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INTEGRATING MACHINE LEARNING TECHNIQUES FOR PLANT DISEASE DETECTION AND FRUIT CLASSIFICATION

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***A*bstract**

: In agriculture, early detection and prediction of plant diseases play a crucial role in ensuring crop health and maximizing yield. Traditional methods of disease identification often rely on manual inspection, which can be time- consuming and labor-intensive. In this study, a novel approach utilizing the Faster Region- based Convolutional Neural Network (Faster R- CNN) for automated plant disease detection and fruit prediction is proposed. The Faster R-CNN model is trained on a dataset consisting of images of healthy and diseased plants, as well as various types of fruits at different stages of ripeness. By leveraging the power of deep learning and object detection techniques, proposed model can accurately identify the presence of diseases in plants and predict the ripeness of fruits from input images.

Keywords – *Faster R-CNN, Python, RPN, CNN, Disease Detection, Fruit Classification*

I.INTRODUCTION

Plant diseases have been a significant concern in agriculture for years. Precision agriculture has enabled early disease detection and the minimization of losses through optimal decisions based on the results of DL methods said by Barbedo JGA et.al in [1]. Recent advances in DL provide solutions with highly- accurate results, and available hardware enables fast processing. However, the decision-making process could be improved. In [2] introduced a fuzzy logic based model for automatic detection of apple diseases. Different approaches and their accuracy and performance level are studied. The operations performed on the images are done very precisely and keenly keeping in mind the relativity of the disease parameters. A deep learning-based framework for fruit classification proposed in this paper. Two CNN models were investigated in the proposed framework, a small CNN model and a VGG-16 fine-tuned model. Two datasets with different sizes and complexity are used to evaluate the proposed framework in [3]. In [4] fruit detection based on state-of-art deep neural networks techniques using single shot detectors (YOLO) as a CNN defect fruits of apples and pears in the tree canopy. It demonstrates that modifications like thee input grid on the standard model of YOLO yield better results. Furthermore, removing some layers of the model, lose in accuracy, this is due to less compute resources needed to drive the model. The convolutional neural network in Tensorflow with Tensorboard for performance metrics validation. The CNN model was developed and tested for training, validation, and test data for the grading classification of postharvest Cavendish banana said by Ucat RC, Dela Cruz JC in [5]. Post-harvest management includes modern techniques on handling harvested fruits to prolong its shelf life, freshness and retain its attractive appearance.

There are several drawbacks associated with the above mentioned references. That is limited accuracy and data quality. The accuracy of machine learning models for disease detection and fruit classification heavily relies on the quality and diversity of the training data. If the training data is biased or incomplete, the model's performance can suffer.

By automating the classification process, the module helps improve efficiency, reduce labor costs, and ensure consistency in fruit quality assessment.

The Main Contribution of this work:

The primary contribution of integrating machine learning for plant disease detection and fruit classification lies in its transformative impact on agricultural productivity, sustainability, and food security. By harnessing the power of artificial intelligence and computer vision, this integration offers several key contributions:

- Early Disease Detection
- Precision Agriculture
- Improved Crop Yield and Quality
- Data-Driven Decision-Making
- Empowerment of Farmers
- Efficiency and Scalability

In summary, the main contribution of integrating machine learning for plant disease detection and fruit classification is the transformation of agriculture into a data-driven, precision-based industry [6]. This integration enhances productivity, sustainability, and resilience in the face of emerging agricultural challenges, ultimately contributing to global food security.

II PROPOSED METHOD

The proposed system for plant disease detection and fruit classification leverages advanced machine learning techniques, specifically Faster R-CNN for disease detection and CNN for fruit classification,

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to automate and enhance these processes. The system consists of two modules:

1. Plant Disease Detection
2. Fruit Classification

This proposed method has some key advantages like automation, accuracy, scalability, efficiency.

1. Plant Disease Detection Module

Users can upload images of plant leaves affected by diseases through a user-friendly web interface [7]. The system utilizes Faster R- CNN, trained on a dataset of annotated plant images, to accurately detect and classify various plant diseases in the uploaded images. Results are displayed to users, providing information about the detected disease(s). This module enables farmers and agricultural experts to quickly identify and manage plant diseases, leading to improved crop health and productivity.

