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GRAPE QUALITY PREDICTION WITH PRE-POST HARVESTING USING FUSION DEEP LEARNING

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ABSTRACT

In modern society, the agriculture industry is crucial. Agriculture industry has to support the load of increasing population, year by year. Implementing robotics in agriculture can heavily rely on computer vision and perception techniques. Machine learning is very useful for object recognition and picture categorization. In this work, machine learning was used to identify grape bunches in vineyards at various phases of development, including the early stage right after bloom and the middle stage, when the grape bunches display an intermediate degree of development.

The dataset is suggested in this investigation because the training inputs are not freely available. So we made a dataset. Separate metrics used to benchmark and explain the models. The results revealed that the built models successfully detect grape clusters from pictures. The suggested system's performance was adequate when considering the approach's minimal resource utilisation, cheap cost, and minimum power hardware device requirements, which allow for simpler models.

Keywords: Machine Learning, CNN, Grape Bunch Detection, agricultural automation, image processing.

I. INTRODUCTION

The agriculture industry is essential to our civilization. Therefore, innovation, research, and development should be encouraged and put into practice in a wide variety of fields related to agriculture. Automation of agricultural operations is becoming more and more crucial in this situation since it may improve productivity and product quality while reducing environmental impact and production costs [1].The term "grape quality" refers to obtaining the ideal grape compositional qualities. Two of them are frequently used to characterize the quality of wine grapes during harvest: sugar and titratable acidity [2]. Particularly, vineyards occupy considerable terrain expansions, which frequently results in strenuous labor. Vineyards are situated along slopes with sharp inclines, such as those in the Douro Demarche Zone, the oldest regulated wine-making region in the world and a UNESCO

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World Heritage Site Perception algorithms may be crucial in providing visual data processing for specialized analysis. These algorithms may be installed on robots to deliver comprehensive providing comprehensive data about the agricultural environments. The traditional approach includes drawbacks such as excessive time consumption, the possibility of manual errors, and recordkeeping being a time-consuming effort [3].

Precision farming is a growing sector due to rising food demand, climate change concerns for agriculture, and economic pressure. The development and marketing of remote sensing applications is also expanding [4]. Early grapevine yield evaluation provides information to viticulturists to help them make management decisions to attain the target grape quality and yield amount. Image analysis has already been investigated for this purpose, but with systems that execute either manually, on a single variety, or near to harvest time, when there are few rectifiable agronomic features [5]. When the crop environment differs due to the field environment's illumination and occlusion, recognition and location accuracy suffer. The researchers used geometric features, picture features, novel image algorithms, and intelligent decision theory to address the challenge [6].

Deep Learning has significantly influenced the advancement of perception & computer vision algorithms during the last several years. This idea can be used for fruit detection in agriculture and for object detection in photos. Since it serves as the foundation for wine administration and marketing, precise forecasting in vineyards is expected to save the wine industry $100 million annually. Over the past several years, a number of decision support systems have been developed to assist winegrowers and farmers manage information based on data collected in the field and processed through AI [7]. Precision agriculture focuses on increasing agricultural yield and quality while lowering operating expenses and emissions. Weather, soil qualities, topography, irrigation, and fertilizer management all have an impact on potential growth and yield. The necessity for timely and accurate monitoring of these inputs in large agricultural fields has encouraged the usage of remote and proximal sensing technology [8]. In recent years, there has been a significant increase in the use of machine learning and deep learning with image processing for fruit inspection. A computer vision technology can be used to capture and analyse a picture of real data before classifying fruit maturity into three stages: ripe, overripe, and unripe.

