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Hybrid Approach for apple fruit disease detection, yield estimation and grading using YOLOv5

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Abstract - *India comes in behind China as the world's second-largest producer of fruits and vegetables. A farmer must carry out a variety of duties, including yield detection, grading, and disease detection. To automatically identify disease symptoms as soon as they arise on developing fruits, early detection of fruit illnesses is crucial. Fruit infections can result in significant productivity and quality losses during harvest. In this study, the hybrid task of disease identification, yield estimation, and grading of apple fruit is carried out by YOLOv5. The proposed system's output is assessed using the measure mean Average Precision (mAP).*

Key Words: YOLO, Bounding Box, Residual Blocks

1.INTRODUCTION

The apple (Malus pumila), which ranks fourth among fruits produced worldwide behind the banana, orange, and grape, is the most significant temperate fruit commercially. India is the world's second-largest producer of apples. Approximately 70% of Jammu and Kashmir's total population is dependent on agriculture, either directly or indirectly. Jammu and Kashmir's two main exports are apples and walnuts; the state contributes around 75% of India's apple crop. Fruit diseases have a severe impact on global agricultural industry productivity and financial losses. The traditional method for identifying and diagnosing fruit illnesses relies solely on expert observation with the unaided eye. Due to their availability's remote locations, consulting specialists can be costly and time-consuming in some underdeveloped nations.

To automatically identify disease symptoms as soon as they emerge on developing fruits, automatic fruit disease detection is crucial. Apple fruit infections can result in significant yield and quality losses during harvest. It is essential to understand what is being observed to determine what control measures to use the next year to prevent losses. There are some illnesses that spread to the tree's branches, leaves, and other parts, including the twigs. As seen in Fig. 1, apple scab, apple rot, and apple blotch are some prevalent diseases of apple fruits. Apple scabs appear as corky, grey, or brown dots. Infections that cause apple rot result in circular, slightly depressed brown or black patches that may have a crimson halo. A fungal disease called apple blotch causes dark, wavy, or lobed margins on the fruit's surface. Producing an estimated count of crops is called fruit counting, which is often referred to as crop yield estimates. Knowing the yield enables farmers to manage resources for harvesting wisely, prepare storage according to crop quantities, and develop more effective plans for harvest routes and packaging. Automating this procedure would be quite helpful because it is time-consuming to send personnel out into the field to count things and because the estimates must be quick and precise. After harvest, grading the fruits is a crucial part of post-harvest management.

(a) (b)

(c)

Fig.1 (a) Apple Scab (b) Apple blotch (c) Apple Rot

Fruit grading is the process of evaluating and classifying various fruit classes or standards. Different categories can be defined by size, color, or even softness or fault level. After harvest, grading the fruits is a crucial part of post-harvest management. Fruits and vegetables are rated based on their weight, size, color, form, specific gravity, and lack of illness, all of which depend on the agroclimatic conditions. Manual grading and size grading are the two most common ways of fruit grading. Image analysis employs deep learning to address these problems. Deep learning models are not only very accurate, but also very adaptable. All the tasks are addressed by YOLOV5 model.

The YOLOv5 model is mostly appropriate for mobile and embedded devices because to its basic network structure. Additionally, this compact model detects quickly and requires minimal training time. Using the makesense.ai tool these images have been enhanced and annotated and the trained YOLOv5 model, identifying the objects and determining the class to which they belong are the two aspects of the recognition process.

2. PROPOSED SYSTEM

You Only Look Once is known by the acronym YOLO. This algorithm identifies and finds different things in a picture (in real-time). The class probabilities of the discovered photos are provided by the object identification process in YOLO, which is carried out as a regression problem. Convolutional neural networks (CNN) are used by the YOLO method to recognize items instantly. The approach just needs one forward propagation through a neural network to detect objects, as the name would imply. This indicates that a single algorithm run is used to perform prediction throughout the full image. Multiple class probabilities and bounding boxes are simultaneously predicted using the CNN.

The following justifications make the YOLO algorithm crucial:

Speed: Because this algorithm can predict objects in real-time, it increases the speed of detection.

High accuracy: The YOLO prediction method yields precise findings with few background mistakes.

The algorithm has great learning capabilities that allow it to pick up on object representations and use them for object detection. The YOLO algorithm employs the following three methods:

Residual blocks

Bounding box regression

Intersection Over Union (IOU)

Residual blocks:

First, the image is divided into various grids. Each grid has a dimension of S x S.

