# Advancements in Precision Agriculture Improving Fruit Classification for Fruit Harvesting

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***Abstract-***.

In this research, we present advancements in precision agriculture by improving fruit classification for automated harvesting through a novel deep learning approach, the Detail-Semantics Enhancement You Only Look Once (DSE-YOLO) model. This model was created to solve the problem of identifying fruits in situations where flora frequently blocks the view of fruits, irrespective of their size or growth stage. Existing methods were constrained by the requirement for manual feature design. The DSE-YOLO model combines substantial feature extraction with semantic information to improve fruit detection at various scales. We offer two loss functions: Double Enhanced Mean Square Error (DEMSE) and Exponentially Enhanced Binary Cross Entropy (EBCE), in addition to correcting class imbalances. Using a large collection of annotated fruit photos, our approach showed considerable gains in detection accuracy. The DSE-YOLO model is an extremely effective instrument for automating fruit picking, outperforming earlier techniques and greatly increasing the productivity and efficiency of modern agriculture.

***Index Terms***- Precision Agriculture, Fruit Classification, Automated Harvesting, Deep Learning, YOLOv5, DSE-YOLO, Multi-Stage Detection.

## I. INTRODUCTION

Strawberries, apples, oranges, and mangoes are among the most popular and widely consumed fruits globally. The conventional techniques of harvesting and monitoring the growth of plants and fruits are time-consuming and labour-intensive due to the wide range of sizes that they have. The labour-intensive method raises the overall cost of production considerably. [1]. Artificial intelligence (AI) is finding its way into agriculture more and more to automate labour-intensive, time-consuming processes that used to require human effort. Included is the number 2. It is essential for intelligent agriculture to be able to automatically identify and categorise these fruits at various stages of development. This will make things easier, such automating harvesting, improving planting management, and getting an accurate estimate of crop yield. Conventional fruit detection systems extract attributes including size, shape, colour, and texture using techniques like threshold analysis, edge detection, region growth, and grey-scale co-occurrence matrices. Strawberry phases were classified using a multi-attribute decision-making approach by Liming et al. [3]. They did this by utilising threshold segmentation to extract the strawberries' form, size, and colour attributes. When used on small fruits, the Arefi et al. [4] threshold analysis method—which incorporated features from RGB, HIS, and YIQ colour spaces—for recognizing mature tomatoes performed poorly. Wang et al. [6] developed a matching method for identifying and categorizing litchi fruits that is based on the geometric centre. Conversely, Lu et al. [5] developed an edge detection technique to recognise fully grown citrus fruits in intricate settings. Although these techniques help identify fruit, they are still dependent on human labour to create features and are unable to automatically extract unique information. They also have the ability to recognise only fully ripe fruits.
In recent times, there has been a growing use of deep learning (DL) in the field of fruit recognition. Popular deep learning methods such as Faster R-CNN [7] have demonstrated encouraging results in this area. Though under constrained experimental conditions, Oo and [9] used image analysis to identify geometric features for the classification of strawberry fruits. Furthermore, [8] presented a faster R-CNN-based method for fruit recognition that is more effective. The 'Mango-YOLO' model was created by Koirala et al. [10] to forecast mango yield. To identify unripe tomatoes, Mu et al. [11] combined transfer learning with Faster R-CNN. Liu et al. [12] enhanced the YOLOv3 [13] model to detect tomatoes, whereas Tian et al. [14] combined Dense-Net [15] and YOLOv3 [13] to distinguish apples. Although these methods can identify fruits, they are not the best for finding fruits in their native habitats, such as apples, strawberries, mangoes, and oranges. Their inadequate capacity to discriminate between immature and mature fruits is the cause of this. The completely grown strawberries shown in Figure 1 are effectively recognised and classified using the DSE-YOLO model. The algorithm correctly distinguishes between ripe and unripe strawberries, and the pink boxes and labels show how ripe the strawberries are. Sub-images (a-c) demonstrate the model's capacity to identify clusters of ripe strawberries, even when the fruits are close together. Sub-images (d–f) further illustrate the model's resilience in actual agricultural settings by showing how well it performs in more difficult circumstances, including as veiled fruits or complicated backgrounds. The images bolster the idea that the model can improve precision agriculture applications such as autonomous harvesting [16].