The Machine Learning approach detects grape picking and can estimate grape production year after year. The development of smart systems capable of carrying out agricultural operations is becoming increasingly dependent on semantic awareness of agricultural environments. ML has had a tremendous impact on the evolution of computer vision and perception algorithms in recent years [7]. Machine learning was used in this study to recognize grape bunches in vineyards at various growth stages, including the early stage shortly after bloom and the middle stage, when the grape bunches have an intermediate degree of development. This concept could be applied to fruit detection in agriculture as well as object detection in photographs. This operation is carried performed using convolutional

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neural networks. They have demonstrated the top performance in a variety of pattern and recognition competitions. Providing machinery capable of doing agricultural-specific duties such as plant harvesting identification. By addressing the issue of automatically identifying grape bunches in photographs while taking into account various development phases, this study aims to can carry out complex operations including fruit picking, yield estimating, and harvesting. The simultaneous Localization and Mapping system can employ grape bunch detection to construct accurate environmental maps that provide the precise 3D position of the crops with fruits. The final classification accuracy is the only factor used to measure model performance in most studies of deep learning for disease detection in plants [9]. Robust fruit detection is extremely difficult due to complex backdrops, occlusion, lighting variations, and low contrast between leaves and fruits. Furthermore, most existing work focuses on detecting only one species of fruit, restricting its utility [10]. Despite the vast studies and startling progress that the machine learning approach to malware categorization has made in recent years, it remains an extremely tough topic [11, 12].

The objective of our proposed system is to determine the significance of Machine Learning in the Agriculture area and collect data that can be stored and evaluated for crop yield forecasts. Preparation of data sets at various stages of grape harvesting. The implementation of a Python for a machine learning model to forecast grape harvesting stage. This allows farmers to select the optimum crop for their needs. The goal of this paper is to provide an accurate and dependable crop yield prediction. The wine industry relies heavily on yield assessment.

This paper is organized as: In section II, analysis of intelligent harvesting decision system based on fruit maturity level is presented. Section III introduces proposed bunch segmentation technique, which is used for Support Vector Machine classifier. In section IV, CNN architecture for image processing showing the use of Mask R-CNN on grape detection and segmentation of image. Section V gives the description of grape harvesting dataset uploaded on Kaggle, whereas the result are shown in section VI. Finally Conclusion is presented in Section VII.

II. Related work

In this experiment showed that the models were more accurate in classifying grape bunches at the medium development stage than those found in the vineyard after bloom since a second class comprises smaller grape bunches. Grape bunches that are more like the surrounding flora in terms of color and texture complicate things in their heir discovery.

Precision viticulture process management relies on sophisticated crop monitoring systems and, in the near future, autonomous machines for automatic site-specific crop management. In this context, the precise detection of vineyards from 3D point-cloud maps generated from unmanned aerial vehicles multispectral photography would be critical, for example, both to achieve better remotely sensed data and to regulate the course and operation of unmanned vehicles [13].

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The association between the estimated and actual number of bunches was weaker than the link between the number of bunches and grape yield. According to the results, estimating the true number of bunches was a difficult assignment for the image analysis model because roughly 70% of the bunches were leaf-covered. YOLOv4 [14].

The statistical analysis revealed that proximate sensing had a higher accuracy in estimating crop production characteristics than satellite sensing-derived estimates. Proximal sensing provided greater correlations earlier in the growing season than satellite sensing, implying that the first method can be employed for on-time scheduling of table grape yield and quality estimation [15].

In viticulture, it is vital to anticipate the productivity levels of distinct vineyard zones in order to implement optimal cropping strategies. The results demonstrated that employing computer vision techniques to differentiate between canopy and soil is required in precision viticulture to produce correct results [16].

The random forest can also be utilised for a variety of agricultural uses. It may be used to predict crop metrics. The importance of machine learning is that the prediction is significantly more reliable when there is a larger training dataset. It aids in fitting the regression model with multiple factors in various combinations and building a better predictive model [17].

Correct crop yield evaluations utilising satellite remote sensing-based technologies are of importance for regional monitoring and the development of policies that improve agricultural resilience and food security. However, existing vegetation productivity models built from global satellite measurements are often too coarse to reflect agricultural variation. The fusion of data from various sensors can provide increased insight and overcome many of the limitations of individual sensors. [18].

An intelligent harvesting decision system based on date fruit maturity level. The system used computer vision and deep learning techniques to detect seven different maturity stages of date fruit [19]. A complete dataset for date fruits that the research community can use for a variety of applications such as automated harvesting, visual yield estimation, and classification tasks. The dataset contains photos of date fruit bunches from various date varieties at various pre-maturity and maturity stages [20].

