Efficiency Requirements for Robotic Fruit Crop Harvesting*

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Abstract. The paper aims to determine the most critical indicators of the efficiency of robots for collecting fruits, based on which gardeners can make informed decisions about the appropriateness of using such robots. The author performs an analysis of the differences between fruit harvesting robots from robots that are successfully used in other industries and makes a report of indicators used to evaluate the effectiveness of fruit-picking robots by developers of such robots prototypes. Based on this analysis, the author identifies quality metrics crucial for making decisions on the advent of fruit harvesting robots. The analysis of 32 papers devoted to fruit harvesting robots revealed that due to the development of convolutional neural networks in machine vision systems, the fruit detection speed has significantly increased. It indicates the inevitability of the introduction of robotic technology for harvesting in gardening. However, the developers of fruit collection robots need to evaluate the undetected fruits rate, the objects mistaken for fruits rate, the average fruit detection time, the average fruit picking time, the share of successfully collected fruits rate among the detected, the damaged fruits rate, the lost fruit rate, and the unpicked fruits rate in order to perform the task.

Keywords: Fruit harvesting robot · Machine vision · Quality metrics

1 Introduction

Horticulture is one of the least automated agricultural sectors to date. In particular, most fruit crops are harvested manually, with seasonal workers engaged in heavy physical labor. The quality of harvesting by seasonal workers is low; in particular, up to 50% of the fruit remains unpicked.

The use of fruit harvesting robots will increase both the acreage of orchards and the efficiency of horticultural enterprises by increasing labor productivity in harvesting and reducing crop shortages.

Fruit picking robots have been developing since the 1970s, while robot productivity has not increased over the past thirty years. (Bac, van Henten, Hemming & Edan, 2014) analyzed 50 prototypes of fruit harvesting robots. The average fruit detection rate was 85%, and the average fruit picking rate was 75% of the detected fruits or 63.75% of the total fruits on the trees. At the same time, robots spend, on average, 33 seconds to pick one fruit.

According to (Alpha Brown, 2017), 27% of 1,300 farmers surveyed would like to buy harvest robots. However, the cost of existing robots for harvesting fruits at the level of hundreds of thousands of euros does not allow such robots to pay off in practical work and does not let farmers consider the potential purchase of these robots.

Therefore, despite many prototypes of fruit harvesting robots developed and the potential willingness of farmers to purchase them, not a single horticultural farm still uses them due to their high cost and low efficiency.

One of the factors hindering the robotic technology introduction for fruit harvesting is the insufficient attention of prototype developers of such robots to the analysis of their efficiency.

The paper aims to determine the most critical indicators of the efficiency of robots for collecting fruits, based on which horticulturists can make informed decisions about the feasibility of using such robots.

The paper analyzes the differences between fruit-picking robots from robots that have long been successfully used in industry and other agriculture sectors. It also analyzes the indicators used to evaluate the efficiency of fruit harvesting by such robot prototype developers. Furthermore, based on this analysis, the author identifies quality metrics crucial for making decisions on the introduction of fruit harvesting robots.

2 Materials and Methods

2.1 Fundamental Features of Fruit Harvesting Robots

Robots are effectively used for operations that require reduced labor or workloads and are best suited for applications that require repeatable accuracy and high performance in homogeneous environments (Holland & Nof, 1999). In horticulture, there is a need to reduce manual labor with repeatable accuracy of fruit-picking operations, but it is almost impossible to ensure uniformity of conditions.

For quite some time now, robots have been used in industry and some agriculture sectors, such as animal agriculture, because a lot can be standardized in these areas: to ensure work area cleanliness and make other conditions close to ideal.

The grain harvesting process can also be standardized. It was standardization that allowed humanity to switch from wheat harvesting with a sickle to the use of human-driven and autonomous combines.

In gardening, such ideal standard conditions cannot be created due to various environmental conditions: changing light, blowing wind, rain leaving drops on fruits and leaves, branches and leaves overlapping fruits, etc. Simultaneously, the robot, for the operation of which it is first necessary to go through the garden and cut off all the leaves that overlap apples, will not be in demand.

