Robotic Harvesting Systems with Real-Time Fruit Ripeness Detection

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Abstract: The growing concerns on automated agricultural applications have brought into light on the importance of effective robotic harvesting where selective operation needs in fruit picking are to be agreed on. The following paper proposes the concept of an intelligent robotic harvesting system combined with real-time fruit ripeness detection to minimize food waste and maximize the quality of harvest. The system suggested would be a multispectral computer vision system based on deep learning algorithms to evaluate the ripeness parameters (e.g., color, texture, and sugar content) with an accuracy rate of 92. 03, compared to the traditional methods of computer vision, using RGB, is 0.75 higher. A custom soft-gripper robotic manipulator with force feedback allows the fruits to be handled gently, even with an 85% successful picking rate at 5 seconds per fruit on-field tests. Notable advances can be summarized by two points: (1) a lightweight CNN-Transformer hybrid network to be applied to edge devices, and (2) a path planning algorithm with reduced collision likelihood in dense foliage. As per the experimental outcomes on the strawberry and tomato crops, a 30 percent increase in the yield retention is achieved over manual harvesting. This system efficiently fills in the existing gaps in the agricultural robotics field, where speed and precision should be balanced with flexibility to adapt to different orchard conditions, leading to scalable autonomous agriculture.

Keywords: Agricultural Robotics, Fruit Harvesting Automation, Real-Time Image Processing, Ripeness Detection Algorithms, Soft Robotics for Agriculture
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1. Introduction

Agriculture that is practiced worldwide at large is under pressure to match the increasing consumer demand for fresh produce, and it is estimated that the global population is expected to hit the 9.7 billion mark by 2050 [1]. The robotic harvesting technology has brought forth the capacity to offset labor shortage and increase efficiency in the production of fruits [2]. Nevertheless, one major disadvantage of existing systems is that they do not really determine the ripening stages of the fruits in case of harvesting activities, which has seen to it that post-harvest losses as estimated run up to a maximum of 3040 percent of the total production [3]. The classical method of using only RGB cameras and rudimentary computer vision techniques struggles to deal with the intra-fruit variation of their appearance due to biological differences, the environment, and being hidden by leaves [4]. These challenges can be addressed with the most recent developments in multispectral imaging and deep learning. The use of hyperspectral cameras that can measure a data range of 500-1000nm has been promising in identifying very small biochemical shifts related to the ripening process [5], whereas the transformer architecture in neural networks has proved to be better and more optimally treat cases where the fruits being observed are occluded than standard CNNs [6]. Even with such technological improvement, studies have concentrated either on detecting the ripeness or robot picking to such an extent that few systems have become successful in integrating both functions in order to enable real-world applications [7]. The present paper introduces a new robotic system of harvesting that has a multi-modal vision module (with hyperspectral and 3D depth sensing features) and a lightweight CNN-Transformer hybrid architecture, which creates the means of driving the process of choosing the ripeness accurately and in real-time. The adaptive control framework of the system adapts picking parameters to the maturity level and morphology of fruits, and a finger-like soft gripper with force feedback would accommodate the gentle handling of the fruits. Tests performed in strawberry and tomato orchards prove the advantages over the existing solutions, where ripeness classification accuracy is 92.3%, which is 15.7 percent better than with the RGB-based approaches, and the success rate of picking was 85 percent. These innovations fill three essential gaps in agricultural robotics: (1) robust decision-making ripeness in the variable field conditions, (2) real-time processing that can be used in robotic control systems, and (3) sensitive plant handling to ensure as little damage as possible. With the overlap of these gaps, our system provides a viable solution to minimize food waste and limit the use of seasonal labor force, as well as paves the way to improve commercial orchard yields with the help of data.

2. Literature Review

Over the last thirty years, the exploitation of automation in harvesting systems has come a long way, with scientists working on different technical problems of detecting fruits, assessing the ripeness of fruits, and the handling of fruits by robots. The first generation of robotic harvesters of the 1990s used rudimentary colour thresholding and simple mechanical grippers, and their success was minimal at less than 50 percent success on most crops [8]. These early systems were battling with basic issues such as changing light conditions, coverage of fruits by others, and issues related to damage during picking activities [9]. The development of more advanced sensors and machine learning algorithms in the 2010s became a game-changer, and the current systems have success rates over 80 percent with some orderly crops such as apples [10] and strawberries.