A thorough examination and comparison of multispectral imaging of vineyards generated by decametric resolution satellite and low altitude UAV platforms is presented by. In the case of crops where the inter-row surfaces involve a significant amount of the farmland, such as vineyards, radiometric information gathered by decametric resolution satellite platforms has difficulty evaluating crop status and variability [21].

Machine learning methods have shown to be a powerful tool for mining data from multi-dimensional maps. As demonstrated in this work, once the ANN models were trained using different VIs, strong correlations between the estimations were discovered [22].

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Climate change is accelerating grape ripening and decoupling sugar and phenolic maturity, influencing wine typicity. Methods and results during two seasons, vines were partially defoliated above the bunch zone under rainfed and deficit irrigation conditions. Under either watering regime, LLR considerably influenced the rate of grape ripening in both varieties, delaying harvest [23].

Table 1. Various methods applications based on their accuracies

References	Performance	Application
[24]	Flower estimate accuracy of 84.3%	At an early stage, automated grape blossom counting can be used to assess probable yields.
[25]	Individual F1 score of 73.0%	Estimation of the number of flowers in bloom.
[26]	88.6% AP and 80.3% average recall	Grape bunch detection is used to automate processes such as grapevine growth monitoring, spraying, leaf trimming, and harvesting.
[27]	99.0% accuracy for both red and white photos	Investigation of the optimal CNN design for detecting grapes in photographs
[28]	The F1 score for quick grape segmentation is 91.0%.	Determine crop status to aid in yield forecast, precision agriculture, and automatic harvesting.
[29]	Green grape detection accuracy of 91.7%	Create artificial illumination technologies for nighttime fruit plucking.
[30]	The classification accuracy between ripened and unripened grapes was 79.5%.	Estimation of grape ripeness

The various methods for grape harvesting with accuracy rates as shown in below table.

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Table 2. Graph harvesting various method accuracies

Method	**Accuracy of grape harvesting (R^2 (avg))**
Machine Learning	95% to97%
Adaboost	60% to 70%
ARD	80% to 90%
SVM	65% to 70%
Deep Learning	90% to 92%

The below graph shows machine learning method is achieves very good accuracy in grape harvesting.

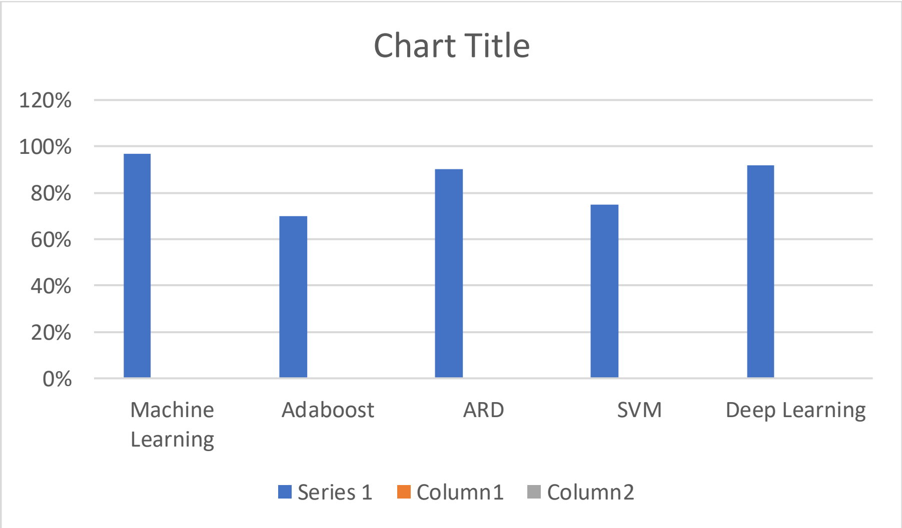

Fig1. Graph of the Method and accuracy of graph harvesting

III. Proposed Model

As we have discussed in the literature review that we observed by using the Machine Learning method we get 97% accuracy. So, we are proposing a model which gives 97% accuracy or any improvements.

