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Agriculture 4.0 for Postharvest of Fruit: A review

Review

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Abstract

This review aims to identify prominent studies related to applications of novel techniques involving sensors and machine learning for fruit storage through the method of narrative literature review, considering the concepts of Agriculture 4.0. The advent of this new phase of agriculture brought new concepts for post-harvest professionals and scholars, such as to sensor technology and automated intelligence. Additionally, a collection of 28 studies focusing on post-harvest of fruit in the span of five years (2018 to 2022) was carefully evaluated in order to discuss the most prevalent techniques explored in the field. Therefore, this review provides a picture of achievements in a relatively new area of knowledge with supporting data and discussion analyzing the current panorama in the PHF context and how effective is the use of sensors associated with artificial intelligence for post-harvest of fruit. Among the latest developments highlighted, the application of support vector machine classifiers as machine learning algorithms alongside computer vision sensors are the most promising technologies in terms of accuracy and popularity among recent scientific developments for post-harvest of fruit. Implementation of such new technologies must consider constraints related to different national contexts.

Keywords: Food engineering; computer science; smart storage.

Highlights

- Contemporary fruit postharvest benefits from sensor technologies and artificial intelligence.
- A myriad of postharvest sensor types and applications have been reported.
- Computer-vision systems integrated with SVM classifiers are prominent among relatable studies.

Introduction

Importance of technology for post-harvest of fruit

Reducing losses of postharvest of fruit (PHF) should be pursued due to the alarming state of food crises around the globe. It is estimated that in the year of 2021, more than 193 million people were considered to be in a state of food insecurity crisis, with 570.000 of these people currently considered to be under a catastrophe phase, demanding urgent action. A state of food insecurity crisis is when local capacities to respond to food shortage are insufficient and demand international aid. A catastrophe phase of hunger is characterized, according to Food Security Phase Classification and Cadre Harmonisé, by displaying widespread starvation and death[1].

With driving factors such as conflicts, extreme weather conditions, and economic shocks being the main drivers of food crises, the mitigation of food waste through enhanced practices on PHF is of uttermost importance. This review aims to identify prominent studies related to applications of novel techniques involving sensors and machine learning for fruit postharvest physiology and quality through the method of narrative literature review. Both topics are discussed as new advents of "Agriculture 4.0" (A4). In order to highlight the newest information available in the field, the review focused on studies from the last five years (2018 to 2022).

Fortunately, this paper also stands as a reference material for basic preliminary knowledge regarding the use of computational algorithms in PHF. Many misconceptions may arise for professionals inserted in PHF but still not aware about the A4 possibilities. Sometimes it is easy to spot basic misconceptions being propagated due to that, like machine learning and artificial intelligence being interpreted as synonyms. Clarifying such concepts, exposing scientific findings and debating about the prospects of A4 in PHF in the world is another priority for this paper.

What is Agriculture 4.0 for Post-Harvest of Fruit?

The terminology "Agriculture 4.0" derives from the similar "Industry 4.0", meaning the fourth era of agriculture. Industry 4.0 (I4) achievements' can be measured with a certain degree of straightforwardness and easiness throughout many scientific reviews, stating a precise definition of I4 might be a point of controversy. The first academic definition has been reported academically in 2014 [2], being formally presented to the public by a German working group in 2013[3].

To avoid similar complications when discussing A4, the paper of Silveira, Lermen & Amaral [4]introduced many words associated with this concept. The authors encountered in their investigation a great variety of synonymous for A4, some of these being ''Smart farm", ''digital agriculture", "smart agriculture" and "Agri Artificial Intelligence". The aforementioned review considers A4 a particular niche of new technological and methodological approaches focusing on obtaining and processing data, while conducting farming operations. An interesting aspect is the fact that the A4 label is commonly associated with sustainable production [5].

Moreover, this paper aims to cover the absence in-depth reviews strictly focused on A4 recent achievements for postharvest of fruit (PHF). With this in mind, this review stablished their parameters of AI4 novelties by treating it as a co-concept of I4, as it was written by Kong et al. [6]Here in this paper, A4 advancements for PHF relates to new processes, algorithms, systems, or devices collectively applied. Such applications should encompass data collection and the use of accurate decision-making tools in a PHF context.

Main concepts

Sensor technology

An acceptable definition for a sensor is to consider it as any device able to receive a signal or stimulus (whether it is physical, chemical, or biological) and capable to answer in the form of an electrical signal. The application of sensor technology reaches an enormous number of practical uses in our daily lives directly or indirectly [7]. Novelty uses for sensors in fruit postharvest research has some remarkable advancements.

