DEVELOPMENT OF INTELLIGEST YIELD ESTIMATION SYSTEM FOR DRAGON FRUIT ORCHARD BASED ON IMAGE PROCESSING

ABSTRACT

Dragon fruit, a tropical fruit renowned for its unique appearance and nutritional value, has gained significant popularity in recent years. The development of an intelligent yield estimation system for dragon fruit orchards can have broader implications for the agricultural industry. It can enable data-driven decision-making, improve supply chain management, and enhance market analysis. The system can also be integrated with existing farm management systems, precision agriculture technologies, and decision support systems to provide a comprehensive solution for farmers. The developed system has utilized advanced sensors and controllers to accurately count the number of fruits, measure their size, and calculate the yield. The detection performance was studied on the basis of accuracy, precision, recall, F1 score, detection accuracy and yield estimation accuracy. The results obtained at different speeds of operation *viz.* 2 km/h, 3km/h and 4 km/h with different deep learning models *viz.* SSD, YOLOv2 and YOLOv3. The maximum size detection accuracy using SSD, YOLOv2, and YOLOv3 was 94.16 %, 92.69% and 94.74% respectively, observed at 2 km/h operating speed. The developed yield estimation system can estimate the yield of dragon fruit with an average 93.92 % yield estimation accuracy at 2 km/h operating speed and 70 cm distance of camera from the tree using SSD model.

Keywords: Yield estimation, Image processing, Deep learning, Dragon fruit

1. INTRODUCTION

A yield estimate is the first step towards precision farming, defined as "the measurement of yield in space and time and the graphical sum of these measurements" (Pierce *et al*., 1997). Modern horticultural techniques, especially in smart farming, use advanced tools like sensors, cameras, and AI-based image processing to enhance plant monitoring and productivity estimation (Behera *et al*., 2021). These innovations reduce labor needs and improve agricultural management (FAO *et al*., 2017; Saiz-Rublo *et al*., 2020). Dragon fruit cultivation has particularly benefited from such technologies, with AI and computer vision automating fruit detection and counting, enabling real-time yield estimation (Dayal V. *et al*., 2018). Traditional methods, prone to labor-intensive errors, are now replaced by digital image analysis, making yield prediction more accurate and cost-efficient (Karma *et al*., 2016; Kumar *et al*., 2016). This system addresses challenges like irregular fruit growth and variable sizes, supporting better farm management and profitability (Wang *et al*., 2020; Gonzalez *et al*., 2017). Image processing and deep learning have proven effective in applications like crop monitoring and disease detection, offering precise yield predictions and enhancing planning capabilities (Zhang *et al*., 2020; Li *et al*., 2019). This integration enables data-driven decisions, improves supply chains, and supports market analysis. Combining tools such as sensors, GPS, and high-resolution imaging, the system provides actionable insights while addressing challenges like irregular fruit shapes and labor-intensive counts (Dayal *et al*., 2018). Leveraging technologies like ESP32, AI, GPS modules, and Raspberry Pi, it promotes sustainable farming and global food security through efficient yield estimation (Behera *et al*., 2021). The sensor-controlled yield estimation system enhances agricultural efficiency by integrating advanced technologies like the ESP32 microcontroller, camera module, AI, NPU, GPS modem, and Raspberry Pi. The ESP32 collects data from sensors monitoring environmental conditions, while the camera captures crop images analyzed by AI for real-time insights. GPS provides precise geolocation, enabling mapping of yield variations, and the Raspberry Pi aggregates and visualizes this data on a user-friendly dashboard. This system allows farmers to monitor crop health remotely, make informed decisions, and optimize productivity, promoting sustainable farming and supporting global food security.

2. MATERIALS AND METHODS

The material required was selected carefully and with reference to previous researches. This research presents a novel approach to intelligent yield estimation in dragon fruit orchards. A robust image processing system was developed, involving data collection, preprocessing, and augmentation to improve model performance. The single shot detector (SSD) model was selected for its efficiency and accuracy in object detection. To facilitate deployment on resource-constrained edge devices, the model was quantized. IoT hardware, comprising ESP32 microcontrollers and GPS modules, was integrated to enable real-time data collection and transmission. The system was further enhanced by a cloud-based API and application, providing real-time insights, yield predictions, and anomaly detection, ultimately contributing to improved agricultural productivity.