**Figure 1:** The comparison shows that different strawberry varieties had minimal impact on detection accuracy across methods: (a) machine vision, (b) CNN, and (c) R-YOLO, thanks to a large and varied training dataset [16].

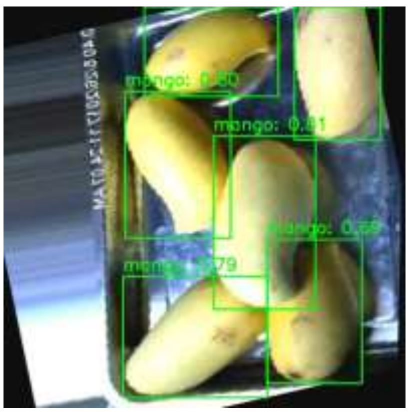

**Figure 2:** Mangoes Detection

Because of their size variation, inclination to blend in with foliage, and similarity in colour and texture to surrounding plants, these fruits are hard to spot. Variation in fruit yield between developmental stages is another major contributor to the foreground-foreground class imbalance. Using Detail-Semantics Enhancement You Only Look Once (DSE-YOLO), this research presents a new multi-stage fruit detecting technique. This paper mainly contributes the following: 1) We build the Detail-Semantics Enhancement (DSE) module to make fruit identification better. Semantic features help with accurate fruit placement, while detailed features allow the model to recognise fruits like mangoes, strawberries, apples, and oranges with more precision. The combination of these characteristics enables fruit detection on multiple scales. We design two loss functions, Double Enhanced Mean Square Error (DEMSE) and Exponentially Enhanced Binary Cross Entropy (EBCE), to address the issue of foreground-foreground class imbalance. While EBCE zeroes in on fruit classification, DEMSE maintains class balance by raising the loss proportion of tiny sample items.

## II. LITERATURE REVIEW

In recent years, agricultural deep learning (DL) models have grown in popularity. These models have improved crop categorization and production forecasting. A study used a Deep Learning model to classify vegetables, calculate productivity, and suggest online marketing strategies. Additional materials were offered by the algorithm. Using the Caffe and Chainer frameworks, researchers classified ten vegetable kinds with over 70% accuracy [17]. A study on mango fruit detection in tree canopies tested SSD, YOLO v2, v3, Faster R-CNN (VGG), and ZF deep learning architectures. Averaging 0.983 and having the highest F1 score of 0.968, YOLOv3 had the highest accuracy of all the models evaluated [18].

YOLOv3 helped Floridian researchers catalog several broadleaf species, sedges, and grasses. Two networks were built for discriminatory and indiscriminate data processing in the research. The discriminative model [19] gives YOLOv3, a successful weed control strategy, F1 scores of 0.96 for grasses, 0.96 for sedges, and 0.93 for broadleaves.

MS-FRCNN uses a region-based convolutional neural network to recognize small fruits. Compared to Faster R-CNN, our model had higher recall, accuracy, and F1-score. More specifically, the F1-score rose from 0.885 to 0.946, recall from 0.922 to 0.962, and precision from 0.850 to 0.931. These results indicate that our model outperforms Faster R-CNN in real-time [20]. By using an improved version of YOLOv3, we were able to reliably distinguish apple fruit development phases. Blur processing, brightness and color balance improvements, and others helped the model recognize overlapping apples in 0.304 seconds [21]. Mask-RCNN, FPN, and RPN fruit identification models were examined. The best model was the mask-RCNN model, with 95.78% precision, 95.41% recall, and 89.85% MIoU [22].

Separate research suggests clustering fruits using Deep Learning. A more efficient Region-based Convolutional Neural Network was used. The Mobile-Net model achieved 99% precision using data collecting [23]. We classified our country's crops using OpenCV-based TensorFlow API object recognition. With 2,000 photos with the SSD Mobile-net v2 coco model, the system detected vegetables with 99% accuracy [24]. The new technology uses a camera and implanted sensor to uniquely identify retail food items. The system included a housing, load cell, camera, LCD, and Raspberry Pi. These components were designed to reduce human participation and inferential processing time. We used multiple convolutional neural networks [25] to detect and evaluate objects.

By estimating agricultural productivity with a simulated deep CNN, farmers can boost output and eliminate pests. This was their conclusion after consulting specialists. Automatic yield prediction in robotic agriculture is possible using modified Inception-Res-Net. This design averaged 91% accuracy on real photographs and 93% accuracy on fake ones during testing [26]. CNNs were used to classify fruit diseases [27].