Adapting for the PHF reality the categories established by Zujevs et al. [8] for sensors used in harvesting activities, the current main sensors applied on PHF can be classified as Computer Vision Sensors (CVS), Chemical Sensors (CS), and Tactile Sensors (TS). CVS works through special algorithms or methods that can process fruit quality traits such as color, geometry, texture, or even a mix of multiple traits, while CS comprises a wide range of sensors intended for the detection of various organic and inorganic substances in air, liquid, and solid samples. The TS are able to measure physical effects on objects or through indirect gripping. The chart below contains a description and application for each sensor.

Internet of Things

Another topic in vogue and widely cited in publications is the terminology Internet of Things (IoT). IoT can be defined as an interconnection between people, animals, or objects that can exchange data over the network without involving human-to-human or human-to-computer interaction[9]. In simple words, it is an emerging paradigm enabling the communication between electronic devices and sensors [10]with the ultimate goal of connecting anything, anyone, at any time [11].

Practical sensor implementation for PHF can be obtainable through the application of the IoT concept. Sensor readings can be stored in computer hardware or online databases for real-time measurements and analyses. This way, it is possible to carry out large data collection in studies involving PHF processes, like storage or grading of fruits. As described by Kaur & Aslam [12]the large amount of data generated from IoT developments is called big data, being a contemporary challenge to handle large sums of data in an effective way. Among the analytical resources able to manage IoT big data, machine learning (a sub-category of artificial intelligence) is cited.

Artificial Intelligence (AI)

Definitions about artificial intelligence (AI) have changed over time, depending on the approaches or contexts. According to Bartneck et al. [13] the common traits defining AI are that it ''involves the study, design, and building of intelligent agents that can achieve goals". AI can be used alongside IoT for practical purposes. Chakshu (2019) has demonstrated a good example of a simplistic and effective application AI and IoT with a user-friendly application able to collect and display real-time data using sensors in a cold chamber containing fruits and vegetables.

At the current scientific stage, AI works best in constrained environments. On the other hand, AIs used in open environments are prone to subjectivity. Current AI possesses limited ability to reason analogically (selecting answers through comparison of similarities on past observations) when facing a new task similar to one anteriorly explored. Thus, such systems are unable to use common sense akin to humans [13].

Machine Learning

According to Bartneck et al. [13], machine learning (ML) is a sub-field of AI focused on the creation of algorithms through previous experience obtained with a given class feedback, with its performance able to improve continuously with the influx of input. The key difference between supervised and unsupervised is that while the first uses labelled data and has a training phase with data, the second does not uses previous classified data does not pass through a training phase [14].

Data sets meant to be analyzed by ML must be well prepared and curated in order to have better accuracy and results. In a study focused on the creation of a dataset in India, more than 19.500 labeled images of apple, banana, guava, lime, orange, and pomegranate were processed for the dataset divided into three categories of fruit quality [15]. Another important detail for the field of machine learning is the recurrent presence of an element called classifier. Classifiers are learning algorithms able to classify new, unseen instances correctly [16].

Methods of classification may vary according to the type of machine learning applied. For unsupervised classification, the K-means clustering and principal component is used. For supervised, some examples of classifiers are KNN clustering, Bayesian classification, Artificial Neural Network, and Support Vector Machine algorithms. In short, computing power is used to learn from experimental data and gives an output of unseen input through mathematical approximation and interpolation[8].

The use of ML may be a way to reevaluate postharvest procedures adopted in commercial environments. In a paper that explored logistics of horticultural goods, new insights were explored with the use of AI. By applying ML in a stock management context, it was determined that onions harvested six days later than usual could hold better during storage, than onions harvested three days later than usual. Such a finding might be a good point to start testing machine learning on fruits and vegetables to determine adequate logistics for whole and retail sales [17].

Applications of ML in PHF

Contactless methods are praised due to their quality analysis in PHF. The use of photographic images for the assessment of fruit quality is a traditional way of cataloging and studying fruits. A contemporary study used fruit pictures of 153 cultivars of persimmon, concluding that shape formation was determined in early developmental stages across cultivars [18]. Another important aspect to be noted is that the traditional way of sorting and grading fruit can be expensive, laborious and inconsistent when accomplished manually [19]. In that case, the use of CVS could help optimizing grading and sorting processes.