2.1 Data collection

This study presents an intelligent yield estimation system for dragon fruit orchards using image processing and deep learning. A diverse dataset of dragon fruit images at various stages was curated from google images and repositories like kaggle. The dataset, encompassing varied lighting, backgrounds, and orientations, was used to train a deep learning model. The resulting system provides accurate yield predictions, helping farmers optimize resources, enhance decision-making, and boost profitability in dragon fruit cultivation.

Fig 1. Image of dragon fruit in different condition

2.2 Data preprocessing

The collected data underwent a rigorous preprocessing phase to enhance its suitability for model training. A variety of image augmentation techniques were applied to increase dataset variability and simulate real-world scenarios, thereby improving the model's generalization capabilities. These techniques involved geometric transformations like rotation, flipping, scaling, translation, and shearing, as well as photometric transformations such as brightness and contrast adjustment, color jitter, and noise addition. Additionally, data augmentation strategies like cropping and padding were employed to further diversify the dataset. By incorporating these techniques, the model was trained to be more robust and accurate in detecting fruits under diverse conditions.

Fig 2. Data preprocessing of dragon fruit image (Rotation, flipping, scaling, translation, shearing, brightness and contrast adjustment, color jitter, noise addition, cropping and padding)

2.3 Model Training

Model training was the next step involved. A comparative analysis of different object detection algorithms was conducted to determine the most suitable model for detecting and classifying fruits. After analyzing algorithms such as YOLO, Faster R-CNN, and SSD (single shot detector), SSD was selected due to its balance between speed and accuracy, making it well-suited for real-time fruit detection on edge devices like raspberry Pi. The model was trained on the preprocessed dataset, using a combination of convolutional neural networks (CNNs) to detect objects and classify them into predefined categories (e.g., raw, ripen or unannotated fruits).

Fig 3. Training and testing image anlysis of model

2.4 Model Quantization for Deployment

To make the trained model suitable for deployment on low-power devices like raspberry Pi, model quantization was applied. This process reduced the model's size and complexity, converting 32-bit floating point operations to 8-bit integers without significantly affecting accuracy. Quantization ensured that the model run efficiently on the Raspberry Pi, using minimal computational resources while still providing real-time detection capabilities.

2.5 IoT Hardware Development

The IoT hardware component was developed using an ESP32 microcontroller and a GPS Modem. The ESP32 was selected for its low power consumption, built-in Wi-Fi, and Bluetooth capabilities, making it ideal for transmitting data wirelessly. The GPS modem was integrated to track the location of the fruit plants, enabling precise identification and monitoring. The hardware collected data, such as the fruit's state and GPS coordinates, and prepared it for transmission to the cloud.

Fig 4. Completely assembled hardware of the system..

2.6 Application programming interface Development (API)

To facilitate communication between the hardware, edge device, and cloud infrastructure, an API was developed. The API enables the transmission of real-time data from the raspberry Pi and ESP32-based IoT hardware to the cloud. This API is designed to handle incoming data from the hardware end, such as fruit images, state classifications, and GPS coordinates. The API also interacts with the cloud database to store and organize the incoming data for further analysis and retrieval.

2.7 Cloud Application Development and Deployment

The developed cloud application utilized a PHP-based API to handle and store data collected from edge devices like Raspberry Pi or ESP32. This data, encompassing plant ID, fruit count, and ripeness classification, was uploaded to the cloud and stored in a database. The cloud application then provided a web interface for users to access this data, enabling them to monitor fruit ripeness, estimate yields, and make informed decisions in agricultural management. This integration of edge and cloud computing streamlined data collection, storage, and analysis, enhancing overall agricultural efficiency.

Fig 5. The dashboard application window to fruit monitor analysis

2.8 Data Visualization:

Provided real-time insights into the state of fruits, the growth phases, and the overall yield predictions based on the data collected from the IoT hardware.

2.9 Yield Analysis:

Used time-series data to predict agricultural productivity and detect anomalies in the growth and yield of fruits over time. The cloud application is hosted on a scalable cloud platform, ensuring that it can handle large volumes of data and provide real-time analysis to the end-users.

