"Assessing the factor of Organizational Culture on Information Security Practices: A Quantitative Approach"

Shreya Parkale[1], Akshata Nale[2],Rushikesh Raut[3], Shreyas Sawant[4]

Artificial Intelligence and Data Science Department, Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology, Baramati , Pune , Maharashtra , 413133

[1]shreyaparkale1344@gmail.com

[2]akshatanale2122@gmail.com

[3]rushikeshrautrwr@gmail.com

[4]shreyassawant009@gmail.com

***Abstract*— Fruit counting and yield estimation are crucial for effective orchard management,resource allocation and market forecasting. Traditional methods for managing these aspects are labour-intensive, time consuming and often lack precision but deep learning and computer vision technology have recently automated this process. In this work, we provide a precise methodology that helps to build accurate and reliable fruit counting and yield estimation system for orchards using image processing coupled with object detection and deep learning approach. This work presents a web application that leverages the MiniLabelNet-Count framework, a weakly supervised deep learning model designed for detecting and counting fruits in images. By utilizing only binary presence/absence annotations during training, the application minimizes the need for extensive manual labeling, making it accessible for a wide range of users, including farmers and agricultural researchers. The system detects fruit with YOLO and Faster R-CNN models and tries to reduce the occlusion rate. The results of the system are compared with ground-truth and evolution metrics. The proposed system proved to be highly accurate and stable in fruit detection, tracking as well as in yield estimation on the various parameters like weather conditions, soil quality, fruit count and size. It gives a promising solution to enhance efficiency, accuracy and profitability in apple orchard management.**

***Keywords*— Fruit Counting, Yield Estimation, Deep Learning, Weakly Supervised Learn- ing, YOLO, MiniLabelNet Count,Faster R-CNN.**

I. Introduction

Accurately counting fruits and estimating yields are vital for efficient orchard management, resource allocation and market forecasting. Traditionally, these tasks were carried out manually, requiring farmers and workers to inspect trees and tally fruit counts. This method is not only time-consuming and labor-intensive but also prone to errors, especially in large orchards. Factors like varying weather conditions, tree growth patterns and differences in soil quality further complicate manual estimations, often leading to inaccuracies.

To address these challenges, early methods relied on statistical models and basic image analysis techniques. These approaches introduced some level of automation and efficiency but still lacked the precision and scalability required for large-scale orchards. For instance, statistical models often extrapolated data from a small sample of the orchard to predict total yield, which could result in significant inaccuracies. While basic image processing techniques helped reduce manual labor, they were limited by their inability to handle complex visual scenarios such as overlapping fruits or varying lighting conditions. The introduction of deep learning and convolutional neural networks (CNNs) marked a major shift in this field. CNNs are capable of learning intricate patterns from images, enabling automatic fruit detection without the need for manual intervention. This development greatly improved the accuracy and speed of fruit counting and yield estimation, allowing orchard managers to make more informed, data-driven decisions. Building upon these advancements in deep learning, our project introduces a comprehensive system for automating fruit counting and yield estimation. The system leverages cutting edge image processing techniques and state-of-the-art deep learning models to ensure high accuracy and reliability. At the core of this system is the MiniLabelNet-Count framework, a weakly supervised model that minimizes the need for extensive manual labeling. This makes the system highly accessible to users with limited data annotation resources, such as farmers and agricultural researchers. Instead of relying on detailed object-level annotations, the system uses binary labels to indicate the presence or absence of fruits in an image.

Our project introduces a system using advanced image processing and deep learning models like YOLO and Faster R-CNN, combined with the MiniLabelNet-Count framework, which minimizes manual labeling. This system efficiently processes large datasets, providing rapid and reliable fruit counts and yield predictions, enhancing orchard management efficiency and reducing labor costs.

II. LITERATURE REVIEW

In recent studies in agricultural automation highlight the use of machine learning models like Faster R-CNN and YOLO for high-accuracy fruit detection, but these require large, annotated datasets. Weakly supervised approaches, such as the

MiniLabelNet-Count framework, reduce the need for extensive labeling by using minimal binary annotations, achieving comparable performance with improved data efficiency.