For example, all apples differ in shape and color, unlike tomatoes, lemons, kiwi, and other fruits.

Fruits are susceptible to environmental and physical conditions, such as temperature, humidity, carbon dioxide content, acidity, pressure, friction, and shock. Fruit production requires accurate and often complex picking operations to ensure sufficient quality. That is why apples are still not harvested by machines like wheat combines: robots for harvesting fruits are much more complicated than harvesting machines for grains.

Unlike industrial robots, which deal with relatively simple, clearly defined repetitive tasks in stable reproducible (not changing day by day) conditions, gardening requires technologies for working with unstructured objects (fruits) in complex, highly variable environments (gardens).

It is a significant problem for commercialization. A robot must be able to move in a volatile environment, and there are many situations in which a robot may fail due to unexpected events. Therefore, all existing fruit-picking robot prototypes are structurally complex and very expensive.

2.2 Approaches to Fruit Harvesting Robots Efficiency Assessment

Confusion matrixes for pixels classification into those belonging to the fruit and those belonging to the background were used for a long time to evaluate the efficiency of fruit harvesting robots (Fig. 1).

		Actual	
		Pixel belongs to fruit	Pixel belongs to background
Predicted	Pixel assigned to fruit	TP_P	FP_P
	Pixel assigned to background	FN_P	TN_P

Fig. 1. Confusion matrix for pixels classification in fruit harvesting robots. *Source:* (Fawcett, 2006).

The following notation is used:

- TP_P (True Positive) – the number of pixels in the image correctly recognized as belonging to the fruit;
- TN_P (True Negative) – the number of pixels in the image correctly recognized as belonging to the background;
- FP_P (False Positive) – the number of errors of the first kind, i.e., background pixels, mistakenly attributed by the machine vision system to a fruit;
- FN_P (False Negative) – the number of errors of the second kind, i.e., pixels that actually belong to the fruit but are mistakenly classified by the system of machine vision as background.

Based on the confusion matrix for pixels classification, many authors calculated the following quality characteristics of machine vision systems:

- $Accuracy_P = \dfrac{TP_P + TN_P}{TP_P + FP_P + TN_P + FN_P}$ – The share of pixels in the image that are correctly recognized by the machine vision system (i.e., correctly assigned to the fruit or background);
- $Precision_P = \dfrac{TP_P}{TP_P + FP_P}$ – The share of pixels actually belonging to fruits among all pixels assigned by the machine vision system to fruits;
- $Recall_p = \dfrac{TP_p}{TP_p + FN_p}$ – The share of pixels correctly assigned by the machine vision system to fruits, among all the pixels truly related to fruits;
- $F1_P = \dfrac{2 \cdot Precision_P \cdot Recall_P}{Precision_P + Recall_P}$ – The harmonic means of precision and recall.

Tables 1 and 2 represent a summary of quality metrics calculated by the developers of known fruit harvesting robots.

From a practical point of view, such indicators only indirectly determine the quality of the robotic harvesting system since the robot collects fruits, not pixels.

With the development of the use of convolutional neural networks to determine the quality of fruit detection systems, the *IoU* (Intersection over Union) metric has become popular.

In Fig. 2, the navy rectangular frame is described around the ground truth fruit, and the red frame is obtained as a result of applying the fruit detection algorithm by the machine vision system.

A fruit detection system is considered to work satisfactorily if

$$IoU = \frac{\sum\limits_{all\ objects} Area\ of\ Intersection}{\sum\limits_{all\ objects} Area\ of\ Union} > 0,5.$$

However, in practice, this indicator and quality indicators calculated based on the analysis of the pixel classification confusion matrix are only an indirect indicator of the quality of the fruit-picking system.

Therefore, current works gradually begin to use quality metrics based on the analysis of the fruit detection confusion matrix (Fig. 3).