CVS can be used to extract features in segmenting pixels utilizing support-vector machine (SVM) to detect small defects on fruits [20]. Although studies have shown that SVM classifier has high precision on detecting defects on apples, pears, pomegranate, and litchi, these studies have also highlighted the absence of pre-trained network required to create a database of defected fruit, which requires time, labor and investments. Further advancements in the development of deep learning-based classifiers for accuracy improvement based on pre-trained networks will enable a reduction in the processing time along with better prediction probability [20]..

CVS works even on microscopic scales. An example is the exploration of a sensor system created initially for the identification and quantification of pollen grains, which was also applied to track fungal spores of Alternaria spp[21].

The possibility to monitor and identify early fungal infections allows the application of control treatments to reduce decay incidence and crop losses before and after harvest. Additionally, real-time monitoring of fungal load in a close environment, such as grain or fruit storage, will allow a more precise estimation of fungal decay incidence, which can be used to optimized control strategies to minimize food losses. For example, CS has been reported to be successfully used to detect bifenazate, paraquat, azinphos-methyl, thiometon, and parathion-methyl in lime fruit [22].

The "electronic nose" sensor has been show to precisely detect four fruit species, pitaya, pear, kiwi, and apple, in storage environments. In addition, the sensor was also able to distinguish between healthy and spoiled fruits [23]. In other study, surface-enhanced Raman spectroscopy (SERS), method based on octanethiol-functionalized core-shell nanoparticles, was able to precisely detect fungicide contaminations in apples and pears[24]. In this study, the sensor was able to detect contamination levels at concentrations of 0,015 and 0,016 ppm in apples and pears, respectively, demonstrating that the silver-coated gold nanoparticles can work as sensitive SERS platforms to detect the fungicide contaminations in fruits [24].

Aiming at AI developments and sensor technologies applications on postharvest of fruit, the research narrowed down to collect studies combining both in postharvest of fruits. All studies were carefully skimmed and had key aspects discriminated in the table below, pointing to each one the data collection methodology, the sensor category, fruit studied, the classifier algorithm applied for analyses, experiment details summarized, conclusions obtained and basic information identifying authors and the publishing year.

The metrics for comparison were the use of different machine learning algorithms applied along with the percentages of success that each sensor achieved when submitted to the evaluation of the classifier, based on recommendations by Baeumner et al. [25]. Our review selected and detailed explored 31 relevant publications that combined sensor technology application with machine learning concepts in PHF. The chosen papers were published between 2018 and 2022 (Chart 1).

Discussion

Sensor technologies in PHF

Widespread utilization of CVS and artificial intelligence applications partly relies on the popularization and accessibility of anthologies. The creation of a collection of photos displaying pictures for a computer vision analysis is called an anthology[51]. Such anthologies must be collected and curated to develop effective algorithms for machine learning. In a paper focusing on the creation of public datasets applicable for computer vision in precision agriculture, it is reported that one of the most crucial bottlenecks regarding the use of technologies connected to artificial intelligence and robotics is the scarcity of public datasets available to be used [52]. Datasets collection were also highlighted throughout the papers explored. It is noticeable that the collection of such data might be a very time-consuming and long endeavor since useful datasets consist of large amounts of photos.

CS can be an alternative in the post-harvest of fruit when there is the necessity of gas detection. The studies exposed interesting possibilities where gas detection by CScan achieved with greatrate of success, like formalin [53]. for fraud detection and ethylene [27] for ripeness assessment. Another positive aspect is the prevalence of studies combing CS with CVS, as it happened for evaluation of mango visual and odor quality analysis [47]and vitamin C detection combined with ripeness assessment on citric fruits[48]. Although the combination of sensors is helpful and provides valuable data for post-harvest processes, a smaller prevalence of studies analyzing CS for post-harvest of fruits might be due to complexities attached to its implementation and maintenance. A recent detailed analysis of contemporary CS applied in science concluded that gas selectivity and long-term stability of its electronical components are challenges to be overcome for the time being [53].

TS were present only in 3 studies but had the advantages of being applied in many different types of fruits, such as apple and mango [48], apple and strawberry [49]and orange, kiwi, tomato and apple [52]. One aspect that might hinder the application in commercial level of such sensor would be the higher mechanical complexity of it. This position holds true especially when the dominant CVS type, present in over 80% of the collected studies, demonstrates a much less overall complexity of machinery. On the other hand, it can useful to rely on TS especially in post-harvest facilities where fruit handling occurs by mechanic apparatus. For such cases the mechanical grappling of fruit can be combined with firmness measurement, for example [8], providing useful information for fruits grading and interesting for commercial purposes.