Alex-Net was used to identify and characterize apple illnesses with 97% success. Early illness diagnosis protects agricultural yield and allows quick response. The study found deep learning models promising for early illness identification.

How accurately could a deep learning system predict harvest success? Reference [28] asked a specific inquiry.

Long Short-Term Memory (LSTM) networks examined soil and meteorological data. A Mean Absolute Error (MAE) of 0.15 shows that the model properly predicted agricultural production using deep learning. Generative Adversarial Networks (GANs) were widely studied in [29] for their ability to improve agricultural data quality. Researchers found that deep learning models trained with simulated crop photographs improved categorization accuracy. Using the GAN-augmented dataset improved crop variety accuracy by 5-10%.

An independent study [30] suggested a deep-learning model that uses CNNs and RNNs for real-time fruit identification and orchard monitoring. This method allows yield tracking and accurate estimations in real-time. The hybrid model outperformed the standard methods with 93% accuracy and 91% recall. The researchers at [31] primarily used deep learning to automate agricultural weed detection. After training a proprietary YOLOv3 framework on several cannabis photographs, the researchers used it. The model's F1 score of 0.89 shows it can be easily integrated into automated weeding systems, reducing chemicals and manpower.

A new deep learning (DL) method was introduced to detect plant nutrient deficits [32]. The researchers used spectral imaging and CNNs to find nitrogen, phosphate, and potassium deficiencies. Sustainable farming and precision agriculture benefit from the model's 95% accuracy. Research [33] shows that conveyor belt technology can help deep learning models sort and organize fruits in real-time. The Inception-v4 architecture achieved 98% classification accuracy, improving packing facility sorting efficiency.

Researchers classified plant growth stages using deep learning algorithms [34]. A unique convolutional neural network architecture accurately detected and categorized crop development phases. The model's 96% phenotypic accuracy helped farmers improve procedures and track crop growth. A recent study [35] used deep learning (DL) to identify and classify crop pests. Scientists trained a ResNet-50 model on bug photos to achieve 92% accuracy. By accurately recognizing pests, this automated method could improve pest control and agricultural loss. Drone imagery analysis was used to develop a deep-learning method for agricultural disease prediction. Spatial distribution maps and CNNs with GIS can detect early illness outbreaks. The method's 94% accuracy rate suggests extensive agricultural surveillance use...

## III. RESEARCH METHODOLOGY

This study aimed to accurately categorize fruits for robotic strawberry harvesting using a methodical approach. We started with data collection. Roboflow helped us gather a large dataset of tagged fruit photographs for deep-learning model training. This information helped the model grasp fruit types' traits.

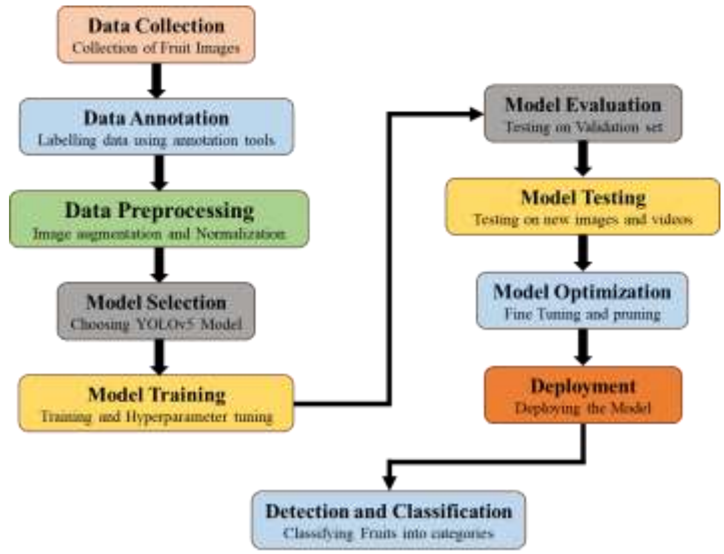


**Figure 3:** Flow Chart

### a. Data collection

Roboflow, an online resource that offers a wide variety of datasets tailored for computer vision applications, is where the dataset was retrieved from. A deep learning network may be trained to classify fruits using this study's dataset, which contains annotated pictures of multiple fruit types. Annotations inform the model of the distinct traits of each fruit class by providing specific labels for each fruit variety. Below, you can find the specifics of the dataset.