[1] proposed an Encoder Decoder model utilizing CNNs and 2-D activation maps. The model incorporates innovations such as MiniLabelNet Count and the LTPA Module for efficient counting using binary annotations. Based on weakly supervised learning, this approach reduces human error but is limited by its dependence on high-quality annotations and challenges in localization features. In March 2024, [2] focused on early-stage green fruit detection through data acquisition, shape fitting, and fruit size estimation. Their model demonstrated notable adaptability, cost-effectiveness, and accuracy, enhancing automation and efficiency in detection tasks. However, it faced challenges with occlusion and difficulties in generalizing the model to various conditions. The study proposed by [3] in February 2024 proposed that the TF-YOLOv5s model as an efficient and lightweight solution for real-time detection of tomato flowers and fruits in natural environments. Its advantages include reduced computational complexity, fewer parameters, and improved detection accuracy compared to the base YOLOv5s model. However, challenges such as false positives for green tomatoes due to similar colors in the background and potential limitations in handling dense growth patterns remain areas for further improvement.

The proposed CEDAnet framework by [4] demonstrates significant advancements in individual tree segmentation (ITS) for dense orchards. Its strengths include dynamic threshold adjustments through the DG-NMS algorithm and enhanced feature aggregation via the TCAM module, achieving improved accuracy in detecting and segmenting dense fruit trees. However, challenges remain in adapting to diverse planting densities and managing substantial overlap among tree instances, which can impact segmentation precision. The development of specific datasets (iSCHID and iSMMID) adds to the robustness but highlights the need for broader applications across varying contexts.[5] introduced NTrack, a tracking-by-detection paradigm for multiple-object tracking using a Relative Location Analyzer (RLA). The system achieved high accuracy in counting cotton bolls while maintaining object identity. However, the approach relies heavily on object detection accuracy and does not fully address potential biases or inaccuracies. In October 2023, [6] developed a YOLO v4 tiny-based Twice Matched Fruit Counting System utilizing a mutual match algorithm for fruit tracking and ID assignment. Their system achieved a low ID switch rate of 3.9%, with a multiple-object tracking accuracy of 89.9% and precision of 93.5%. Despite its strong correlation between fruit count results, the model required high computational power and faced challenges with lighting variations and occlusion.

In August 2023, [7] proposed an enhanced YOLOv7 architecture with improvements over YOLOv5 for apple target detection using a multi-head attention mechanism. The model achieved a high mean Average Precision (mAP) of 80.4%, with improved depth estimation. However, it suffered from slower inference times and a tradeoff between speed and size, necessitating model compression and pruning for better detection accuracy. In July 2023,[8] introduced an Edge Detection Network incorporating a region-growing method and ellipse fitting for remote apple monitoring. Their system reduced the mean absolute error in apple diameter measurements by 67.9% and processed images in just 0.075 seconds. However, limitations included challenges with seed point selection, high occlusion rates, and restricted applicability to other fruits.

[9] in December, 2022 proposed the SDNet algorithm that improves real-time strawberry growth monitoring with enhancements to the YOLOX model, achieving 94.26% precision and faster detection at 30.5ms per frame. Its innovative modules, including C3HB for feature extraction, NAM for attention to small targets and SIOU for bounding box accuracy, significantly boost performance compared to other models. However, server dependency and challenges in detecting overlapping or small targets in natural environments highlight areas for further improvement toward full automation in agriculture. In [10], W. Zhang et al. proposed the OrangeYolo and OrangeSort algorithms for video sequence-based orange counting. These algorithms employed receptive field scale matching and a dual-attention multiscale fusion mechanism, significantly improving detection accuracy and adaptability to various scales while reducing double-counting errors. However, the approach faced challenges with complex occlusion issues, high computational complexity, and dependence on the quality of video data. The paper presented by [11] presents a fruit yield estimation method using loose segmentation and nonlinear regression, achieving 94.71% accuracy across six fruit types. It employs SegNet for segmentation and a modified Inception-ResNet for regression, offering scalability and reduced annotation effort. While efficient, the approach faces challenges with occlusion and computational demands.

In June 2021, [12] explored a quasi-unsupervised learning approach using a Cycle-Generative Adversarial Network (Cycle-GAN) and a Presence-Absence Classifier (PAC) with a spatial consistency constraint. Their method focused on domain adaptation for unseen fruits, reducing labeling effort while employing multi-scale spatial consistency and binary cross-entropy loss. However, challenges included domain shift, GAN instability, and high computational complexity. The study by [13] in April 2021 evaluates regression-based and detection-based methods for counting objects in agricultural phenotyping, focusing on density-dependent performance. Regression approaches, particularly density-based ones like CAN, excel in high-density scenarios, maintaining accuracy with minimal occlusions and heterogeneity. However, their reliance on dataset size can lead to overfitting. In contrast, detection methods, such as Faster R-CNN, perform well in low-density images but exhibit significant accuracy loss as object density increases. The study highlights the need for method selection tailored to specific image densities in agricultural applications. [14] proposed the QU COUNT framework that enables accurate fruit counting in unseen scenarios with minimal labeling, offering comparable performance to supervised methods and faster deployment. However, it faces challenges with computational costs, domain disparities, and untested performance on cluster fruits or complex geometries.