2.10 Parameters for the study of deep learning models

To evaluate the performance of deep learning models for yield prediction in dragon fruit orchards, metrics like F1 score, precision, recall, and accuracy are crucial. Precision measures the model's ability to correctly identify true positives, while recall assesses its capacity to identify all actual positive cases. The F1 score, a harmonic mean of precision and recall, provides a balanced measure of model performance. Accuracy, reflecting the overall correctness of predictions, is essential for reliable yield estimation. By analyzing these metrics, we can assess the effectiveness of the deep learning model in the developed yield monitoring system for accurately predicting dragon fruit yields.

True positives (TP): The number of fruit correctly identified by the system as fruit.

False positives (FP): The number of non-fruit incorrectly identified by the system as fruit.

True negatives (TN): The number of non-fruit correctly identified by the system as non-fruit.

False negatives (FN): The number of fruit missed by the system and incorrectly identified as non-fruit.

These metrics can be used to calculate the following performance metrics:

2.10.1 Overall Accuracy

The accuracy is the total observation rate of the correctly classified observation. It can be calculated using the following equation:

$$\textbf{Accuracy} = \frac{\mathbf{TP+TN}}{\mathbf{TP+FP+TN+FN}}$$

2.10.2 Precision

It shows the effectiveness of neural networks in the identification of true positive labels. The best precision is considered at 1.0; whereas the poor precision is at 0.0. It was calculated as,

$$\textbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP+FP}}$$

2.10.3 Recall

It measures how the neural network identifies the targets. Its value varies from 0 to 1 and can be calculated as,

$$\textbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP+FN}}$$

2.10.4 F1 Score

It measures the harmonic mean of precision and recall and gives the accuracy of detecting positive labels by neural network. The best F1 score is 1.0, the worst is 0. It can be calculated as.

$$\textbf{F1 Score} = \frac{2*(\text{precision}*\text{recall})}{(\text{precision}+\text{recall})}$$

10.2.5 Detection accuracy It is the measure of how accurately the size of dragon fruit was detected. It is calculated as follows:

$$\textbf{Detection accuracy (\%)} = [1- (\frac{\text{Size of fruit detected cm2}}{\text{Actual size of fruit cm2}})]$$

10.2.6 Yield estimating accuracy

The yield was calculated by measuring the size of each dragon fruit. For estimation of weight of dragon fruit, initial a relation between size of fruit and its weight was developed by physical measurement. This relation was used for calculating weight of detected sized dragon fruit by the developed system. The yield estimating accuracy was calculated as:

$$\textbf{Yield estimating accuracy (\%)}=[1- (\frac{\text{Calulated weight from dected size of fruit}}{\text{Actual weight of fruit measured}})]\times 100$$

3. RESULT AND DISCUSSION

3.1 Plant Detection Performance of Developed Yield Estimation System at Different Operating Speeds.

An experiment was conducted to assess the effectiveness of ArUco markers for plant detection at various operating speeds and distances. Two 4x4x50 mm markers were used to indicate the plant's beginning and end. The markers successfully detected plants at speeds of 2, 3, and 4 km/hr and distances of 5, 10, and 15 ft from the crop. (Table 1) summarizes the successful detections across different distances.

Table 1. The distance-wise detection table for the ArUco markers

Sr. No.	Marker Type	Speed (km/hr)	Distance from Camera (Feet)	Detection Status
1	Start Detection Marker	2	5	Detected
2	Start Detection Marker	2	10	Detected
3	Start Detection Marker	2	15	Detected
4	End Detection Marker	2	5	Detected
5	End Detection Marker	2	10	Detected

6	End Detection Marker	2	15	Detected
7	Start Detection Marker	3	5	Detected
8	Start Detection Marker	3	10	Detected
9	Start Detection Marker	3	15	Detected
10	End Detection Marker	3	5	Detected
11	End Detection Marker	3	10	Detected
12	End Detection Marker	3	15	Detected
13	Start Detection Marker	4	5	Detected
14	Start Detection Marker	4	10	Detected
15	Start Detection Marker	4	15	Detected
16	End Detection Marker	4	5	Detected
17	End Detection Marker	4	10	Detected
18	End Detection Marker	4	15	Detected

3. 2 Dragon fruit Detection Performance of Developed Yield Estimation System at Different Operating Speeds Using Different Model Architectures.

The detection performance in terms of counting number of dragon fruits grown on a plant was conducted at 2 km/hr, 3 km/hr and 4 km/hr operating speed using three deep learning model architectures viz. SSD, YOLOv2, and YOLOv3. The data obtained from the tests, with 10 replications, are presented in (Table 2 and Figure 6).