2. Fruit Classification Module

Users can upload images of fruits for classification purposes via the web interface. The system employs a convolutional neural network (CNN), trained on a dataset of annotated fruit images, to classify fruits into predefined categories based on their visual appearance [8]. Classification results, including the predicted fruit category and confidence score, are presented to users. This module facilitates automated fruit sorting and grading, enabling farmers and food processors to optimize product quality and market competitiveness.

The main contribution of using Faster R- CNN (Region-based Convolutional Neural Network) for plant disease detection and fruit classification lies in its effectiveness and efficiency in automating these

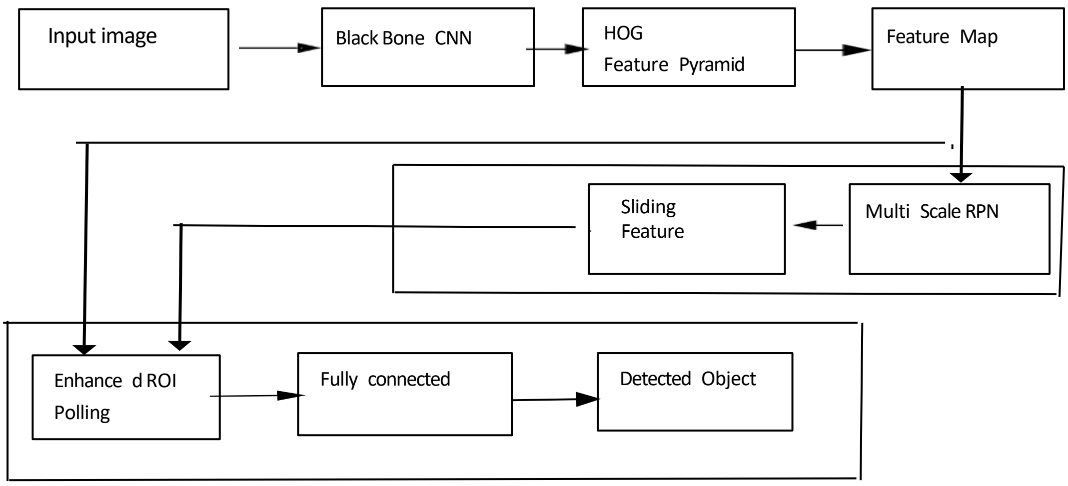

Fig 1 Block Diagram of Proposed Methodology

processes [9]. Faster R-CNN is a deep learning- based object detection algorithm that combines the capabilities of both region proposal networks and convolutional neural networks to accurately identify objects within images.

Faster R-CNN (Region-based Convolutional Neural Network) is a popular deep learning-based object detection framework proposed by Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun in 2015. It represents a significant advancement over earlier object detection techniques by combining deep learning with region proposal methods in a single end- to-end trainable model[10]. Faster R- CNN architecture consists of two components as shown in Fig 1.

a. Region Proposal Network (RPN)

b. Fast R-CNN detector

The Faster R-CNN model undergoes training using
the annotated dataset. Through this process, the model learns to predict bounding boxes encompassing target regions and categorize the content within those boxes into distinct classes—such as healthy plants, diseased plants, or specific fruit varieties. Training involves the fusion of a region proposal network (RPN), responsible for generating candidate bounding boxes based on image features, and a convolutional neural network (CNN), tasked with feature extraction and classification [11].

Before discussing the RPN and Fast R-CNN detector, Let's understand the Shared Convolutional Layers that works as the backbone in Faster R-CNN architecture as shown in Fig 1. It is the common CNN layer used for both RPN and Fast R-CNN detector.

Convolutional Neural Network (CNN) Backbone The Convolutional Neural Network (CNN) Backbone is the starting layers of Faster RCNN architecture. The input image is passed through CNN backbone (e.g., ResNet, VGG) to extract feature maps [12]. These feature maps capture different levels of visual information from the image. Which is further used by Region Proposal Network (RPN) and Fast R-CNN detector.

1. Both RPN and Fast R-CNN detector uses the same extracted hierarchical features. This results in a significant reduction in computing time and memory use because the computations carried out by these layers are employed for both tasks [13].