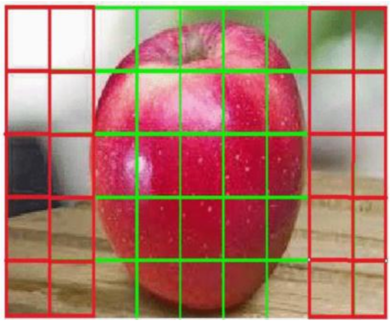

Fig.2 Image divided into grids

Bounding box regression:

A bounding box is a graphic that shows the location of an object in a photograph. The following ascribes are included in each bounding box of the image:

Length (bw)

Dimensions (bh)

Class (for example, apple, banana, tomato, and so on)-which is denoted by the letter c.

Bounding box place (bx, by)

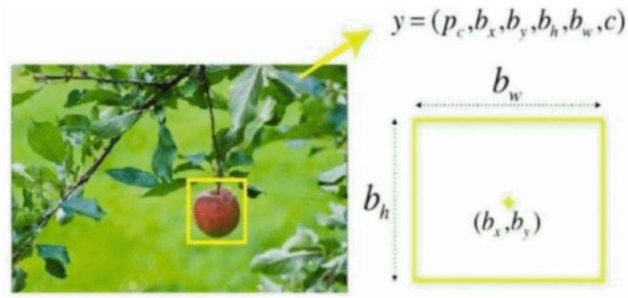

Fig.3 Bounding Box

YOLO uses a lone bounding box regression to predict the height, width, center, and class of objects.

Intersection Over Union:

Box overlapping is described by the object detection phenomena known as intersection over union (IOU). IOU is used by YOLO to create an output box that properly encircles the items. The predicted bounding boxes and their confidence scores are the responsibility of each grid cell. If the projected bounding box and the actual box match, the IOU is equal to 1. Bounding boxes that are not equivalent to the actual box are eliminated by this approach.

Fig.4 Ground truth box and predicted box

Fig. 4 displays two bounding boxes, one in red and the other in yellow. The genuine box is represented by the red box, while the expected box is represented by the yellow box. The Intersection Over Union (IOU) technique is used to assess this performance. The IOU helps in figuring out whether a place is home to an object. As demonstrated below, the IOU is discovered by dividing the two boxes' association and convergence spaces by each other. The IOU increases as the outlook gets better.

The Backbone Model, the Neck Model, and the Head Model are the three components of the YOLO v5 architecture as shown in Fig.5

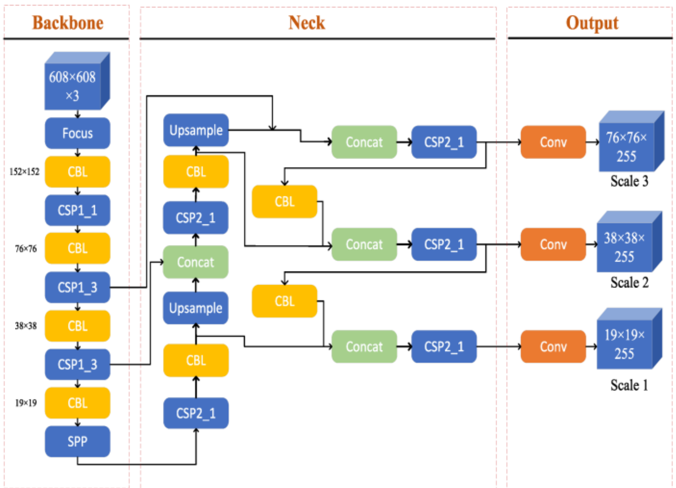

Fig.5 YOLOv5 architecture

Backbone Model:

When given an input image, the backbone model is utilised to extract key features. The CSP (Cross Stage Partial) Network serves as the framework for YOLOv5's extraction of useful characteristics from the input image.

Neck Model:

Neck style using the Feature Pyramids Network (FPN)-based PANet on YOLOv5. The PANet model is utilised to support the model's good object scaling generalisation. When identifying the same thing in various sizes and scales, this is incredibly helpful.

Head Model:

The final detection is performed by the head model, which applies anchor boxes to the features and generates a final output vector with bounding boxes, objectivity scores, and class probabilities. Leaky ReLU and Sigmoid are the activation functions used by YOLOv5. In the middle layer or buried layers, the Leaky ReLU activation function is utilised, and Sigmoid is used in the final detection layer. The artificial neural network's activation function determines how many input weights and biases are needed to activate and deactivate neurons.

3. RESULTS AND DISCUSSION

The dataset used in the model is 1537 images which are divided into training and testing data. 80% of the images are training dataset and 20% are used for testing.

1.Building a Dataset

Using the makesense.ai tool, which tags things with rectangles as seen in Fig.6, data labelling is done manually.