The suggested bunch segmentation technique in this study consists of three basic steps: preprocessing of the photos, training on a sample set of segmentation, and images on the test set. Morphological procedures are used for both groups in the HSV color space in order to separate the original group of hypotheses, and then it uses a form filter to filter out the wrong bundles. Then, a selection of real bunch regions is made by hand as the training set for

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feature extraction. A Support Vector Machine Bunches in the test set are segmented [7]. The planned properly for cluster data processing and segmentation is shown in Figure 1 and block 11 photographs were used to create the algorithm.

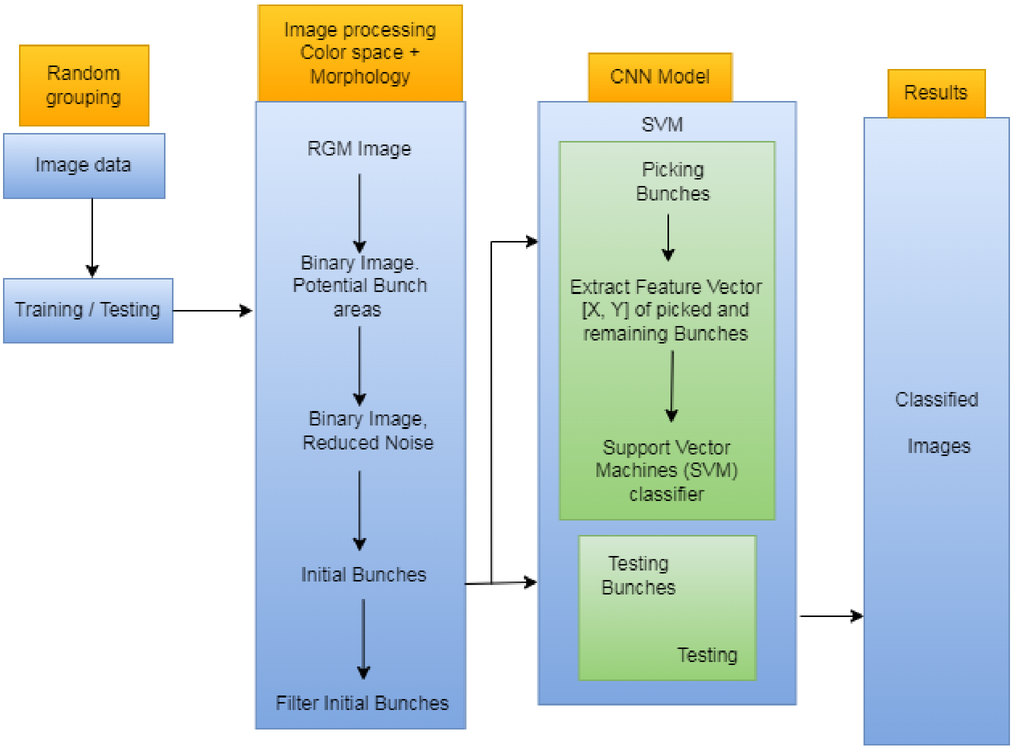

Fig2. The flow chart for bunch detection is presented in this work

As shown in Figure 2, a total of 80 photos from Block 11 were preprocessed, with some false positive areas discovered in some images. Each discovered location was then manually categorized as correct or wrong. A 58-dimensional feature vector is retrieved for each bunch discovered via pre-processing, containing properties such as closeness, solidity, extent, and compactness, as well as texture information in each channel in RGB, HSV, and L*a*b color spaces. The misclassification rate was utilized as the criterion for minimizing feature subsets in sequential feature selection. To be more exact, sequential forward selection is used by adding features to a feature candidate set in a consecutive manner. The criterion is calculated indefinitely until the criterion is satisfied. SFS stops increasing and chooses 21 characteristics.