(Figure 6) shows that, the SSD model performed best, achieving perfect detection at 2 km/hr as 5 and maintaining a high detection ability of 4.3 and 4.2 out of 5 fruits even at 3 km/hr and 4 km/hr respectively. This consistency underscored SSD's reliability for field-based applications where both speed and accuracy are critical. Conversely, the YOLOv2 model showed a considerable drop in accuracy of detection as speed increased, with only 3.2 fruits detected at 2 km/hr and further declines to 2.2 detections at 4 km/hr. YOLOv3 performed moderately well, with 4 detections at 2 km/hr but experienced a reduction similar to YOLO at higher speeds. The reason for drop in detecting number of fruits with increase in operating speed might be due to the hardware multithreading capabilities. The model chosen can also be another reason where in the model input size and the hardware frame processing capabilities will cause the detection rate to drop due to the higher operating speeds.

From (Table 2 and Figure 6) it can be can be concluded that SSD architecture provided comparatively accurate and stable detection across different speeds, suggesting it was the most suitable for real-time yield estimating applications. YOLOv3 performs reasonably well at slower speeds but saw a decline in detections as speed increased, while YOLOv2 struggled to maintain accuracy under higher-speed conditions. The results favored SSD for scenarios requiring reliable detection over a range of operating speeds, making it a robust choice for agricultural field applications. This might be due to the fact that the yolo architecture relies on single CNN for predictions making it difficult to handle blurred data which is inevitable as the speed increases. This happens if we cannot have higher fps processing hardware with the increase in operating speeds.

Table 2. Dragon fruit Detection Performance of Developed Yield Estimation System at Different Operating Speeds Using Different Deep Learning models.

Deep learning model	Operating Speed, km/h	Detected number of fruits out of 5 fruits										
		Test-1	Test-2	Test-3	Test-4	Test-5	Test-6	Test-7	Test-8	Test-9	Test-10	Average
SSD	2	5	5	5	5	5	5	5	5	5	5	5
SSD	3	5	4	4	4	4	5	4	4	5	4	4.3
SSD	4	4	4	4	5	4	4	4	5	4	4	4.2
YOLOv2	2	4	3	3	4	3	3	3	3	3	3	3.2
YOLOv2	3	3	3	4	3	3	3	3	3	3	3	3.1
YOLOv2	4	3	2	3	2	2	2	2	2	2	2	2.2
YOLOv3	2	4	4	3	4	5	4	4	4	4	4	4
YOLOv3	3	4	3	4	3	3	3	4	3	3	3	3.3
YOLOv3	4	5	2	3	4	3	3	3	3	3	3	3.2