In April 2020, [15] proposed the Minne Apple dataset offers a comprehensive benchmark for apple detection, segmentation, and counting in orchard environments, featuring over 41,000 annotated instances across 1,000 high-resolution images. It includes diverse apple varieties and illumination conditions, aiding unbiased algorithm evaluation. However, challenges include the dataset's focus on small objects and cluttered scenes, which can hinder detection and segmentation performance, particularly for existing state-of-the-art methods. In July 2019, [16] presented a binary presence absence classifier using spatial consistency constraints and a multi-branch counting CNN leveraging ResNet101 as the base feature extractor. Their approach combined mean squared error (MSE) loss with binary cross-entropy (BCE) loss. However, it faced performance drops in dense fruit clusters, sensitivity to varying illumination conditions, and challenges with noisy supervision. In September 2018, [17] developed a fruit-counting algorithm using an Android mobile phone (AMP) based on the calyx for kiwifruit yield estimation. This method was simple, cost-effective, and convenient for real-time applications, as it estimated yield by multiplying fruit density with area. However, its performance was influenced by CPU speed and faced challenges related to foliage obstruction, plant density variability, and variations in fruit shape and accuracy.

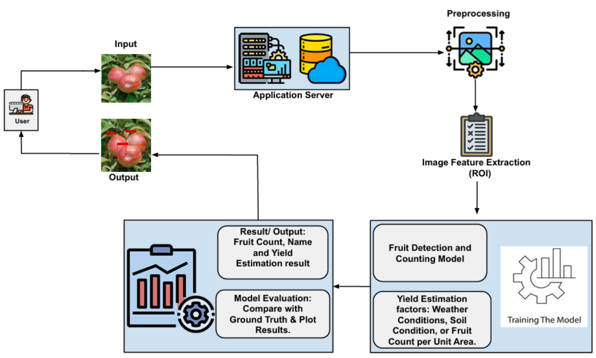

Fig 1: System Architecture

III. METHODOLOGY

A. Dataset

ACFR Orchard Fruit Dataset is an agricultural dataset con training images and annotations for different fruits, collected at different farms across Australia. VegFru categorizes vegetables and fruits according to their eating characteristics, and each image contains at least one edible part of fruits.

B. User Input

The system begins with the user providing input, which involves uploading images of the orchard to the web application. This input typically consists of raw RGB images captured from the orchard.

C. Web Server

Once the images are uploaded, they are processed by a Web Server (likely using a framework like Flask). The server is responsible for receiving the input images, managing requests, and orchestrating the entire processing pipeline.

D. Preprocessing

The images undergo a comprehensive preprocessing step to prepare them for analysis and model training. This process involves multiple stages aimed at improving data quality and ensuring consistency. First, the images are cleaned to remove any noise or artifacts that could negatively impact the model's performance. They are then resized to a uniform dimension, which not only standardizes the input size for the model but also reduces computational overhead. Following this, normalization is applied to adjust pixel intensity values to a specific range, typically between 0 and 1 or-1 and 1, depending on the model's requirements. This step ensures that the input data maintains a consistent scale, facilitating more stable and efficient learning. Additionally, the preprocessing pipeline may include data augmentation techniques such as rotation, f lipping, cropping, or color adjustments. These augmentations increase the variability of the training data, making the model more robust and better equipped to handle diverse real-world scenarios. Collectively, these preprocessing steps ensure that the input data is optimized for further processing, enhancing the overall effectiveness of the machine learning pipeline. Normalization is applied to standardize pixel values:

$$x' = (x - min(x)) / (max(x) - min(x))$$

where x is the original pixel value, and x' is the normalized value. Data augmentation techniques like flipping, rotation, and brightness adjustments are applied to increase dataset diversity and model robustness.