**Table 1:** Summary of the Fruit Classification Dataset

| Class | No. images |
|---|---|
| Apple | 1050 |
| orange | 1000 |
| Mango | 2000 |
| strawberry | 2500 |

### b. Algorithm selection

Oranges, strawberries, apples, and mangoes are classified better in this research to improve YOLOv5 architecture-based automated harvesting. Yolov5 is ideal for complicated agricultural detection and classification jobs due to its real-time object recognition accuracy.

### c. YOLOv5 Architecture

#### i. Input Layer

Send a size-standardized input image over the network first. The study extrapolates data from fruit photographs to span all fruit growth stages.

#### ii. Focus Layer

This layer creates deeper feature maps by segmenting the input image into numerous smaller parts, allowing for the extraction of more precise fruit information.

### iii. CBL Blocks

Convolution, Batch Normalisation, and Leaky ReLU layers extract key features. Their integration gives the model fruit shape, color, and texture.

### iv. CSP (Cross Stage Partial) Layers

YOLOv5's CSP layers split and merge feature maps to boost learning. This strategy improves the model's memory for network node information, allowing it to locate fruits in complicated surroundings, even when they are partially or totally obscured by vegetation.

### v. Path Aggregation

The architecture aggregates feature maps from different layers and scales. This step is crucial for ensuring the model can accurately detect and classify fruits that differ significantly in size and appearance.

### vi. Detection Layers

Finally, YOLOv5 generates three different feature maps corresponding to small, medium, and large objects (fruits in this case), enabling effective detection and classification of fruits at various stages of maturity.

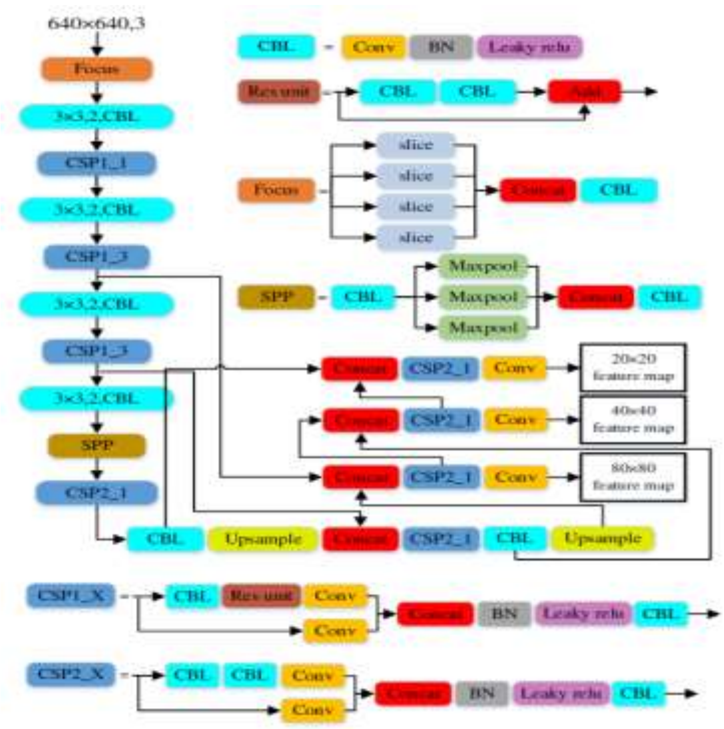


**Figure 4:** YOLOv5 Architecture

### d. Training Process

The training procedure includes a few steps. First of all, the datasets obtained from Roboflow for each class was integrated and generated a combined dataset for training the selected computer vision algorithm, then the dataset was splatted in the following order 70% was assigned for training, 20% for validation, and 10% for testing, and the number of training epochs were chosen be 20 to ensure the best model performance

### e. Testing Process

The model was evaluated on different test pictures and video footages of different classes of fruits After completion of training of the model, The Performance evaluation was done using precision, recall, confusion matrix and Mean Average Precision(mAP50&mAP50-95) these metrics provided a complete understanding of model's potential to detect and categorized various types of fruit accurately

## IV. RESULTS AND DISCUSSION

This research shows that the suggested DSE-YOLO model is good in detecting and classifying different fruits at different stages of growth, such as strawberries, apples, oranges, and mangoes. Several criteria, including recall, precision, and mean average precision (mAP), were used to evaluate the model, and their combined results showed that it performed exceptionally well in complicated agricultural settings. Examining the confusion matrix and precision-recall curves provides more evidence of the model's resilience, demonstrating its capacity to keep high accuracy in difficult situations like partially hidden fruits by vegetation or a large size range in the fruits. The results show that the model's capacity to handle class imbalances and detect fruits at multiple scales was greatly enhanced by the addition of the Detail-Semantics Enhancement module and the custom loss functions to the standard YOLOv5 architecture. As a result, the model is now a valuable tool for precision agriculture.