Classifiers in PHF

There are drawbacks currently in the algorithm application of ML. They are complex, expensive, consume high power and requires large hardware setup for realistic implementation. The optimization of ML classifiers (such as k-fold cross-validation, that uses smaller datasets) followed by single-sensing devices with low-power consumption are welcomed ways able to make the technology sustainable and attainable for practical scenarios [53].

It is been established that most of the studies collected brought a high percentage of accuracy at least with one of the classifiers applied, with paper frequently exploring more than one classifier. Overall, many diverse classifiers can be used in the context of PHF, but SVM stands as the most popular classified among the collected papers. Moreover, it is also noticeable the wide variety of fruits explored in the universe of works presented, demonstrating the applicability of this technology for many distinct kinds of fruits.

Due to the exploratory nature of this paper focused on PHF applications, a deeper discussion regarding the architecture and other advanced details for algorithm classifier, this paper will not overstretch on mathematical and computing details for every programing architecture adopted on every study. Focusing on identifying classifiers posed as a more practical information for PHF. Nevertheless, the classifiers are an aspect to be reckon in PHF as a way of identifying the main element enabling the operation of ML systems.

The least used classifiers should not be necessarily understand as being less effective. As Rivai et al. showed a three nearest neighbors (3NN) architecture able to provide accuracy of 91% for durian fruit ripeness recognition [27]. Sreeraj et al. also reported using convolutional neural network (CNN) for a cast of tropical fruit and obtained over 90% of overall precision [29]. Other classifiers that appeared only one time were k-means clustering for the sweetness grading of watermelon (Nazulan et al., 2020), and it appears that the authors based his choice also acknowledging that previous studies applied similar classifiers.

The same can be observed with Cavallo et al. results where accuracy reached 92% for Victoria and 100% Italia grape cultivars by using Random Forest Classifier (RFC) [35]or Santos et al. findings obtaining a 95.6% of precision of vitamin C detection among citric fruits by using Linear Discriminant Analysis (LDA) [47]. By no means has this paper wanted to spark discrimination among algorithm architectures, since there is a variety of reasons on why certain studies might adopt specific algorithms on top of others and such topic would demand a paper by their own. However, diverse algorithms approach can be beneficial since every type of sensor and fruit targeted might have different performance. Having more than one classifier tested and also measuring other aspects like speed of processing time [41]can be the best approach in order to get objective answers for post-harvest of fruit.

SVM classifiers were present in 11 papers collected, being the most prevalent classifier with evaluation rates indicating successful results. The dominance of CVS implementing SVM models ere noticed in a big quantity of recent experiments. SVM showed successful use for apple, pear litchis, mosambi and pomegranate [20]; cape gooseberry [31]; dragon fruit [34]; lemon, apple, avocado, banana and orange [19]; oleaster [39]; papaya [41], oil palm [38]; mango [46]; apple and mango [48]and orang, kiwi, tomato and apple [50].

In a particular instance, SVM also had associations with HOG features that enable 100% of accuracy with SVM, such as quadratic, fine Gaussian and cubic. However, KNN associated with HOG displayed an outstanding 100% of accuracy for machine learning approach for papaya classification of maturity status with a much lesser training time of 0.0995 seconds. In this case, it is worth noticing that the training time wasn't took into consideration in the other studies and such information is crucial for practical applications that would require fast processing times ideally [41].

Another interesting aspect is the fact that when used in papers analyzing CVS modifications with electrical pulse device (TS) for ripeness detection of oil palm fruit [38], CVS combined with CS for qualitative discrimination of mango quality [46]. It is worth noticing the high accuracy of SVM for TS sensors being detected on two of the three papers involving such category of sensor. This can be an advantageous aspect of SVM for this particular kind of sensor technology.

For this group, apple and mango quality outperformed KNN and D-Tree by using SVM for moisture analysis in all 4 days evaluated when considering overall accuracy when observing the quality metrics for each obtained from leave-one-observation-out-cross-validation technique [48]. In other studied that analyzed orange, kiwi, tomato, and apple hardness recognition, TS with SVM got an overall performance of 94,27% of accuracycompared to 90,03 obtained from KNN.This highlights the importance of the classifier being a good tool for development of robots able to perform non-destructive picking [50].

Other classifiers also had a noticeable rate of appearance, the CNN classifier appeared 4 times in different researches [29, 30, 34, 36] while ANN figured 5 times on papers [31–33, 42, 43].

Implementing A4 solutions under different economical contexts

Generally speaking, developed countries are investing heavily on AI technology and such implementations are both widely researched and used. Such nations are already undergoing through the process of adoption of AI for various purposes. Post-harvest of fruit is also one of these invested areas. In a research about the impact of AI and computer visions systems on agriculture, it is mentioned that developed countries tend to be the first ones where innovations replaces the old-machinery. It happens due to a great investment on R&D able to be inserted on public use [54].