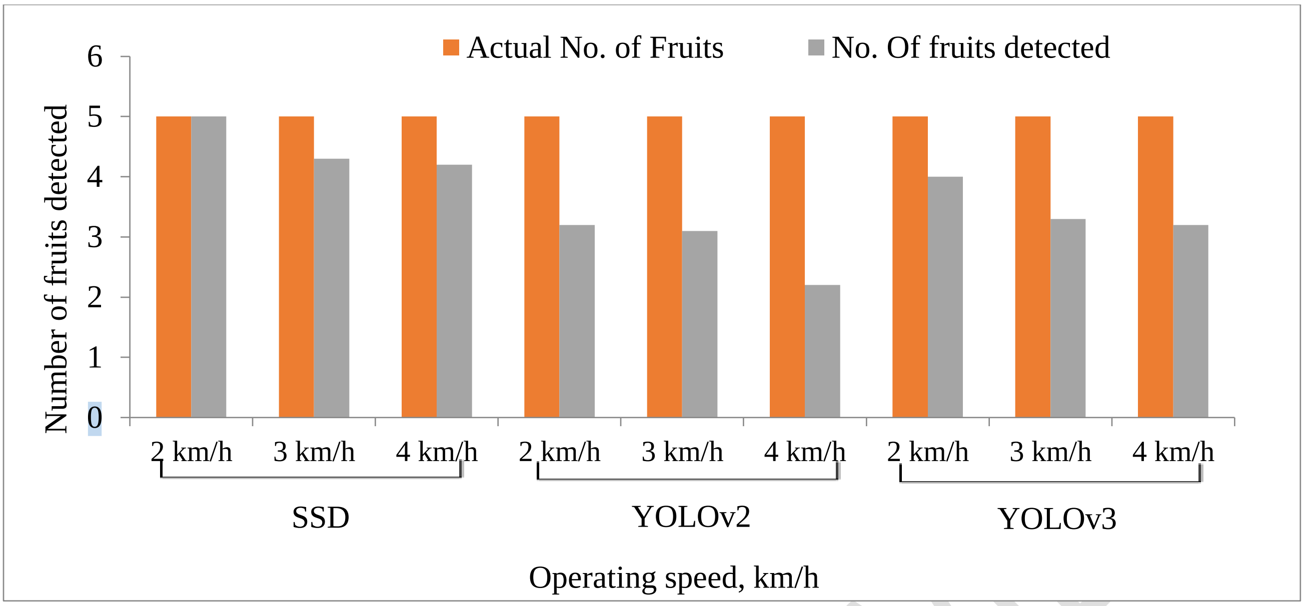

Fig. 6. Dragon fruit Detection Performance of Developed Yield Estimation System at Different Operating Speeds Using Different Deep Learning models

4.3 Dragon Fruit Size Detection Performance at Different Operating Speeds Using Different Deep Learning models.

Three deep learning models (SSD, YOLOv2, and YOLOv3) were tested for detecting dragon fruits at varying speeds (2-4 km/hr) and camera distances (50-70 cm). Results showed that detection accuracy increased with distance up to 70 cm, then declined. This trend was consistent across all models and speeds, likely due to the camera's fixed focus and field of view. The study found that detection accuracy decreased with increasing operating speed (2-4 km/h) for all three deep learning models (SSD, YOLOv2, and YOLOv3). YOLOv3 showed the highest accuracy (94.74%) at 2 km/h, but SSD outperformed YOLOv3 at higher speeds. YOLOv2 had the lowest accuracy across all speeds. The results highlight the importance of selecting a model architecture based on specific operational requirements (Table 3 and Figure 7).

Table 3. Dragon Fruit Size Detection Performance of Developed Yield Estimation System at Different Operating Speeds Using Different Deep Learning models.

Vehicle Speed, km/h	**Distance from Camera to plant**	**Actual Fruits Size**			**Detected fruits size using SSD**				**Detected fruits size using YOLOv2**				**Detected fruits size using YOLOv3**			
		W, cm	L, cm	Cross sectional area	W, cm	L, cm	Cross sectional area	Detection Accuracy %	W, cm	L, cm	Cross sectional area	Detection Accuracy %	W, cm	L, cm	Cross sectional area	Detection Accuracy %
2	50	13	16	208	15.9	17.9	284.61	63.17	16.1	18	289.8	60.67	15.7	17.6	276.32	67.15
2	60	13	16	208	12.3	19.3	237.39	85.87	12.6	19.5	245.7	81.88	12.9	17.8	229.62	89.61
2	70	13	16	208	11.9	18.5	220.15	**94.16**	12	18.6	223.2	**92.69**	12.3	17.8	218.94	**94.74**
2	80	13	16	208	13.6	17.8	242.08	83.62	13.9	17.9	248.81	80.38	13.5	17.5	236.25	86.42
2	90	13	16	208	14.7	18.3	269.01	70.67	14.9	18.7	278.63	66.04	14.3	18.3	261.69	74.19
3	50	13	16	208	16	17.9	286.4	62.31	16.4	18.5	303.4	54.13	16.1	18.1	291.41	59.90
3	60	13	16	208	12.6	18.8	236.88	86.12	12.7	19.7	250.19	79.72	12.5	19.4	242.5	83.41
3	70	13	16	208	12.3	18	221.4	**93.56**	12.5	18.8	235	**87.02**	12.1	18.6	225.06	**91.80**
3	80	13	16	208	13.7	17.6	241.12	84.08	13.9	18.7	259.93	75.03	13.8	17.9	247.02	81.24
3	90	13	16	208	14.7	18.2	267.54	71.38	15.2	18.8	285.76	62.62	14.9	18.6	277.14	66.76
4	50	13	16	208	15.8	18.1	285.98	62.51	16.6	18.6	308.76	51.56	16.2	18.2	294.84	58.25
4	60	13	16	208	12.7	19.1	242.57	83.38	12.6	19.6	246.96	81.27	12.6	19.6	246.96	81.27
4	70	13	16	208	12.2	18.3	223.26	**92.66**	12.7	18.9	240.03	**84.60**	12.3	18.7	230.01	**89.42**
4	80	13	16	208	13.7	18	246.6	81.44	14.2	18.3	259.86	75.07	13.9	18.1	251.59	79.04
4	90	13	16	208	14.8	18.9	279.72	65.52	15.5	19.3	299.15	56.18	15.1	18.9	285.39	62.79