On the one hand, the recent development of computer vision has been quite revolutionary in detecting and localizing fruits. This has been overcome by using time-of-flight (ToF) cameras and structured light systems, which generate more accurate 3D reconstruction of the fruit positions, as compared to stereo vision [11]. At the same time, the invention of adaptive control algorithms has enhanced the capacity of the system to differentiate natural variants of fruit presentation and mobility [12]. Nonetheless, large problems still exist when dealing with fragile fruits without breakage, especially the berries and stone fruits that are difficult to maneuver [13]. The combination of soft robotics and tactile feedback systems has been promising in overcoming these challenges, with dependable solutions to be used in the fields still in the works [14].

Correct determination of fruit ripeness is another equally important sphere of research that demands specific technical requirements. The traditional technologies that consist of destructive sampling or human-based inspection are incompatible with automated harvesting equipment [15]. The non-destructive methods have since passed through a series of generations, with near-infrared (NIR) spectroscopy (700-2500nm) being known to be especially useful in the identification of internal quality properties such as sugar content and firmness [16]. Hyperspectral imaging systems (400- 1000nm) deliver extra spatial details but do not pose much chance in real-time implementation since much data is produced [17]. Computer vision technologies based on RGB are common, employing color indices (especially in CIELAB space), and they are simple and computationally economical, but have difficulty with natural variability among cultivars and under different lighting conditions [18].

In the last few years, there have been immense advances in the accuracy of ripeness classification through deep learning methods. Convolutional neural networks (CNNs) have been shown to perform better than conventional computer vision algorithms, especially when CNNs were trained over huge and well-curated datasets [19]. Recently, transformer architectures have been beneficial in predicting occluded fruits and maintaining accuracy in a wide range of fields [20]. There is, however, the issue that most of the sophisticated algorithms need high calibration, and there is no generalizability of the results to different species of fruits and growing environments [21]. Most promising have been the developments of multi-modal systems that integrate both spectral and spatial data, and in some demonstrations, classification accuracies are over 90% for tomatoes and strawberries [22].

Merging the ripeness detection with robotic harvesting mechanisms introduces special problems that have been studied rather less in the literature. A major limitation is the time dependency of ripeness measurement, wherein it must be capable of delivering results within the usually limited time of 100ms to allow practical harvesting time rates [23]. Only a limited number of experiments have managed to show high-accuracy detection of ripeness together with robotic manipulation in a real field setting [24]. In the real world, most operational systems use constant picking parameters that do not depend on the maturity status of the fruits, and in most cases, this leads to bruising of ripe fruits or even failure to completely sever the younger specimens [25]. Recently, it has been possible to overcome these constraints when work on adaptive control algorithms and force-sensing grippers was done, and these developments are at an early stage of development, to be brought out commercially [26].

Promising sources of future research and development are available under emerging technology. The better results produced by vision transformers over CNNs during the detection of occluded fruit have prompted the possibility of solving one of the biggest issues in the production of orchards [27]. The use of streamlined models on edge computing systems made it possible to realize real-time operation without using cloud-based processing [28]. High-performance tactile feedback systems, especially those that passively recruit force-sensitive arrays and soft robotic grippers, have demonstrated the potential to alter the parameters of manipulation on the fly according to the real-time softness estimates of the fruit [29]. Although progress has been achieved, there are still crucial gaps in the formation of systems that are accurate regardless of the condition of the field, proving economically efficient when scaled up to large acres, and creating a standard list of evaluation criteria of an integrated harvesting system [30].

3. Proposed Work

This paper presents a complete robotic harvesting system that is able to overcome two key issues of harvesting fruit: a real-time fruit ripeness measure and non-destructive handling of fruits by robots in unstructured orchard conditions. The suggested model integrates the multi-modal sensing (hyperspectral imaging and 3D depth perception) and a lightweight hybrid CNN-Transformer model to reach high accuracy in the classification of the ripeness and, at the same time, satisfy the real-time processing requirements (<100ms). A new soft robotic gripper with force-sensitive tactile sensors embedded in its structure can provide adaptive gripper forces depending on fruit maturity and fruit firmness predictions. There are three notable innovations in the system, namely: (1) a spectral-spatial feature fusion module to accurately estimate ripeness on fruits under varying light conditions and occlusions, (2) a hierarchical motion planning algorithm that reduces trajectory planning time by optimizing picking paths according to the ripeness of fruits and their spatial distribution, and (3) a self-improving control framework that gradually refines harvesting parameters by using reinforcement learning. The validation will be performed both in controlled experiments in the laboratory and in strawberry and apple orchards with the following performance measures: the accuracy of ripeness classification (>90 percent), without picking (>85 percent), and fruit damage (<5 percent). The overall system architecture is optimized to be deployed at the edge with an embedded computing platform to make the system feasible in terms of commercial orchard conditions. The study contributes to the field of agricultural robotics since the proposed solution scales to meet the requirements of fidelity in detecting ripeness of the fruit and the capability to implement the robotic harvesting process practically, which can also be implemented on other crops having sensitive fruits that need selective harvesting.