Modern measures were employed in the evaluation to assess the deployed ML models. Precision, recall, F1 score, precision-recall curve, and inference time, were employed in this study. To determine these metrics, the following group of ideas was applied:

Interception over Union (IoU): determines the overlap between two bounding boxes;

True Positive (TP): an accurate detection that meets the IoU criterion;

False Positive (FP): an incorrect detection, such as an IoU threshold;

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False Negative (FN): failure to detect a ground truth bounding box.

In light of the aforementioned, the measures were determined as follows:

Precision: is computed as the percentage of TP and is supplied by: Precision is defined as the capacity of a given model to identify only relevant items.

$$\text{Precision} = \frac{TP}{TP+FP} \qquad \text{.... (1)}$$

Recall: Recall is the percentage of TP discovered divided by all the ground truths and is the measure of a model's capacity to locate all the ground truth bounding boxes.

$$\text{Recall} = \frac{TP}{TP+FN} \qquad \text{..... (2)}$$

F1 score: referred to as the harmonic mean of recall and accuracy, it is determined by:
A curve that illustrates the trade-off between accuracy and recall for each type of object.
The input dataset was separated into three groups training, test, and evaluation to ensure a fair evaluation of the ML models. The ML models were trained using the bigger set, the training set. The test set was employed to conduct the TensorFlow model assessment process during training. The testing set was exclusively used to compute the aforementioned metrics in order to evaluate the models.

IV. CNN architecture for image processing

The hierarchical design of CNN is mimicked by the grape bunch detection. As a figure 4a during the initialization step, the pictures are divided into small-size patches that are gradually merged with their nearby neighbors in deeper detection layers. By computing self-attention using the non-overlapping windows, the computational cost is reduced from quadratic to linear. The link between each window would be lessened by this divide, though. In order to tackle this issue, the model adopts the shifted window method [31].

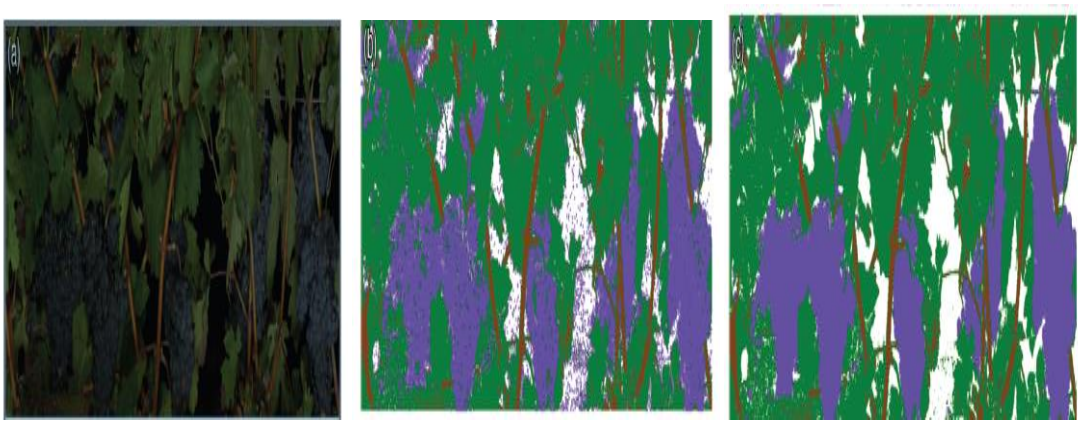

Fig3. Result of the image processing and analysis

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Figure 4b displays the bunch detection general architecture. As a result, each group has a feature dimension of 4 by 4 by 3. The projected feature dimension into an arbitrary dimension is also given a linear embedding layer. To create the hierarchical feature representations, the changed patch tokens are passed through a number of bunch detection blocks. A grape bunch detection block is in charge of learning feature representations, while the group merging layer is in charge of increasing dimension. Constant grape bunch blocks might be written as follows:

$f^{\wedge L=}W - MSA\left(LN\left(f^{L-1}\right)\right) + f^{L-1}$………………………... (1)

$f_L = MLP(LN(f^{\wedge L})) + f^{\wedge L}$……………………………….. (2)

$f^{\wedge L}{}^{+1} = SW - MSA\left(LN(fL)\right) + f^{L}$……………………… (3)

$f^{L+1} = MLP\left(LN\left(f^{\wedge L}{}^{+1}\right)\right) + f^{\wedge L}{}^{+1}$……………………… (4)

The number of STL is always multiples of two, where one is for window multi-head self-attention (W-MSA), and the other is for shifted-window multi-head self-attention. Where LN(:) denotes as Layer Normalization, MLP is multilayer perceptron which has two fully connected layers with Gaussian Error Linear Unit (GELU) activation function [32].