Underdeveloped countries shall have extra challenges for post-harvest in agriculture in general. Specialized research points out many problems related to AI initiatives on developing countries across the globe. One of the issues is the lack of human resources with enough expertise. The precarious state of technological infrastructure is also an issue to be reckoned. Other setbacks brought into light for countries with ongoing industrialization are insufficient financial capabilities, data availability, regulatory framework, interdisciplinary collaboration among other issues [55].

The findings of a review focusing on the impact of the generative AI use in developing countries indicates the necessity of educational systems incorporating AI teaching and infrastructure in order to provide an inclusive development through AI in many applications instead. Otherwise, the non-expansion of digital infrastructure along with AI investment might generate broader inequalities for developing countries [56].

Government support might be a valid way for the promotion of AI solutions in agriculture on developing countries. India in particular have been cited as one of the nations with the fastest growing market for AI and it correlates with government efforts for the promotion of AI research, development and adoption, according to the Grand View Research statistical report [57].

With so many challenges ahead, developing countries can adopt measures to increment AI improvements on post-harvest. In regards on how developing countries can enhance the implementation in large scale of AI solutions in agriculture, a specialized study recommends collectives approaches focusing on formulation of new regulatory policies and public and private investments. Such approaches must be held also with a sustainability goal in mind for an adequate development of these countries [55].

Data collected by FAO [58]shows that losses during post-harvest ranges between 9 to 10% of Latin America, Asia and Africa total food loss in these nations. For industrialized Asia, North America, Oceania and Europe, losses are estimated between 5 to 8%. It is debated that solutions for these problems should be tailored according to each socioeconomically context, not being a simple solution applicable to every nation [59].Onyeaka et al. [60] states that AI in the food industry can improve energy efficiency, extend food shelf-life and enhance decision making processes.

According to Aderibigbe et al. [61]a valid route to ensure food security is through massive investment on AI solutions. The authors state that public initiative and private endeavors must direct efforts to enable AI development as whole in the society. An interesting approach was adopted by the educational sector, where a special learning program for farmers and future was designed in order to provide topics about AI applied for precision agriculture [62]. Similar educational approaches can be adapted and applied for the training and education of professionals related to the A4 novelties in the PHF field.

Market share of sensor technologies and AI in PHF

Implementation of artificial intelligence integrated with sensors as practical solutions for fruit industry is already a reality. In a recent review about the state of the art of AI for agriculture encompassing the analysis of 586 papers from 1994 to 2022, it was perceived a higher volume of papers focusing on AI applications for PHF between 2009 and 2022. Among the total of papers analyzed, China stands as the country with the highest number of publications (307) followed by the USA (129) and India (109) [63].

Numbers brought by data research institutions indicates that in 2023, all of the end-use of AI in the market (such as advertising, healthcare, manufacture, agriculture and others) was worth around $196.63 billion. Future projects estimates that by 2030, the global AI market shall accrue $1.81 trillion, according to Grand View Research estimative (2024). It is reasonable to conclude that AI came to stay, being already a viable option for PHF commercial enterprises.

The future of sensor technologies and AI in PHF

The diverse objectives from each study demonstrate that developments in sensor technology can be of great flexibility for PHF, especially regarding ripeness parameters and grading processes, which is positive for more efficiency. CVS main challenges are variable light conditions in PHF environments, occlusion, clustering of grouped fruits, uncontrolled environment, and variable physical proportions of fruit[8]. Further studies embracing diverse classifiers and sensor concepts for PHF are expected. SVM classifiers along with CVS appears to be promising candidates for future successes. Assessing the processing speed of algorithms along with a wide variety of fruits might be the key to bring this technology to an even broader audience outside academy.

Final Considerations

This paper intended to contribute in the discussion of contemporary postharvest science by exposing novelties in Agriculture 4.0. It provided basic explanation of computer science concepts in the context of post-harvest of fruits. It was detected a rich landscape regarding classifiers and sensor technology in PHF, being it a lucrative market according to recent numbers. In order to favor more AI endeavors in PHF worldwide, it is necessary continuous investment in countries under intermediary stages of development, including investment in the training of PHF professionals, in order to have a work force able to apply such AI novelties. It is of uttermost importance academic studies focusing on PHF solutions viable for tropical countries under development due to their higher waste during post-harvest.

Conflict of interest statement

Nothing declared.

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