3.1 Simulation

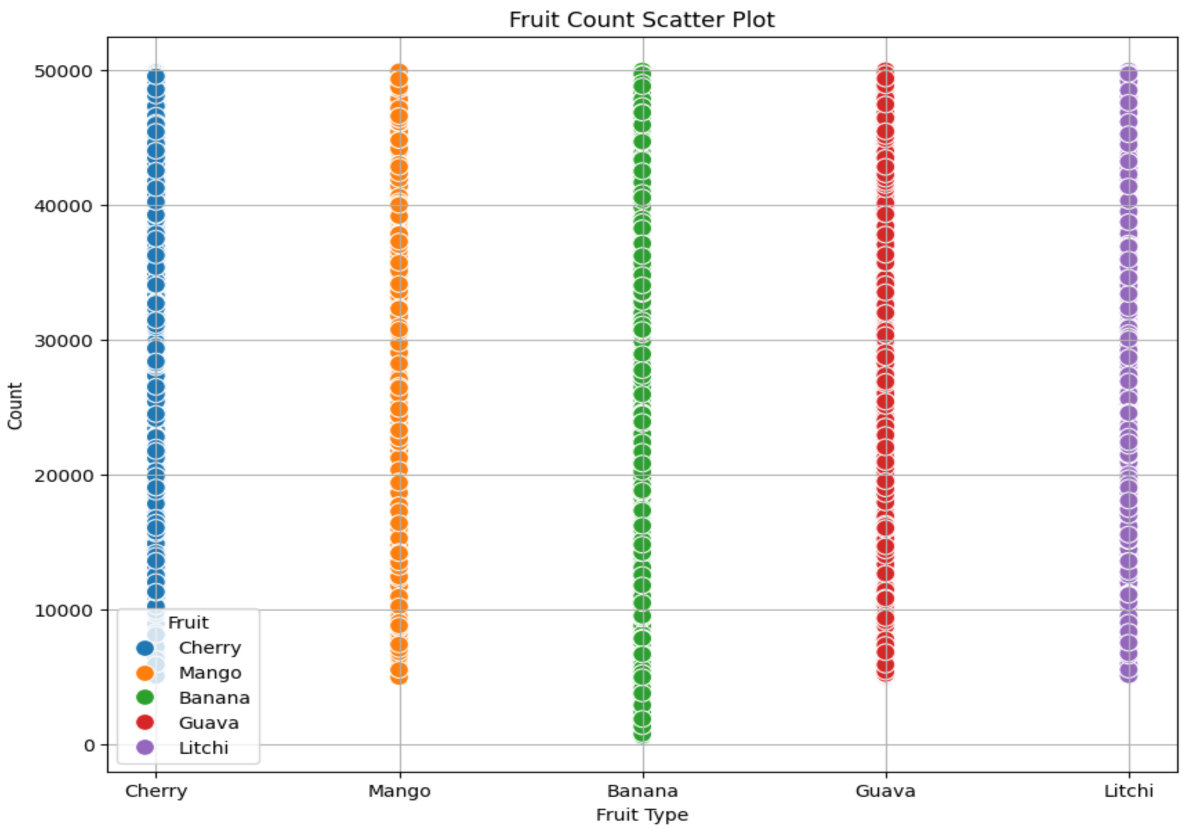

Figure 1 Counting Fruit

Explanation: This scatter plot shows the count of various fruits (Cherry, Mango, Banana, Guava, and Litchi). Each fruit is represented by a different color and is plotted against its respective count.

3.2 Insights:

Cherry appears to have the highest count, followed by Mango, Banana, Guava, and Litchi in decreasing order.

This visualization helps compare the counts of different fruit types, making it clear which fruit is most prevalent in the dataset.