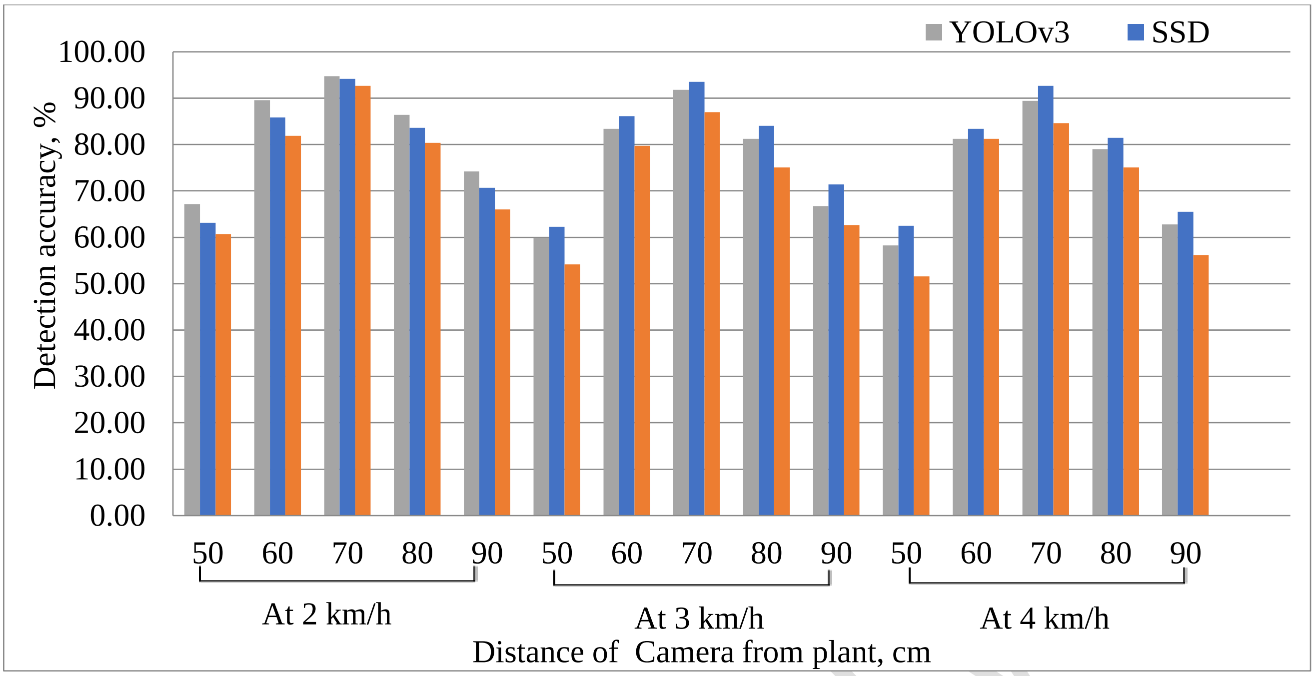

Figure 7. Dragon Fruit Size Detection Performance of Developed Yield Estimation System at Different Operating Speeds Using Different Deep Learning models.

3.4 Performance of developed system at different operating speeds using different deep learning models.

The detection performance was studied on the basis of accuracy, precision, recall and F1 score. The results obtained at different speeds of operation viz. 2 km/h, 3km/h and 4 km/h with different deep learning models *viz.* SSD, YOLOv2 and YOLOv3 are presented in (Table 4).

The data showed in (Table 4) that an accuracy at different speeds of operation ranged from 1 to 0.8, 0.6 to 0.4 and 0.8 to 0.6 for SSD, YOLOv2 and YOLOv3 respectively. Also it can be seen that, accuracy decreased with increase in speed of operation selected for the study. The decreased overall accuracy with an increase in speed of operation might be due to less opportunity time available for correct detection of the fruits that might increase the incorrect detection of non fruit (FN).

A precision remained equal (1.0) for all the speeds of operation with all the deep learning models (Table 4). As the speed of operation had not affected FP (Correct Detection of Non Fruits) hence, the precision remained almost equal.