This is an example showing the use of Mask R-CNN on grape detection and segmentation of image is describe in above figure 3.

Fig4a. Object Detection

Fig4b. Image Segmentation

Table 3 gives an example of Confusion matrix in which it explains an approach to convolutional neural networks for the detection and identification captured by high-speed cameras.

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Table 3. Example of Confusion matrix for the raw CNN classification[33]

		Predicted				
		Neutral	Positive	Negative	Surprise	Accuracy
Actual	Neutral	1941	81	533	10	75.65%
	Positive	5	57	0	0	91.33%
	Negative	25	61	336	0	79.62%
	Surprise	41	0	6	65	58.02%

Each time the CNN analyses a difference picture between an onset frame and an apex frame or an apex frame and an offset frame, it produces one of the following classes: non-micro, positive, negative, or surprise. Images from three freely accessible micro-expression databases were used to train the network.

V. Dataset

It is a component of artificial intelligence and the study of algorithms, where an improvement is increased by employing the data or information related to it and applying previous experience. Using tagged data, Machine learning makes predictions about the results. Labeled data provides input data with the appropriate result. Images categorized and degrees of ripeness are used to identify bananas from their peels.

Fig5. Grape bunch recognition images

In this study, a unique dataset for grape bunch recognition is proposed, taking several growth phases into account. Several tests were conducted taking into account various stages of the grapevine in order to construct the dataset. Throughout all of the studies, this platform had two monocular RGB cameras installed on the humanoid manipulator and pointed at the grapevine canopy. The QG Raspberry Pi—Sony IMX477 cameras were utilized to create the suggested dataset and the color camera OAK-D.

Three stages were used to complete the data collecting process: video recording, picture extraction, and image storage. Neither rectification nor calibration was carried out throughout the data-gathering process. Therefore, it was anticipated that throughout the inference process, the models will also receive unrectified pictures.

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We have created grape harvesting dataset uploaded it to the Kaggle. This dataset contain various images from grape producer farmer, which includes stages of grape bunch. The details of datasets are as mentioned below:

Datasets Name	Size	Total Images
Grape Harvesting 1	22 MB	14
Grape Harvesting 2	34 MB	18
Grape Harvesting 3	39 MB	19

VI. Result

Table 5 shows the effectiveness of detecting grape bunches using an IoU of 50% and Machine Learning of 97% and varying the confidence threshold for three distinct values.

Table 5. Effectiveness of detecting grape bunches

Model	Confidence (%)	Class	Precision (%)	Recall (%)	F1 Score (%)	AP (%)	mAP (%)
SSD MobileNet-V1	30	tiny -rape -bunch medium -grape -bunch	17.3 28.53	61.72 66.44	27.12 39.92	40.38 49.48	44.93
SSD Inception-V2	30	tiny -rape -bunch medium -grape -bunch	35.81 64.62	44.88 37.59	39.83 47.53	26.95 29.68	28.32
SSD MobileNet-v1	50	tiny -rape -bunch medium -grape -bunch	49.28 45.59	50.44 64.26	49.85 53.34	36.29 48.54	42.47
SSD Inception-V2	50	tiny -rape -bunch medium -grape -bunch	51.36 70.86	30.57 29.90	38.33 42.06	20.50 24.45	22.48

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SSD MobileNet-V1	70	tiny -rape - bunch medium - grape -bunch	78.12 71.95	11.85 41.99	20.58 53.03	9.86 35.04	22.45
SSD Inception-V2	70	tiny -rape - bunch medium - grape -bunch	67.17 79.12	12.05 17.46	20.44 28.60	9.30 15.08	12.19

The impact of changing the confidence threshold is shown in the table 5. It is evident; in particular, that precision rose in tandem with an increase in confidence score. The removal of low-confidence detections was the cause of this. As a result, if we focused just on the model would be better suited to identify just pertinent detections for high-confidence detection grape blooms that would boost the precision.