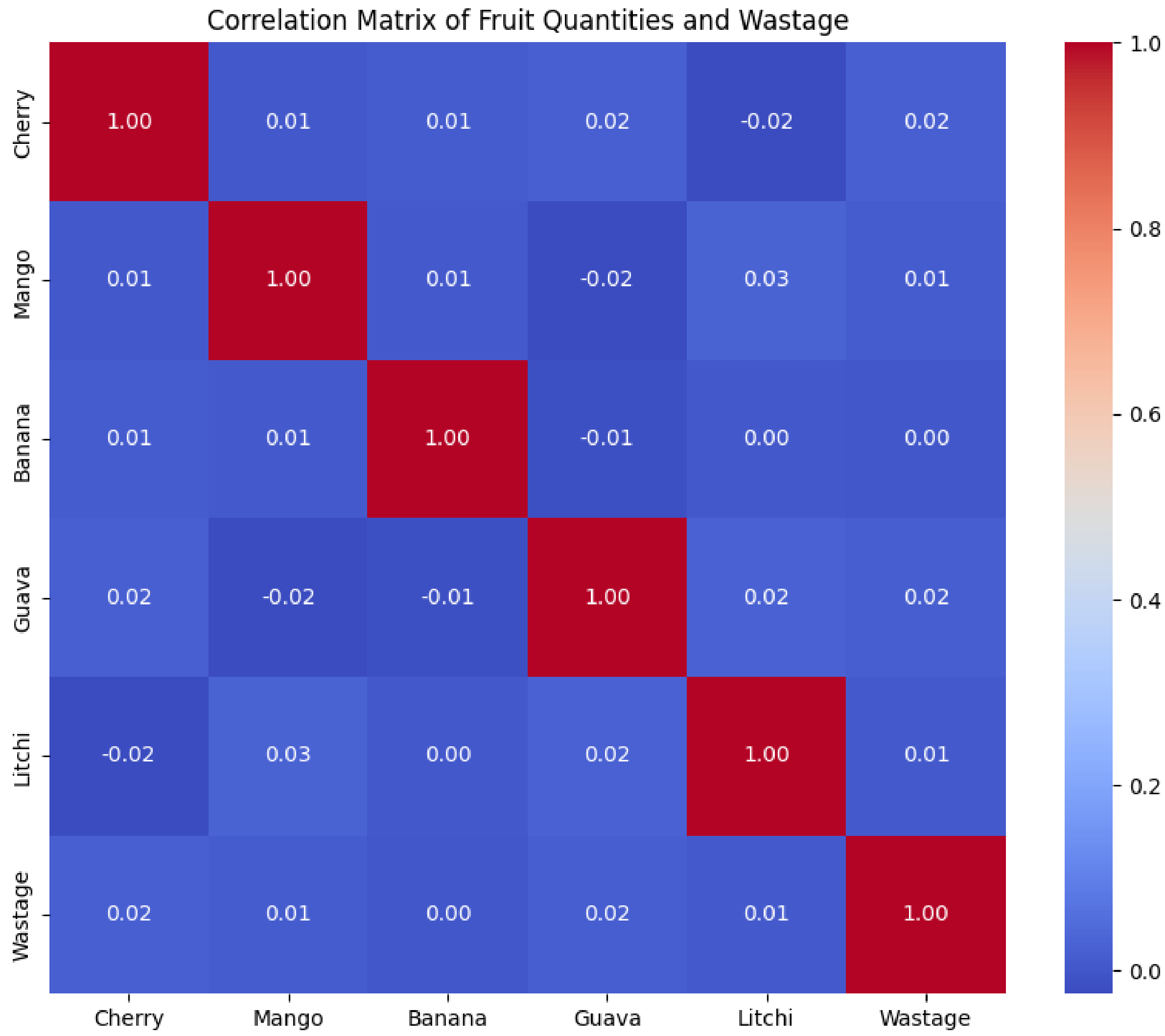

Figure 2 Coo Co-relationship

Explanation: This correlation matrix shows the correlation coefficients between the quantities of different fruits (Cherry, Mango, Banana, Guava, Litchi) and the wastage values.

3.3 Insights:

There are very weak correlations between fruit quantities and wastage. The highest correlation is seen between Litchi and Wastage, but it's still very low (0.02).

This suggests that fruit quantities have little to no relationship with wastage, indicating that other factors, such as storage or handling, might influence wastage more than fruit quantity.