Figure 5 shows the training and validation processes in detail, showing how important metrics and losses have changed throughout 10 epochs. The model is getting better at predicting bounding boxes and object classification with less overfitting, as seen by the decreasing box, classification, and distribution focal losses in the training and validation sets. At the same time, the model's increasing competence in fruit detection is reflected in the sharp rises in both recall (approaching 85%) and precision (nearing 90%). The model's success is further validated by the growing mAP values for both the 0.5 IoU and the tighter 0.5-0.95 IoU thresholds, which show that the model consistently performs well at different levels of intersection-over-union criterion. This figure showcases the DSE-YOLO model's strong training development, which results in a fruit identification system that is both accurate and well-generalized, making it ideal for precision agriculture.

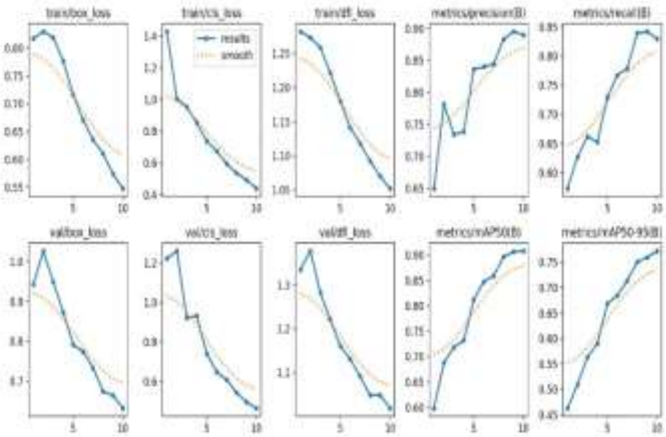


**Figure 5:** Training and Validation Losses and Performance Metrics

When testing a classification model, the Precision-Recall (PR) curve is a useful visual aid, particularly when dealing with unbalanced classes. A variety of threshold settings are represented by the curve, which plots recall against precision. By asking, "Of all the fruits predicted as a particular class, how many were that class?" precision reveals how well the favourable predictions fared. To find out how well a model can identify all relevant instances, we may look at its recall, also called sensitivity. This number tells us how many fruits in a certain class the model successfully detected. For various threshold settings, the PR curve illustrates the trade-off between recall and precision. To illustrate, the value of'mango' at (0.95, 0.97) suggests a recall of 97% and a precision of 95%. This indicates that 97% of the real mangoes were identified properly, while 95% of the fruits projected as mangoes were accurate. The model's performance and resilience are demonstrated by its high recall and precision values across classes such as strawberry and mango.

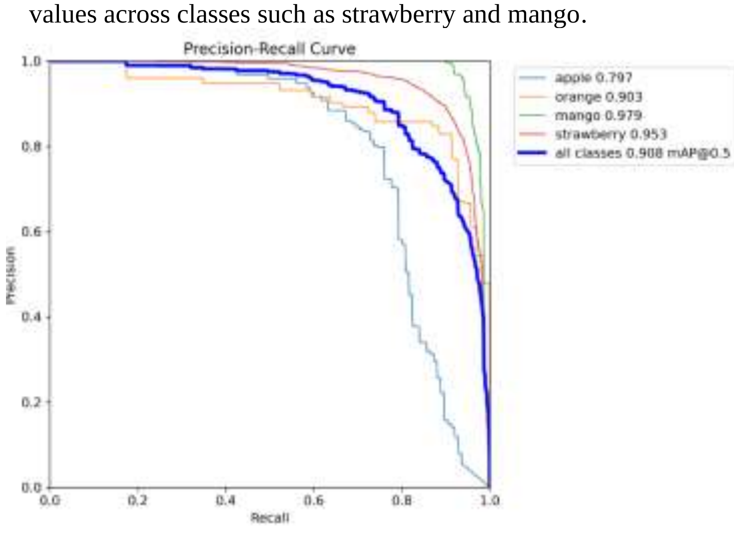


**Figure 6:** The P-R curve of the trained model.

A detailed confusion matrix contrasts real and projected classes to show the model's performance. This data collection has real class instances and anticipated class instances in every row and column.