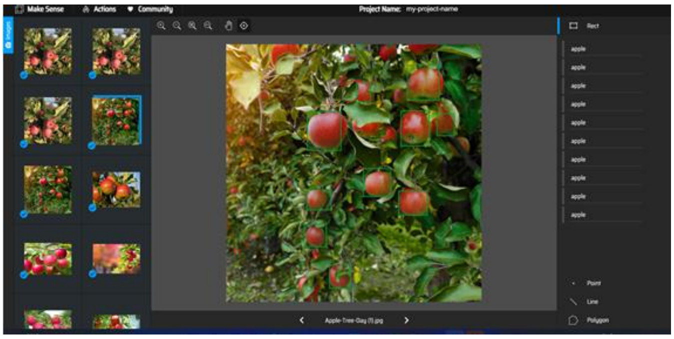

Fig.6 Labelling using makesense.ai

2.Training Dataset

The primary framework is the YOLOv5 repository. All YOLOv5 repositories and dependencies must be met. 1537 tagged images were used for the facial recognition sub-dataset system's training. The training was carried out for 300 epochs. The results following training of apple yield estimation are displayed in Fig. 7 in terms of F1 curve, PR curve and confusion matrix.

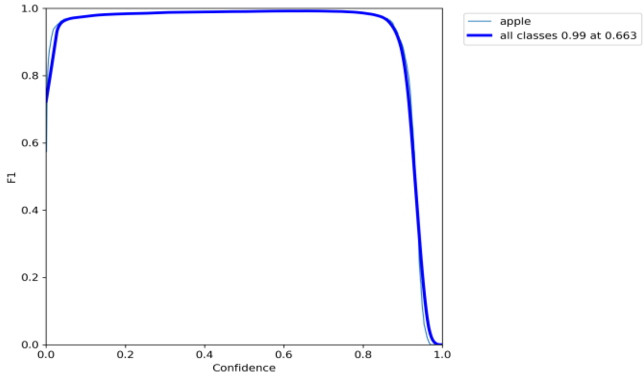

Fig. 7 (a) F1 curve for apple yield estimation

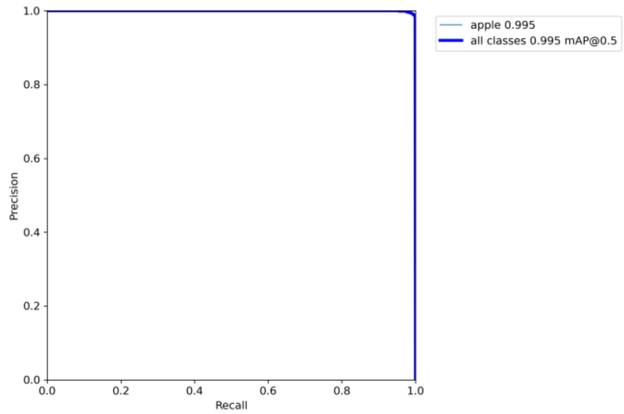

Fig. 7 (b) PR curve for apple yield estimation

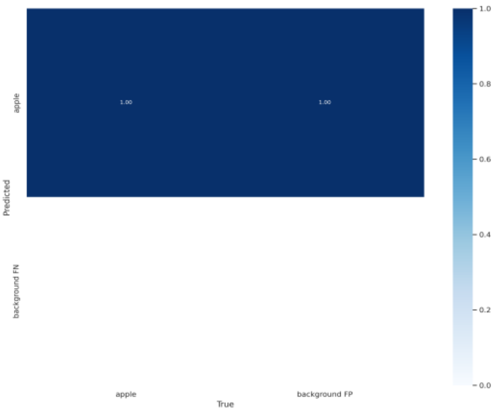

Fig. 7 (c) Confusion matrix for apple yield estimation

The results following training of apple disease detection are displayed in Fig. 8