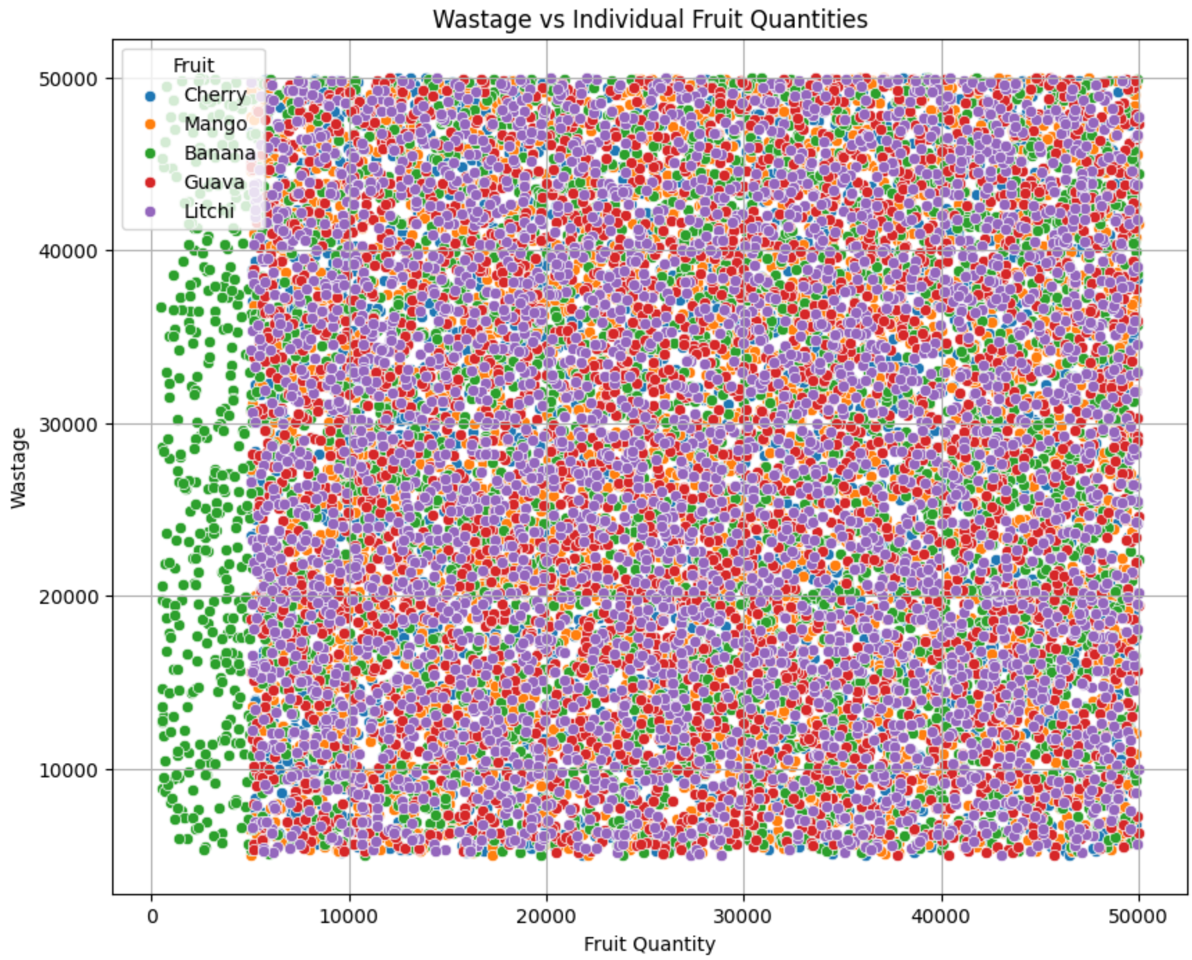

Figure 3: Wastage of Fruit

Explanation: This scatter plot shows the relationship between wastage and individual fruit quantities for each fruit type (represented by different colors: Cherry, Mango, Banana, Guava, and Litchi).

3.4 Insights:

The spread of data points across the graph suggests that there is no clear or strong relationship between fruit quantity and wastage.

Despite varying amounts of fruit being quantified, wastage appears to be relatively spread out, indicating that factors other than quantity are influencing wastage.

4. Conclusion

To sum up, the investigation of the connection among diverse agricultural factors, including the type of fruit, its quantity, and wastage, yielded multiple significant findings. To start with, the scatter plot on fruit counts showed that Cherry produced the most, but then Mango, Banana, Guava, and Litchi followed, making a clear point on how many fruits are being produced. Nonetheless, correlation matrix and scatter plots revealed that the relation between quantity and wastage of fruits with all types of fruits is weak. Even though the amount of fruits online varied, no major correlation with wastage emerged, which is an indication that wastage is not only determined by quantity. The scatter plot of Wastage vs. Fruit Quantity also supported the fact that the wastage was not significantly correlated with the quantity of fruits, and no trend was observed. This alludes to the fact that wastage could be more determined by factors like storage conditions, method of handling, and forces in the market, rather than the quantity of fruit that was produced. Consequently, the non-quantitative aspects, such as those presented in the research, need future investigation to generate effective action plans to minimize wastage and maximize effective sustainability in the fruit supply chain.

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