy at Epoch 23 and the highest validation accuracy at Epoch 21. Training accuracy is the accuracy the model has when it classifies data it has already seen, while validation accuracy is the accuracy it has when classifying unseen data.

The highest validation accuracy at Epoch 21 shows the model generalized well before any overfitting. The total accuracy of nearly 99% indicates the efficiency of the Custom CNN in distinguishing Healthy, Ringspot Virus-infected, and Powdery Mildew-infected papaya fruits. Overall, the Fig. 3 shows that good learning and model improvement during training and validation accuracy increased progressively to higher values over the course of 30 epochs.

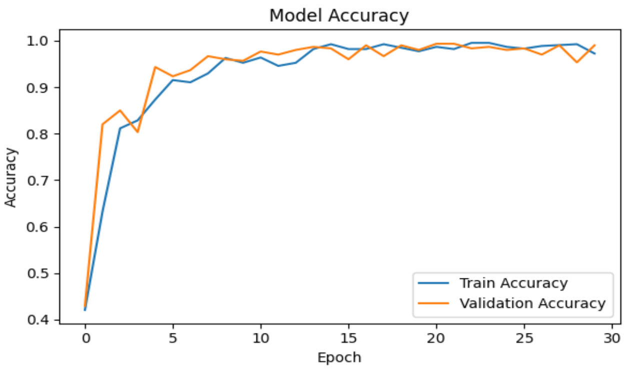

Fig. 3 Model Training Accuracy of Identification of Ringspot Virus, Powdery Mildew and Healthy Papaya Fruit

3) Identification of Mite and Mealy bug and Healthiness of the fruit and leaf

The training accuracy curve demonstrates a steady and rapid improvement during the initial epochs, with accuracy crossing 90% within the initial 5 epochs. The model also continues to strengthen its learning with training, with accuracy gradually plateauing around 100% around the 25th epoch, indicating good feature extraction and classification being undertaken by the DenseNet121 model. The trend shows that the model has successfully minimized classification errors on the training dataset with good convergence. However, more testing on validation and test datasets is required to ensure generalization as well as detect potential overfitting. Fine-tuning measures, such as regularization and data augmentation, could be considered in order to boost the model's robustness for real-world application in papaya disease classification.

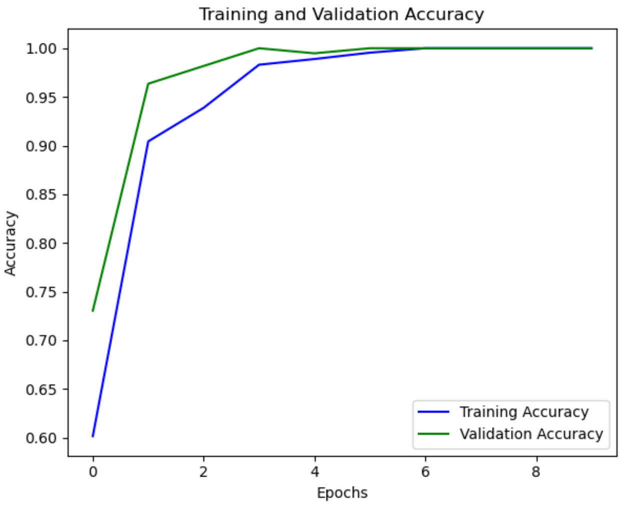

Fig. 4 Model Training Accuracy of Identification of Mite and Mealy bugs and Healthiness of the fruit and leaf

1) Papaya Maturity Detection

This Fig. 5 chart represents the training and validation accuracy of a DL model over multiple epochs. Initially, the training accuracy starts low but increases rapidly, signifying effective learning. Similarly, the validation accuracy also rises quickly, suggesting good generalization. Around the third or fourth epoch, both training and validation accuracy approach nearly 100%, indicating that the model has learned to classify the data almost perfectly. Beyond this point, the accuracy stabilizes, showing that further training does not significantly improve performance. While the high accuracy suggests a well-trained model, there is a potential risk of overfitting if the model has memorized the training data instead of generalizing well. However, since validation accuracy remains high, it indicates good generalization rather than overfitting.

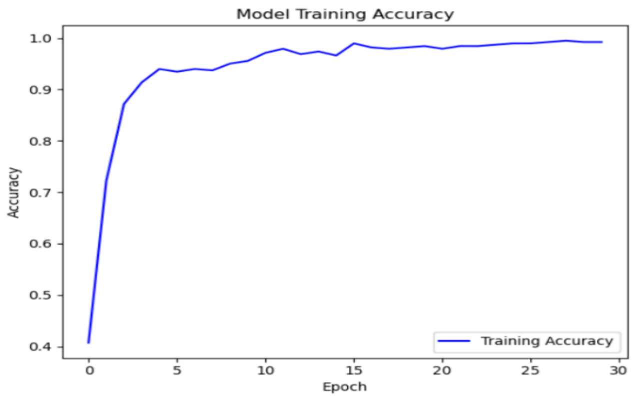

Fig. 5 Model Training Accuracy of Papaya Maturity Detection

The high overall accuracy of the model underscores its potential utility in agricultural applications, particularly in automating the sorting and grading process of papayas based on maturity. The superior performance in identifying mature and not mature fruits aligns with the model's training emphasis on these categories, which are crucial for market readiness and supply chain decisions.