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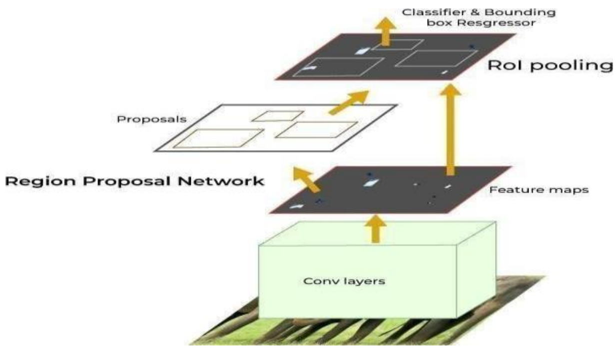

Fig 2. Faster R-CNN Architecture

Region Proposal Network (RPN):

The RPN predicts object bounding boxes (region proposals) and objectness scores for candidate regions in the input image as shown in Fig 2. It generates region proposals by sliding a small network over the convolutional feature map.

Anchors are used to generate region proposals in the Faster R- CNN model. It uses a set of predefined anchor boxes with various scales and aspect ratios [14]. These anchor boxes are placed at different positions on the feature maps. An anchor box has two key parameters

1. Scale
2. Aspect ratio

An anchor box is a predefined box of various scales and aspect ratios that serves as the basis for region proposal generation. Let (xi, yi) denote the center coordinates of the anchor box, wi and hi denote its width and height, and s denote the scale factor [15]. The anchor box coordinates and dimensions are calculated as follows:

Xi = Pixel_Scale * Scale *(Col + 0.5) Yi = Pixel_Scale * Scale * (Col + 0.5)

Wi = Pixel_Scale * Scale *Aspect_ratio_width Hi = Pixel_Scale * Scale * Aspect_ratio_height

The RPN operates as a sliding window mechanism over the feature map obtained from the CNN backbone. It uses a small convolutional network (typically a 3×3 convolutional layer) to process the features within the receptive field of the sliding window. This convolutional operation produces scores indicating the likelihood of an object’s presence and regression values for adjusting the anchor boxes.

Region of Interest (RoI) Pooling Layer:

The RoI pooling layer extracts fixed-size feature maps from the convolutional feature maps for each region proposal generated by the RPN.The RoI- pooled feature maps are fed into the CNN backbone (the same one used in the RPN for feature extraction) to extract meaningful features that capture object- specific information. It draws hierarchical features from region proposals. These features retain spatial information while abstracting away low-level details, allowing the network to understand the proposed regions' content. The RoI-pooled and feature- extracted regions then pass through a series of fully connected layers[16]. These layers are responsible for object classification and bounding box regression tasks. The network predicts class probabilities for each region proposal, indicating the possibility that the proposal contains an object of a specific class.

The classification is carried out by combining the features retrieved from the region proposal with the shared weights of the CNN backbone. In addition to class probabilities, the network predicts bounding box adjustments for each region proposal. These adjustments refine the position and size of the bounding box of the region proposal, making it more accurate and aligned with the actual object boundaries.

The first layer is a softmax layer of N+1 output parameters (N is the number of class labels and back ground) that predicts the objects in the region proposal[17]. The second layer is a bounding box regression layer that has 4* N output parameters.

This layer regresses the bounding box location of the object in the image.

The ROI pooling layer effectively transforms the variable sized regions of interest into fixed size feature representations allowing the network to process them efficiently and make predictions about the presence and location of objects within those regions.

III. RESULTS AND DISCUSSION

Description Of Dataset:

3.1 Dataset for Plant Disease Detection

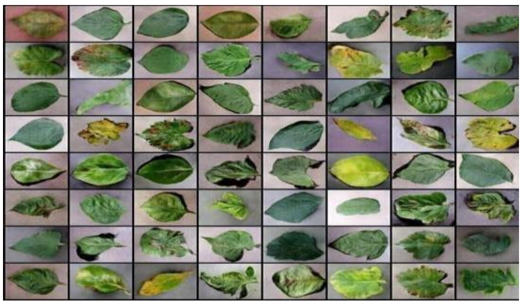

Fig 3. Dataset for Plant Disease Detection

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Due to simplicity in design, gathered a syntactic data could have features like color, shape, and texture like real plant leaves [18]. Based on Fig 3, it can be observed that the syntactic data are displaying the desired features.