The notation in the fruit detection confusion matrix has the following meanings:

- TP_F (True Positive) – the share of fruits correctly detected by the machine vision system;
- FP_F (False Positive) – the number of errors of the first kind, i.e., background objects in the image, mistakenly accepted by the machine vision system as fruits;
- FN_F (False Negative) – the number of errors of the second kind, i.e., fruits not detected by the machine vision system.

TP_F, FP_F, FN_F, can calculate the following quality metrics for a fruit detection system:

- $Precision_F = \dfrac{TP_F}{TP_F + FP_F}$ – The share of actual fruits among all the objects that the machine vision system called the fruits;
- $Recall_F = \dfrac{TP_F}{TP_F + FN_F}$ – The share of fruits detected by the machine vision system;
- $F1_F = \dfrac{2 \cdot Precision_F \cdot Recall_F}{Precision_F + Recall_F}$ – The harmonic means of precision and recall.

Table 1. Fruit detection quality metrics in harvesting robot prototypes (Before CNNs).

Source	Fruit	N	$Accuracy_P$	$Recall_p$	$Precision_F$	$Recall_F$	t
(Sites & Delwiche, 1988)	Apple, peach		0.90				
(Plebe & Grasso, 2001)	Orange	673			0.15	0.87	7.1
(Zhao, Tow & Katupitiya, 2005)	Apple	20				0.90	
(Mao, Ji, Zhan, Zhang & Hu, 2009)	Apple		0.90				
(Hannan, Burks & Bulanon, 2009)	Orange	82				0.90	
(Bulanon, Burks & Alchanatis, 2009)	Citrus			0.74			
(Seng & Mirisaee, 2009)	Various fruits	14	0.90				
(Bulanon & Kataoka, 2010)	Citrus	22				0.89	7.1
(Wachs, Stern, Burks & Alchanatis, 2010)	Apple	180		0.74			
(Kurtulmus, Lee & Vardar, 2011)	Citrus	64				0.75	
(Arefi, Motlagh, Mollazade & Teimourlou, 2011)	Tomato	110	0.96				
(Patel, Jain & Joshi, 2011)	Apple			0.90			
(Linker, Cohen & Naor, 2012)	Apple	9	0.85				
(Ji et al., 2012)	Apple	22				0.89	
(Zhan, He & Shi, 2013)	Kiwi	215			0.93	0.97	
(Wei et al., 2014)	Apple	80				0.95	
(Lu, Sang & Hu, 2014)	Citrus	20	0.87				
(Zhao, Gong, Huang & Liu, 2016)	Tomato	171			0.84	0.97	
(Tao & Zhou, 2017)	Apple	59			0.95	0.90	

Source: Compiled by the author.

Table 2. Fruit detection quality metrics in harvesting robot prototypes (CNN models).

Source	Fruit	N	$Accuracy_P$	IoU	$Precision_F$	$Recall_F$	$F1$	t
(Sa et al., 2016)	Various fruits	118			0.81	0.84	0.90	0.40
(Liu et al., 2020)	Kiwi	2518			0.90	0.91		0.13
(Bargoti & Underwood, 2017)	Apple, mango, almond	488			0.96	0.86	0.90	
(Mureşan & Oltean, 2018)	Various fruits	15.563	0.96					
(Gan, Lee, Alchanatis, Ehsani & Schueller, 2018)	Citrus	50				0.96	0.90	
(Williams, Jones, Nejati, Seabright & MacDonald, 2018)	Kiwi	1456				0.76		
(Peebles, Lim, Duke & McGuinness, 2019)	Asparagus	74					0.73	
(Yu, Zhang, Yang, Zhang, 2019)	Strawberry	100		0.90		0.96	0.95	
(Jia, Tian, Luo, Zhang & Zheng, 2020)	Apple	120				0.97	0.96	
(Gené-Mola et al., 2020)	Apple	1021					0.87	
(Tian, Yang, Wang, Li & Liang, 2019)	Apple	480		0.90			0.81	0.30
(Kang & Chen, 2020)	Apple	560		0.87	0.87	0.88	0.87	0.70
(Wan & Goudos, 2020)	Orange, apple, mango	490				0.90		0.58

Source: Compiled by the author.