Recall at different speeds of operation ranged from 1 to 0.8, 0.6 to 0.4 and 0.8 to 0.6 for SSD, YOLOv2 and YOLOv3 respectively. Similarly, F1 score at different speeds of operation ranged from 1 to 0.88, 0.75 to 0.57 and 0.88 to 0.75 for SSD, YOLOv2 and YOLOv3 respectively (Table 4). Also it can be seen that, the Recall and F1 score decreased with increase in speeds of operation selected for the study. Due to less opportunity time available for correct detection of the fruits that might increase the incorrect detection of non fruit (FN) with increase in speed of operation.

Table 4. Performance of developed system at different operating speeds using different deep learning models.

Model	Speed (km/h)	Correct Detection of Fruits (TP)	Incorrect Detection of Fruits (FN)	Correct Detection of Non Fruits (FP)	Incorrect Detection of Non Fruits (TN)	Accuracy	Precision	Recall	F1 Score
SSD	2	5	0	0	0	1	1	1	1
SSD	3	4	1	0	0	0.8	1	0.8	0.88
SSD	4	4	1	0	0	0.8	1	0.8	0.88
YOLOv2	2	3	2	0	0	0.6	1	0.6	0.75
YOLOv2	3	3	2	0	0	0.6	1	0.6	0.75
YOLOv2	4	2	3	0	0	0.4	1	0.4	0.57
YOLOv3	2	4	1	0	0	0.8	1	0.8	0.88
YOLOv3	3	3	2	0	0	0.6	1	0.6	0.75
YOLOv3	4	3	2	0	0	0.6	1	0.6	0.75

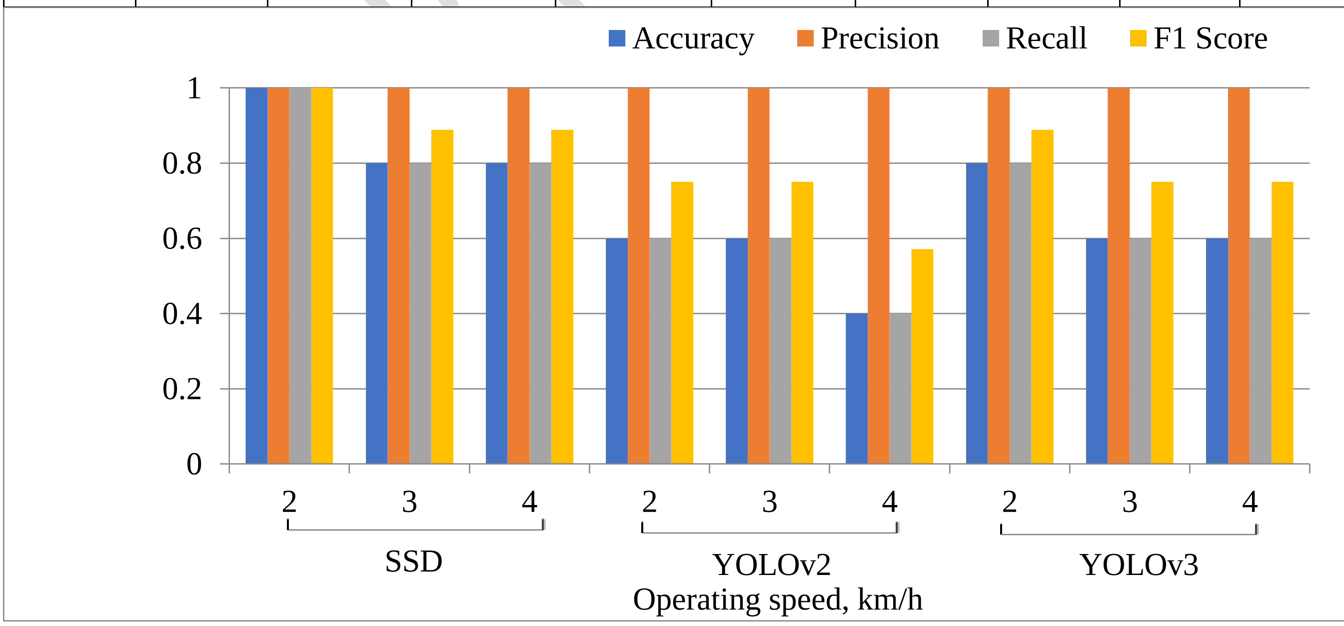

Figure 8. Performance of developed system at different operating speeds using different deep learning models.