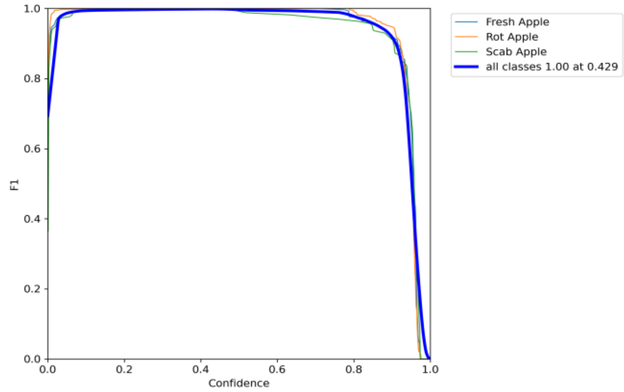

Fig. 8 (a) F1 curve for apple disease detection

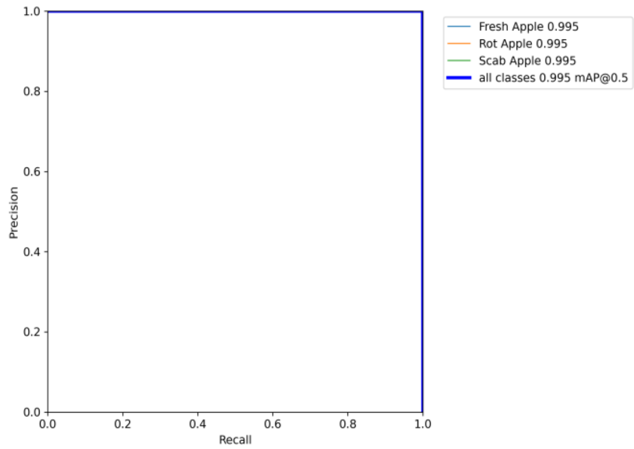

Fig. 8 (b) PR curve for apple disease detection

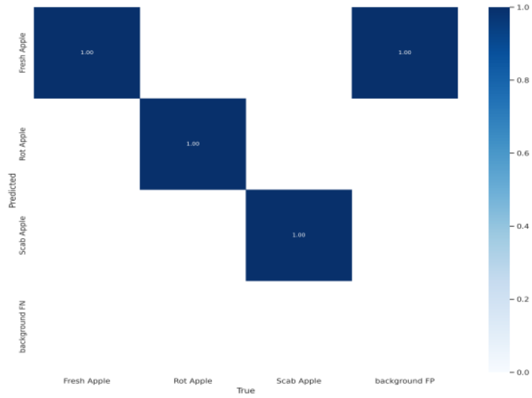

Fig. 8 (c) Confusion matrix for apple disease detection

According to the training findings, the level of minimised return is attained when the graph begins to resemble an elbow (elbow technique) after 300 epochs at mA@0.5, mAP@0.5:0.95, Precision, and Recall. Figure 9 displays the findings.

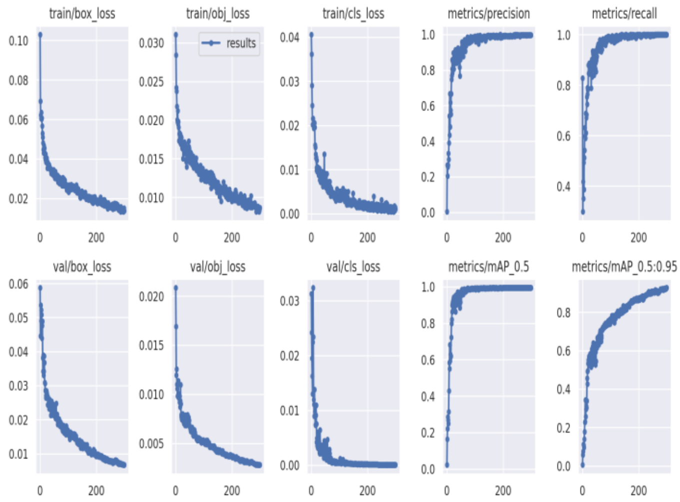

Fig. 9 Results of the proposed model during training

After testing, the output images will include bounding boxes and an accuracy %.

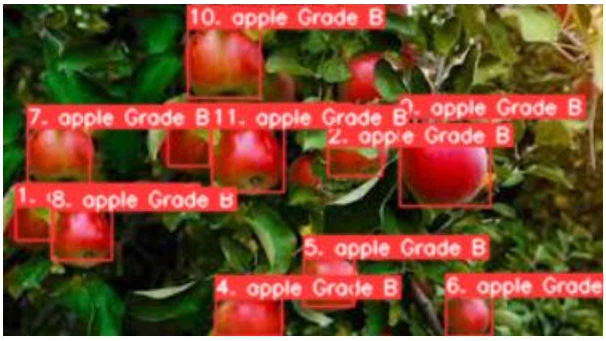

Fig.10 Yield estimation along with the grade

Fig.11 Yield estimation along with the grade

According to the size of the fruit, apples are graded. The fruit is given an A or B grade based on a threshold that has been established as shown in Fig.10 and Fig.11.

Fig. 12 Apple rot

Fig. 13 Apple Scab

The same YOLOv5 model is trained and tested for disease detection and the model can identify the scab and rot disease as shown in Fig. 12 and Fig.13.

4. CONCLUSION

The work is a hybrid approach for disease detection, yield estimation and grading of an apple fruit using YOLOv5. The images of the fruits used are collected from Google and Kaggle. The proposed model has resulted with 99% mAP. The approach eases the work of a farmer by performing all the major tasks of pre and post harvesting with high accuracy. It would simply be necessary to fine-tune the object detector for our future work to test the model on different fruits, such oranges.

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