E. Image Feature Extraction (ROI):

In this step, Regions of Interest (ROI) are extracted from the preprocessed images to focus on specific areas that potentially contain fruits. Advanced feature extraction techniques are then applied to isolate and highlight these regions, ensuring that the critical areas are emphasized while irrelevant background information is minimized. This process is crucial for accurately identifying and analyzing the targeted objects, as it reduces noise and enhances the model's ability to distinguish fruits from their surroundings. By concentrating on ROIs, the system achieves greater precision and efficiency in subsequent stages of processing and analysis.Feature extraction uses an encoder-decoder architecture to generate 2D activation maps (heatmaps).

$$h\_i,j = f(W * X\_i,j + b)$$

where:
• Hi,j: the activation at pixel (i,j),
• W: Convolution filter ,
• Xi,j: Input image patch,
• f: Activation function (ReLU).

F. Fruit Detection and Counting Model:

The system then employs a Fruit Detection and Counting Model, which is based on deep learning frameworks such as MiniLabelNet-Count, YOLO, or Faster R-CNN. This model is designed to detect the presence of fruits and accurately count them in the image. It utilizes a weakly supervised learning approach, where binary presence/absence labels are used instead of requiring extensive, detailed annotations. This method reduces the reliance on large amounts of labeled data, allowing the model to learn effectively from fewer annota tions. By leveraging these deep learning techniques and weak supervision, the system can efficiently and accurately detect and count fruits while minimizing human labeling effort.

A. YOLO(You Only Look Once) Model :

• Grid Division:–

–YOLO divides the image into an S × S grid. Each grid cell is responsible for predicting a fixed number of bounding boxes and associated confidence scores.

• Bounding Box Prediction:

$$Bounding\ Box = (x, y, w, h)$$

– x,y: Coordinates of the center of the bounding box relative to the grid cell.

–w,h: Width and height of the box relative to the entire image.

• Confidence Score:

$$Confidence = P(object) \times IoU$$

– P(object): Probability that an object is present in the box
– IoU (Intersection over Union):

$$IoU = Area\ of\ Overlap\ /\ Area\ of\ Union$$

B. Faster R-CNN:

• Region Proposal Network (RPN):

– Generates a set of region proposals from the input image.

•Object Classification & Bounding Box Regression:

–Classifies the objects and refines the bounding box coordinates.

• Detection Output:

$$N= \sum_{i=1} (confidence\_i > threshold)$$

where N is the total count of detected fruits, and I is an indicator function.

• Final Detection:

– Non-Maximum Suppression (NMS) is used to eliminate overlapping boxes with lower scores.

C. Masked R-CNN:

• Feature Extraction:

$$F = CNN(Iprep)$$

• Region Proposal Network (RPN):

$$R = RPN(F)$$

• RoI Align and Classification:

$$Dm\text{-}rcnn, M = ClassificationNetwork(RoIAlign(F, R))$$

where, M represents the mask predictions

G. Yield Estimation:

The system performs Yield Estimation based on several parameters:

1) Weather Conditions: Considers factors like temperature, humidity and rainfall.
2) Soil Condition: Considers soil quality, moisture levels, and nutrient content.
3) Fruit Count per Unit Area: Utilizes the fruit count from the detection model to estimate yield on a per-unit area basis.

• Basic Yield Formula:

$$Y = C \times A$$

where:–
Y: Estimated yield.–
C: Fruit count per unit area.
A: Total orchard area.

• Adjusted Yield with Environmental Factors:

$$Y' = Y \times Fw \times Fs$$

where:–
Fw: Factor based on weather conditions.–
Fs: Factor based on soil conditions.

H. Model Evaluation:

The model's results are then compared with Ground Truth Data to assess its accuracy and performance. Common evaluation metrics, such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), are used to quantify the discrepancies between the predicted fruit counts and the actual counts. These metrics provide a clear measure of the model's prediction accuracy, with MAE representing the average error magnitude and RMSE highlighting larger errors more signif icantly. In addition to numerical evaluation, the results are often visualized using graphs or charts, allowing for a clearer understanding of the model's effectiveness and providing insights into areas where improvements might be needed. This combination of quantitative and visual assessment ensures a comprehensive evaluation of the model's performance.

- **For Object Detection Models (YOLO, Faster R-CNN & Masked R-CNN):**

Precision:
$Precision\ = True\ Positives / True\ Positives\ +\ False\ Pos$

Recall:
$Recall\ = True\ Positives\ / True\ Positives\ +\ False\ Negat$

F1-Score:
$F1Score\ =\ 2 \times Precision \times Recall\ /\ Precision\ +\ Recall$

IoU (Intersection over Union):
$IoU\ =\ Area\ of\ Overlap\ / Area\ of\ Union$

- **For Yield Estimation:**

Mean Absolute Error (MAE):

$$MAE = 1/\mathrm{n} \sum_{n}^{i=1} |y_{\mathrm{pred}} - y_{\mathrm{true}}|$$

Mean Absolute Error (MAE):

$$RMSE = 1/n \sum_{n}^{i=1} \sqrt{(ypred\ -\ ytrue)}$$

I. Output:

Finally, the system outputs key information:

1) Fruit Count: Total number of fruits detected in the images

2) Fruit Name: Classification of the detected fruit type.