The cell at the intersection of the first row and first column showed that 72% of the fruit were correctly classified as apples. According to the cell value of 0.05 at the first row-second column intersection, 5% of apples were misidentified as oranges. The 0.01 cell at the first row-third column intersection misidentified 1% of apples as mangoes. In the cell at the intersection of the first row and fourth column, 0.04 indicated that 4% of apples were mistaken for strawberries. The cell at the first row and fifth column has 0.18, meaning 18% of the apples were mislabeled background. The cell at the junction of the second row and second column showed that 97% of the oranges were correctly classified as oranges. According to the cell value of 0.05 at the second row-first column intersection, 5% of oranges were misidentified as apples. According to 0.01 in the cell at the second row-fourth column junction, 1% of oranges were mistaken for strawberries. In the cell at the second row and fifth column, 0.03 indicated that 3% of the oranges were mislabeled background.

The cell at the intersection of the third row and third column shows a 95% accuracy rate in categorising mangoes as mangoes. The cell at the junction of the third row and first column is 0.01; 1% of mangoes were mislabeled apples. According to the value of 0.04 in the cell at the third row and fourth column, 4% of mangoes were mislabeled strawberries. The cell value of 0.05 at the intersection of the third row and fifth column mislabeled 5% of mangoes as background.

A result of 0.93 in the cell at the junction of the fourth row and fourth column indicates that 93% of strawberries were correctly identified. The strawberry–apple classification error was 8% in the cell at the intersection of the fourth row and the first column (0.08). According to 0.08 in the cell at the intersection of the fourth row and second column, 8% of strawberries were mistaken for oranges. Based on the value of 0.04 in the cell at the intersection of the fourth row and third column, 4% of strawberries were mistaken for mangoes. A value of 0.07 in the cell at the fourth row-fifth column intersection showed a 7% strawberry background categorization error.

The cell where the fifth row and column meet accurately recognised 79% of background occurrences as background. Value 0.79 indicates this. A cell with a value of 0.18 at the fifth row and first column intersection demonstrates that 18% of background cases were misclassified as apples. The cell at the fifth row and second column intersection is 0.03; 3% of background occurrences were wrongly classified as oranges. The cell value of 0.05 at the fifth row and third column misidentified 5% of background occurrences as mangoes. The fifth row and fourth column cell contain a value of 0.07, indicating that 7% of background occurrences were misclassified as strawberries.

The confusion matrix demonstrates that the model correctly classified most examples in the 'Apple,' 'Orange,' 'Mango,' 'Strawberry,' and 'Background' classes. The model misclassified a percentage of cases shown by those figures that don't fit on the graph. The model did well at orange classification (97% accurate), but it might do better at distinguishing apples from backgrounds (18% misclassified apples as backgrounds). This detailed evaluation helps improve the model.

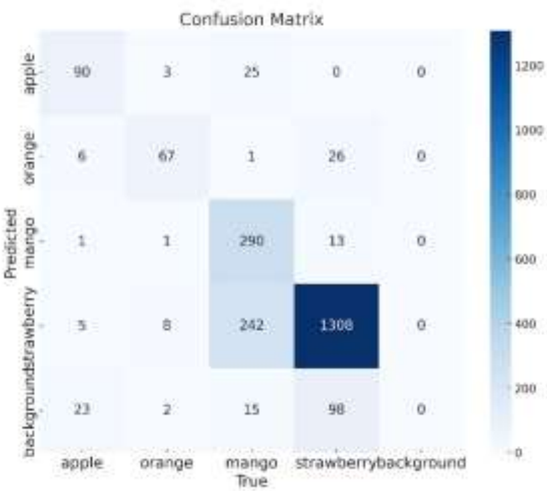


**Figure 7:** Confusion matrix of the trained model

The F1 curve shows class F1 scores at different confidence thresholds. The harmonic mean of precision and memory, the F1 score, balances both. Calculated as:

$$F1 = 2 * \frac{precision * recall}{precision + recall} \qquad (1)$$

If the F1 score is high, it means the model minimises false positives and false negatives while keeping recall and accuracy in a healthy equilibrium.