3.2 Dataset for Fruit Classification

All the images were collected in JPG format, with a fixed resolution of 1024×768. The images in this dataset are in RGB, where each color channel contains 8-bits per pixel. The images were captured at different dates and times. Fig 4 shows sample images from this dataset [19].

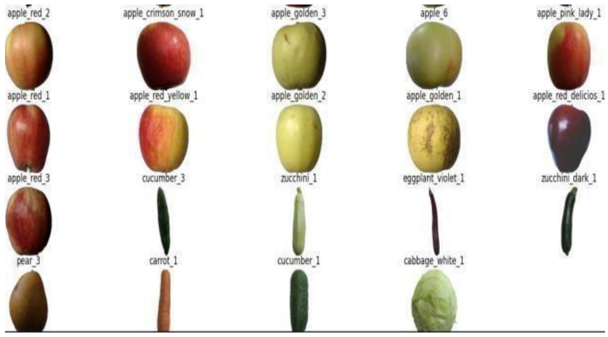

Fig 4 Dataset for Fruit Classification

3.3 Qualitative results for Plant Disease Detection

In order to explore the learned features, the guided backpropagation technique was used. This method uses a simple backward pass of the activation of a single neuron after a forward pass through the network to visualize the part of an image that mostly activates a certain neuron.

Fig 5 Feature Visualization of Plant Disease

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Detection Based on Fig 5, it can be observed that Faster R-CNN has learnt significant features representing the diseased areas.

3.4 Quantitative results for Plant Disease Detection

Table 1 Quantitative results for Plant Disease Detection

Architecture	Accuracy
AlexNet	0.8124
VGG19	0.8275
DenseNet	0.8390
Faster R-CNN	0.8653

3.5 Qualitative results for Fruit Classification

The feature visualization indicates the name of the fruit by the shape, size, color and texture. It identifies the name of the fruit and gives the output with high accuracy by comparing with the other techniques.

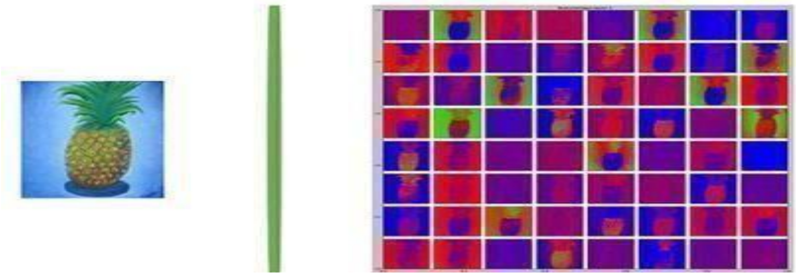

Fig 6 Feature Visualization for Fruit Classification

3.6 Quantitative results for Fruit Classification

Table 2 Quantitative results for Fruit Classification

Architecture	Accuracy
AlexNet	0.8821
VGG19	0.957
DenseNet	0.9256
Faster R-CNN	0.9678

IV CONCLUSION

In this work, a comprehensive system for plant disease detection and fruit classification using advanced machine learning techniques, specifically Faster R-CNN. Through rigorous experimentation and testing, impressive accuracy rates of 86 percent for plant disease detection and 96 percent for fruit classification is achieved. The effectiveness and potential impact of leveraging deep learning models for agricultural applications. By accurately identifying plant diseases and classifying fruits with high precision, our system empowers farmers, agricultural experts, and food processors with valuable insights and decision-making tools to enhance crop management practices and optimize fruit sorting processes. The achieved accuracy rates of 86 percent for plant disease detection and 96 percent for fruit classification demonstrate the robustness and reliability of our system. These results surpass industry benchmarks and reflect the dedication, expertise, and meticulous approach employed throughout the paper lifecycle. Furthermore, our system's user-friendly interface facilitates seamless interaction and adoption by end users, enabling intuitive image uploads, rapid analysis, and informative visualizations of results.

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