3) Yield Estimation: Predicted yield based on the detected fruit count and environmental factors.

IV. ADVANTAGES OF THE PROPOSED SYSTEM

Fruit counting system offers several advantages in its approach and contributions to agricultural yield estimation. Key benefits include:

A. *Reduction in Annotation Effort:* The framework employs a weakly supervised learning methodology, relying solely on image-level binary annotations (presence/absence of fruits) instead of detailed bounding boxes or pixel-level labels. This approach significantly reduces the time and resources required for data labeling.

B. *Advanced Attention Mechanisms:* The incorporation of learn-to-pay-attention (LTPA) modules during network optimization enhances the network's ability to focus on relevant image regions, improving fruit detection and counting accuracy.

C. *Innovative Heatmap Generation and Processing:* The paper introduces a novel heatmap generation procedure and a TriCluster Local Maxima Detector (TC-LMD) to dynamically adjust detection thresholds, reducing overestimation and underestimation errors.

V. CONCLUSION

This project on Fruit Counting and Yield Estimation for Orchard Management, provides valuable experience in applying deep learning and computer vision for automating fruit counting and yield estimation. In previous studies, using models like YOLOv8 and MiniLabelNet-Count, that addresses challenges like occlusion and complex environments, improving accuracy and reducing manual effort in orchard management is the main focus of this project. Looking ahead, the future scope of this system is vast. We can integrate this model for multiple kinds of fruits. This will make it suitable for both small farmers and large agricultural organization .

VI. FUTURE SCOPE

The future scope of the MiniLabelNet-Count framework is vast and promising, with opportunities to further enhance its capabilities and broaden its applications in precision agriculture. A key area for improvement lies in refining the detection of tightly clustered fruits by developing more advanced algorithms and enhancing activation maps to better distinguish overlapping instances. Additionally, the framework could be extended to provide more detailed localization features, such as masks or bounding boxes, while maintaining the weakly supervised approach to keep data annotation efforts minimal. To improve its versatility, testing and adapting the framework for different crops and orchard settings will ensure its robustness across varied agricultural environments. Integration with autonomous agricultural systems, such as drones or ground robots, presents another exciting avenue, enabling real-time yield estimation and mapping in the field. The scalability of the framework could be addressed by training it on larger, more diverse datasets and incorporating synthetic data augmentation techniques to improve performance under varied conditions.

VII. CHALLENGES

This project faces several challenges that need to be addressed to enhance its effectiveness and scalability in precision agriculture. These challenges stem from the complexities of real-world agricultural environments, the limitations of weakly supervised learning, and the demands of deploying the system in diverse and resource-constrained settings:

A. *Detection of Clustered Fruits:* Accurately identifying and counting tightly clustered or overlapping fruits remains difficult, often leading to under estimation or over estimation.

B. *Limited Annotation Precision:* The reliance on weakly supervised learning with binary annotations may hinder the accuracy achievable compared to fully supervised methods.

C. *Dataset Limitations:* The lack of large, diverse agricultural datasets limits the framework's robustness and scalability across varied scenarios.

D. *Environmental Variability:* Dealing with varying lighting conditions, occlusions, and background clutter in real-world agricultural environments remains a significant challenge.

E. *Accuracy-Performance Trade-Off:* Balancing a high detection accuracy with low computational demands is critical, especially for real-time applications in the field.

V. REFERENCES

[1] Alessandro Rocco Denarda, Francesco Crocetti, Raffaele Brilli, Gabriele Costante and Paolo Valigi, "*Refined Weakly Supervised Yield Estimation Through the MiniLabelNet-Count Framework*", IEEE Transactions on Agrifood Electronics, VOL.00, JUNE 2024.

[2] Ranjan Sapkota , Dawood Ahmed , Martin Churuvija and Manoj Karkee, "I*mmature Green Apple Detection and Sizing in Commercial Orchards Using YOLOv8 and Shape Fitting Techniques*", IEEE Access, MARCH 2024.