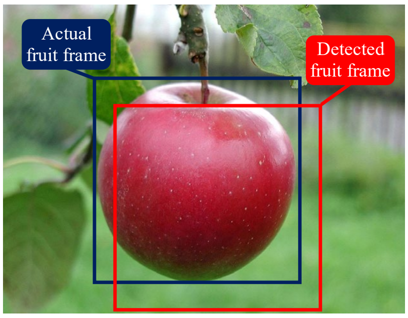
3 Results

From a practical point of view, the following indicators are the essential metrics of the machine vision systems quality to assess the quality of fruit harvesting robots:

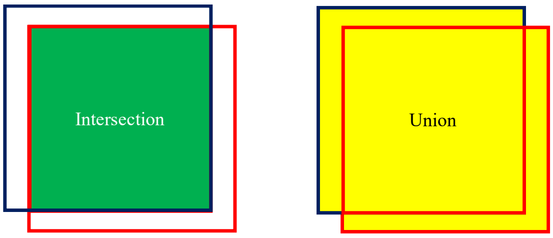
$False\,Negative\,Rate_F = FNR_F = 1 - Recall_F = \dfrac{FP_F}{TP_F + FN_F}$ – The share of undetected fruits;

$False\,Positive\,Rate_F = FPR_F = 1 - Precision_F = \dfrac{FP_F}{TP_F + FP_F}$ – The share of objects mistaken for fruits, which affects the harvesting speed.

It is also necessary to understand which part of the detected fruits a robot can pick in order to make decisions on the fruit harvesting robot's purchase. In the process of robot creation, it is essential to assess the share of successfully harvested fruits among those identified. Besides, essential characteristics of the robot are the average fruit detection time (this indicator in seconds is presented in column t of Tables 1 and 2), as well as the average fruit harvesting time, the share of damaged fruits, the share of lost fruits, and the share of uncollected fruits.



(a) Ground truth fruit bounding box and detected fruit bounding box



(b) Intersection (c) Union

Fig. 2. Intersection over Union for fruits detection. *Source:* Compiled by the author.

	Actual	
	Fruit	Background
Detected fruits	TP_F	FP_F
Undetected fruits	FN_F	–

Fig. 3. Confusion matrix for fruit detection in harvesting robots. *Source:* (Fawcett, 2006).

4 Discussion

The proportion of fruits not detected by the robot and the percentage of objects mistakenly considered to be fruits are estimated by less than half of robot developers, which can be seen from Tables 1 and 2.

An absolute minority of developers provide data on the average time of fruit detection, and almost no one gives information on the average time of fruit picking and the shares of successfully picked fruits among the detected, damaged fruits, lost fruits, and uncollected fruits.

Of all the papers examined, only (Williams et al., 2018) noted that the robot could detect 76% of kiwi, while the manipulator could reach 55% of the fruits. In the field trials, the robot harvested in the garden, which had 1,456 kiwi fruits. As a result, 50.9% of the fruits were harvested, 24.6% were lost during the harvesting process, and 24.5% remained in the trees. Picking one fruit took, on average, about five seconds. The work of neural networks took most of the time. Nevertheless, nowadays, it is one of the fastest harvesting robots.

5 Conclusion

The development of fruit-picking robots will replace the heavy manual labor in horticulture, increase the area of orchards, reduce cost, and reduce crop shortages.

The analysis shows that the speed of fruit detection had increased significantly with the development of the use of convolutional neural networks in machine vision systems of fruit harvesting robots. It indicates that robotic harvesting technology will be introduced to horticulture very shortly. Nevertheless, robots should become much cheaper for gardeners to start thinking about switching to robotic technology. Thus, gardeners should get a clear justification for the efficiency of the robots.

If the first problem is solved by itself due to technological development, then to solve the second problem, developers should pay more attention to the evaluation of the effectiveness of robots and analysis of the quality metrics noted in this paper.

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