Important points to note from the F1 curve are the 85% F1 confidence scores earned by the "strawberry," "mango," "apple," and "orange" classes, which show how well the model categorizes these fruits. Results showing high F1 scores in all of these classes show that the model does a good job of both accurately detecting fruits and avoiding misclassifications.

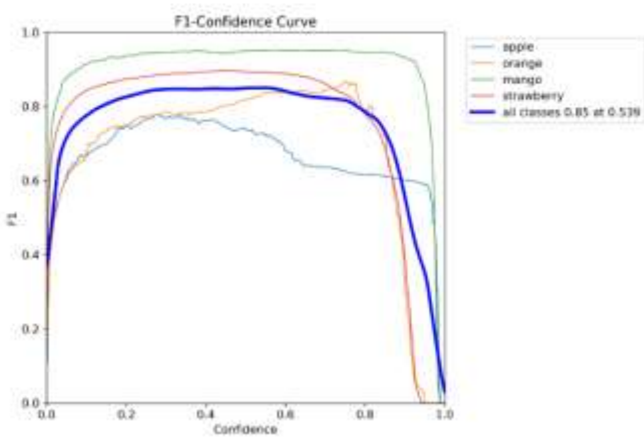


**Figure 8:** F1 curve of trained model

The Precision-Confidence Curve for apple, orange, mango, and strawberry and a combined curve for all classes show how confidence levels affect model accuracy. As confidence approaches 1.0, the apple curve becomes quite accurate, indicating that the model is dependable for this class. Oranges exhibit better precision as confidence rises, but lower thresholds are less certain. The robust curve displays the model's remarkable mango detection ability, which is good across most confidence levels and rapidly approaches near-perfect precision. As confidence rises over 0.8, the strawberry curve shows a consistent improvement in accuracy. The aggregated curve for all classes shows that the model is precise at 0.999. All cross-class predictions are true at the highest confidence level.

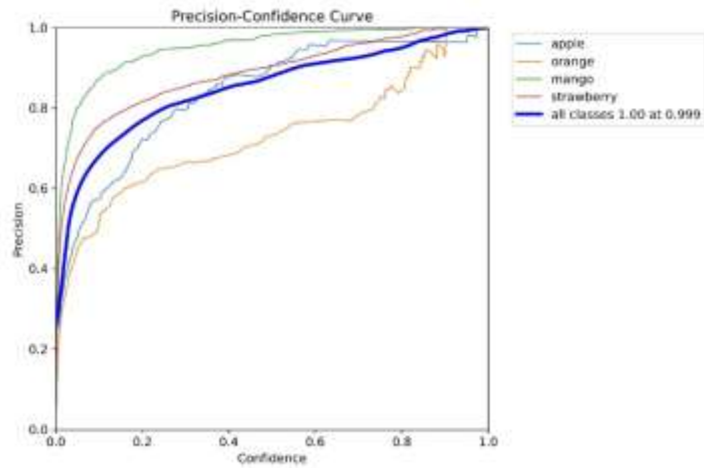


**Figure 9:** Precision-confidence curve for the different fruit classes

We found that the DSE-YOLO model improved fruit classification and detection across growth stages and fruit species. With the aid of innovative loss functions and thorough feature improvement techniques, the model was able to control class imbalances and perform effectively in challenging agricultural contexts. The model may be utilised for automated fruit picking, which would boost agricultural productivity while lowering labour costs, given its excellent levels of accuracy, recall, and mAP across a variety of fruit classes.

## V. CONCLUSION

This study showcases the potential of the DSE-YOLO model to improve precision agriculture by accurately identifying and classifying fruits. The model employs sophisticated techniques for extracting intricate features and employs tailored loss functions to adeptly address the difficulties associated with detecting fruits in multi-stage scenarios that are intricate in nature. The model's performance, robustness, and dependability may be evaluated using several measures such as mAP, recall, and accuracy. There is hope that the labor-intensive activities associated with modern agriculture can be solved, since the findings indicate that the DSE-YOLO model has the potential to greatly improve automated fruit picking. Future work will primarily focus on enhancing the model's real-time deployment capabilities and expanding its predictive skills to a wider range of crops.

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