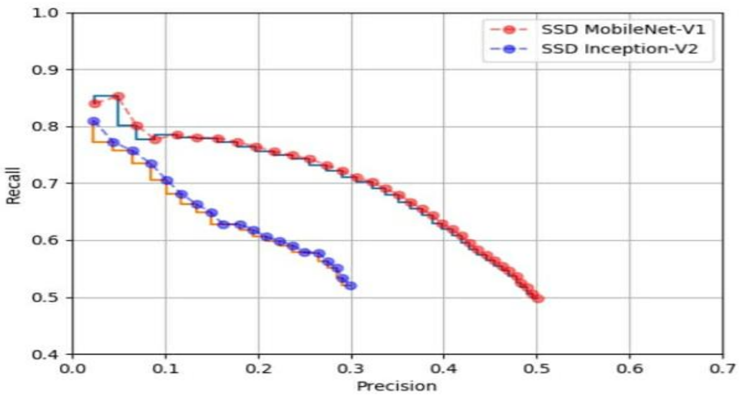

Fig6. Graph of tiny-grape-bunch

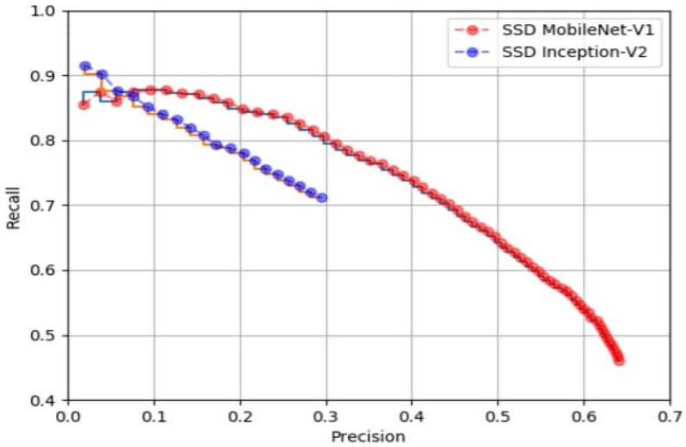

Fig7. Graph of medium-grape-bunch

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Figure 6 and 7 shows the precision and recall curves for both models and classes when using a 50% IoU and Machine Learning with a 97% confidence score. It is possible to confirm that this parameter can be utilized to get rid of FPs that are typically present low levels of confidence.

Fig8. Grape harvesting image analysis

The trials carried out to evaluate the suggested strategy are described in this section. First, the system evaluation metrics are given. The overall strategy is then evaluated after that. Finally, a comprehensive analysis of the outcomes is provided. Acted upon the above image is of grape harvesting. How many grapes have been grown in grape harvesting and how many days they will be harvested from the field can be done using machine learning and the CNN algorithm. Images were taken on each day in the morning and the evening to allow for various lighting conditions.

VII. CONCLUSION

We proposed a method for the detection of grape harvesting in which Machine learning was employed to identify grape bunches in vineyards at various growth phases, including the early stage just after bloom and the middle stage, during which the grape bunches display an intermediate degree of development. In this study, the issue of obtaining photos from cameras of smartphones to detect grape bunches at various development stages was addressed. grape harvesting 1, grape harvesting 2, and grape harvesting 3 datasets were created that included various images collected from a vineyard and their corresponding annotations, taking into account various phases of grape bunches.

The dataset was created by visiting a vineyard four times to collect the data. Two models were trained to recognize grape bunches with speed, economy, and low power and deployed in an embedded device after being quantized. The outcomes demonstrated a good trade-off between runtime performance and detection.

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