3.5 Field Performance of developed system

The most accurate detection of number of fruits and fruit size detection accuracy along with different performance parameters viz. accuracy, precision, recall and F1 score are observed at 2 km/h operating speed and 70 cm distance of camera from the tree using SSD model hence, The field performance was studied by choosing the same operating speed, distance of camera from the tree and deep learning model to check the yield estimation accuracy. The yield estimation accuracy was calculated by comparing the actual number of fruits, size and the weight of the respective fruit with detected number of fruits and detected size and estimated weight of the respective fruit. The results obtained from three trees with different number and size of fruits was selected for the study. The test was replicated for 5 time and average values were obtained. Yield estimation accuracy was varied between 91.69 % to 96.21 % with an average of 93.92 % (Table 5).

Table 5. Field Performance of developed system at 2 km/h operating speed and 70 cm distance of camera from the tree using SSD model.

Tree No.	Actual No. of Fruits	Actual fruit size			Actual weight, g	Detected fruit size			Estimated weight, g	Yield estimation accuracy (%)
		W, cm	L, cm	Cross sectional area		W, cm	L, cm	Cross sectional area		
1	10	7.3	17.1	124.83	321	7.6	17.7	134.52	346	92.24
		8.1	16.5	133.65	343	8.5	17.0	144.50	371	91.88
		8.3	18.2	151.06	388	8.6	18.7	160.82	413	93.54
		8.2	19	155.8	400	8.7	19.1	166.02	427	93.44
		8.5	19.5	165.75	426	8.8	20.1	176.88	454	93.29
		8.3	18.4	152.72	392	8.4	19.0	159.60	410	95.50
		7.9	18.6	146.94	378	8.1	19.2	155.52	400	94.16
		8.6	19.1	164.26	422	8.7	20.1	174.87	449	93.54
		7.8	18.5	144.3	371	8.0	19.1	152.80	393	94.11
		8.1	16.9	136.89	352	8.3	17.2	142.76	367	95.71
2	8	7.4	16.8	124.32	316	7.6	17.1	129.96	334	94.33
		8.9	19.7	175.33	396	9.0	18.9	170.10	437	89.63
		7.8	18.4	143.52	374	8.0	19.1	152.80	393	95.02
		8.3	16	132.8	392	8.7	17.8	154.86	398	98.49
		7.9	18.3	144.57	376	8.3	18.9	156.87	403	92.80
		8.3	19	157.7	410	8.6	19.8	170.28	438	93.33
		8.5	19.5	165.75	431	8.8	19.8	174.24	448	96.15
		8.3	18.4	152.72	397	8.4	19.1	160.44	412	96.21
3	5	7.4	17.5	129.5	333	7.6	18.1	137.56	353	93.78
		8.6	16.9	145.34	373	8.9	17.4	154.86	398	93.45
		8.4	18.6	156.24	401	8.6	19.4	166.84	429	93.22
		8	18.9	151.2	389	8.3	19.2	159.36	409	94.60
		8.5	19.5	165.75	426	8.8	20.4	179.52	461	91.69
Average		**8.15**	**18.23**	**148.74**	**382.93**	**8.40**	**18.79**	**158.09**	**406.19**	**93.92**

4. SUMMARY AND CONCLUSION

1. The developed estimating system work well and successfully detects the number of fruit size and fruit yield estimation
2. Highest accuracy, precision, recall and F1 score were found at 2 km/h operating speed with SSD deep learning model.
3. SSD model performed best, achieving perfect detection at 2 km/hr and maintaining a high accuracy of detection.
4. YOLOv3 performs reasonably well at slower speeds but saw a decline in detections as speed increased, while YOLOv2 struggled to maintain accuracy under higher-speed conditions.
5. At all the operating speeds and with all the deep learning model architectures, a distance of 70 cm between camera and plant was observed as most suitable distance.
6. The maximum size detection accuracy using SSD, YOLOv2, and YOLOv3 was 94.16 %, 92.69% and 94.74% respectively, observed at 2 km/h operating speed.
7. Yield estimation accuracy was varied between 91.69 % to 96.21 % with an average of 93.92 % at 2 km/h operating speed and 70 cm distance of camera from the tree using SSD model.

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