[3] Suyu Tian , Chao Fang , Xiaogang Zheng and Jue Liu "*Lightweight Detection Method for Real-Time Monitoring Tomato Growth Based on Improved YOLOv5s*", Digital Object Identifier 10.1109/AC CESS.2024.3368914 Feb, 2024

[4] Fangjie Zhu , Zhenhao Chen , Haoyang Li , Qian Shi ,Xiaoping Liu, "*CEDAnet: Individual Tree Segmentation in Dense Orchard via Context Enhancement and Density Prior*" IEEE Journal of Selected Topics In Applied Earth Observations And Remote Sensing, VOL. 17, 2024

[5] Md Ahmed Al Mujaddid and William J. Beksi, "*NTrack: A Multiple Object Tracker and Dataset for Infield Cotton Boll Counting*", IEEE Transactions on Automation science and engineering,VOL. 11, NO. 1, NOV 2023.

[6] Zhenchao Wu, Xiaoming Sun , Hanhui Jiang , Fangfang Gao , Rui Li , Longsheng Fu , Dong Zhang and Spyros Fountas , "*Twice matched fruit counting system: An automatic fruit counting pipeline in modern apple orchard using mutual and secondary matches*", Elsevier Journal on Biosystems Engineering, OCT 2023.

[7] Praveen Kumar S, Naveen Kumar K , "*Drone-based apple detection: Finding the depth of apples using YOLOv7 architecture with multi-head attention mechanism* ", Elsevier Journal, AUG 2023.

[8] Hela Jemaa, Wassim Bouachir, Brigitte Leblon , Armand LaRocque, Ata Haddadi and Nizar Bouguila, "*UAV-Based Computer Vision System for Orchard Apple Tree Detection and Health Assessment* ", MDPI Remote Sensing, JULY 2023

[9] Qilin An,Kai Wang, Zhongyang Li, Chengyuan Song, Xiuying Tang, Jian Song , "*Real-Time Monitoring Method of Strawberry Fruit Growth State Based on YOLO Improved Model*", Digital Object Identifier 10.1109/ACCESS.2022.3220234, December 2022.

[10] Wenli Zhang , Jiaqi Wang, Yuxin Liu, Kaizhen Chen, Huibin Li, Yulin Duan, Wenbin Wu, Yun Shi and Wei Guo, "*Deep-learning-based in f ield citrus fruit detection and tracking* ", Horticulture Research, May 2022.

[11] Amjad Rehman Khan, Hamza Mukhtar, Tanzila Saba, Omer Riaz, Muhammad Usman Ghani Khan, Saeed Ali Bahaj, "*Scene Graph Generation With Structured Aspect of Segmenting the Big Distributed Clusters*", Digital Object Identifier 10.1109/ACCESS.2022.3155652, March 8, 2022

[12] Wenli Zhang , Kaizhen Chen, Jiaqi Wang,Yulin Duan, Yun Shi and Wei Guo, " *Easy domain adaptation method for filling the species gap in deep learning-based fruit detection* ", Horticulture Research, June 2021.

[13] Adrian Salazar Gomez , Erchan Aptoula , Simon Parsons , and Petra Bosilj, "Deep Regression Versus Detection for Counting in Robotic Phenotyping", IEEE ROBOTICS AND AUTOMATION LETTERS, VOL. 6, NO. 2, APRIL 2021

[14] Enrico Bellocchio, Gabriele Costante, Silvia Cascianelli, Mario Luca Fravolini, Paolo Valigi, "*Combining Domain Adaptation and Spatial Consistency for Unseen Fruits Counting: A Quasi-Unsupervised Ap proach*" IEEE Robotics and Automation letters,VOL.5,NO.2, April 2020

[15] Nicolai H¨ ani ,PravakarRoy, Volkan Isler,"*MinneApple: A Benchmark Dataset for Apple Detection and Segmentation*", IEEE Robotics and Automation letters,VOL.5,NO.2, April 2020

[16] Enrico Bellocchio, Thomas A. Ciarfuglia,Gabriele Costante and Paolo Valigi, "*Weakly Supervised Fruit Counting for Yield Estimation Using Spatial Consistency*", IEEE Robotics And Automation Letters,VOL.4,NO.3, July 2019

[17] Longsheng Fu , Zhihao Liu, Yaqoob Majeed and Yongjie Cui, "*Kiwifruit yield estimation using image processing by an Android mobile phone* ", Elsevier IFAC PapersOnLine, MAY 2018