The relatively lower accuracy in classifying partially mature and rotten papayas may stem from the inherent variability and overlapping features within these categories. Partially mature fruits often exhibit characteristics common to both mature and immature stages, making precise classification challenging. Similarly, the varying degrees of decay in rotten papayas can introduce complexities in consistent identification.

In conclusion, the model demonstrates significant promise in accurately determining papaya maturity, with potential applications in improving efficiency and consistency in the agricultural sector. Ongoing refinements targeting the identified limitations will further bolster their robustness and practical applicability.

V. CONCLUSION AND FUTURE WORK

Looking ahead, we plan to enhance Papaya Buddy by introducing a crop monitoring feature that will allow farmers to continuously track the health status of their crops. This feature will focus on assessing the nutritional levels and overall well-being of the plants, helping to identify nutritional deficiencies and providing targeted recommendations for fertilizers and soil amendments. Through this, we aim to support more efficient crop management and increase overall yield quality. Additionally, we intend to integrate AI-powered models that not only predict and diagnose growth, offering a more holistic approach to crop care. To improve the model’s accuracy and robustness, we plan to train our models with a larger dataset of images, ensuring that the system can handle a broader range of crop conditions and environmental factors.

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VII. REFERENCES

[1] T. A. Mir, D. Banerjee, M. Kumar, R. Rawat, Y. Chanti, "Hybridized Model for Improved Papaya Leaf Disease Classification: CNN and Random Forest Integration," *2024 5th International Conference for Emerging Technology (INCET),* pp. 1-6, 2024.

[2] R. Jahangir, T. Sakib, R. Baki, M. M. Hossain, "A Comparative Analysis of Potato Leaf Disease Classification with Big Transfer (BiT) and Vision Transformer (ViT) Models," *2023 IEEE 9th International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE),* pp. 58-63, 2023.

[3] M. K. R. Asif, M. B. Shams, M. M. Islam and M. T. Habib, "Machine Vision Based Papaya Maturity Recognition.," *Computing Communication and Networking Technologies (ICCCNT).* , no. 13th International Conference Kharagpur, India, pp. 1-6, 2022.

[4] C. A. Garillos-Manliguez and J. Y. Chiang, "Multimodal Deep Learning via Late Fusion for Non-Destructive Papaya Fruit Maturity Classification.," *Computing Science and Automation,* vol. 2, no. 18th International Conference on Electrical Engineering, pp. 1-6, 2021:.

[5] S. Gayathri, T. U. Ujwala, C. V. Vinusha, N. R. Pauline and D. B. Tharunika., "Detection of Papaya Ripeness Using Deep Learning Approach," vol. 2, no. 3rd International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, pp. 1755 - 1758, 2021.

[6] Hossen, Md. Sagar and Haque, Imdadul and Islam, Md. Saif and Ahmed, Md. Tanvir and Nime, Md. Jannati and Islam, Md. Ashiqul, "Deep Learning based Classification of Papaya Disease Recognition," pp. 945-951, 2020.

[7] Nagaraj, P and Muneeswaran, V. and Anurag, T and Srinivas, A Shankar and Kumar, V D M Pavan and Saketh, V Ragava, "A Novel Scheme for Papaya Fruit Disease Prediction and Classification using Convolutional Neural Networks," vol. 01, pp. 1-6, 2022.

[8] Hridoy, Rashidul Hasan and Tuli, Mosammat Rokeya Anwar, "A Deep Ensemble Approach for Recognition of Papaya Diseases using EfficientNet Models," pp. 1-6, 2021.

[9] de Moraes, Jairo Lucas and de Oliveira Neto, Jorcy and Badue, Claudine and Oliveira-Santos, Thiago and de Souza, Alberto F., "Yolo-Papaya: A Papaya Fruit Disease Detector and Classifier Using CNNs and Convolutional Block Attention Modules," *Electronics,* vol. 12, 2023.

[10] Munasingha, L.V., Gunasinghe, H.N. and Dhanapala, W. W. G. D. S., "Identification of Papaya Fruit Diseases using Deep Learning Approach," 2019.

[11] Y. E. K. P. I. S. Wahyuni Eka Sari, Papaya Disease Detection Using Fuzzy Naïve Bayes Classifier, Yogyakarta, Indonesia: IEEE, 2020.

[12] M. S. I. M. S. H. M. U. E. M. S. K. Md. Ashiqul Islam, Machine Learning based Image Classification of Papaya Disease Recognition, Coimbatore, India: IEEE, 2020.

[13] R. A. Boukabouya, A. Moussaoui, M. Berrimi, "Vision Transformer Based Models for Plant Disease Detection and Diagnosis," *2022 5th International Symposium on Informatics and its Applications (ISIA),* 2022.

[14] K. Harika, M. N. Nachappa, "A Study on Deep Learning Methods to Identify the Infected Regions from Papaya Fruit Images," *2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE),* pp. K. Harika and M. N. Nachappa, "A Study on Deep Learning Methods to Identify the Infected Regions from Papaya Fruit Images," 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE), Ballari, India, 2, 2023.

[15] W. E. Sari, Y. E. Kurniawati, P. I. Santosa,, "Papaya Disease Detection Using Fuzzy Naïve Bayes Classifier," *2020 3rd International Seminar on Research of Information Technology and Intelligent Systems (ISRITI),* pp. 42-47, 2020.