Review of AI Application in Post-Harvest Processing Technology

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***Abstract*— Post-harvest processing is one of the important aspects of farming. A lot could be hinged on it to make or mar the whole farming process either through increased shelf life for the harvested crop or the introduction of contaminants and other impurities. Several post-harvest processing technologies have been developed and used over the years. The paper conducted a systematic literature review of articles that have proposed Artificial intelligence (AI) in their post-harvest process. A total of ten (10) articles with publication dates ranging from 2018 to date were selected and reviewed based on set selection criteria. The work has highlighted the level of success, AI has brought to post-harvest processing as a whole and identified areas for improvement. The study has shown Convolutional Neural Network (CNN) dominance across several post-harvest processing segments. It has also identified features such as Image, Size, and weight as some of the key features/parameters used by the AI model used across the post-harvest processing operation segment. The study has also identified post-harvest segments such as cleaning and sorting as segments that will require more AI innovation.**

***Keywords*—eAgriculture, Artificial Intelligence, Machine Learning, Post-harvest processing**

I. INTRODUCTION

In recent years, the world has witnessed an extraordinary transformation in the agricultural landscape, with technological advancements playing a pivotal role in maximizing efficiency and sustainability. Among the most groundbreaking innovations, Artificial Intelligence (AI) has emerged as a powerful force, reshaping the post-harvest processing sector in ways never imagined. As global food demand continues to surge, optimizing post-harvest handling is becoming increasingly crucial to minimize losses, enhance quality, and ensure food security for a burgeoning population.

Traditionally, post-harvest processing has been a labour-intensive and error-prone process, leading to substantial losses of perishable produce during transportation, storage, and distribution. However, AI has opened a new realm of possibilities by empowering agricultural stakeholders with data-driven insights, real-time monitoring, and predictive analytics. From smart sorting systems and autonomous robotic technologies to intelligent decision-making algorithms, integrating AI into post-harvest processing promises to revolutionize how we handle and preserve our precious agricultural yield [1].

In this article, we conducted a systematic literature review on works that have proposed AI-powered post-harvest processing technology taking into account the various segments in post-harvest processing operations i.e. cleaning, sorting, grading, and storage to provide us with a clearer understanding of the extent of contribution done in this regard and to highlight areas that require more research.

This article is organized as follows. Section II discussed related works done in this area of study. In Section III, the criteria and processes for paper selection are defined. In Section IV, results were presented and discussed. Finally, this survey is concluded in Section V,

II. RELATED WORKS

Kutyauripo et al. [1] conducted a systematic review by analyzing about 110 articles. The review assessed the application of artificial intelligence in all stages of the food system, including crop production, livestock production, harvesting/slaughtering, post-harvest management, food processing, food distribution, food consumption, and food waste management.

Overall, the findings of the research highlight the wide range of applications of artificial intelligence in the agrifood sectors, contributing to improved efficiency, productivity, and quality throughout the food system. Therefore, their work looked at the application of AI in the whole agricultural value chain.
While Lutz & Coradi [2] looked at the application of Internet of Things (IoT) and Machine Learning (ML) technologies in further enhancing the monitoring and predictive capabilities of grains, during the post-harvest stages, overall, the paper reviewed works that adopt ML and IoT in grain storage strategies to improve the monitoring and prediction of grain quality. Their work emphasized grain storage.

Singh et al. [3] reviewed the use of a Machine learning framework to mitigate post-harvest losses in fruits and vegetables. The findings of the paper include the successful application of machine learning frameworks, such as Convolutional Neural Networks (CNNs)-based U-Net, DeepLab, and Mask R-CNN models, for detecting and predicting post-harvest deterioration zones in stored apple fruits.

The authors above all carried out a literature review work on the application of AI in one form or the other in agricultural post-harvest processing. However, it is observed that their works are either too broad or completely in a different direction from our research objective. Thus, there is a need for this review. Ours intends to narrow the scope to key segments in postharvest processing specifically cleaning, sorting, grading, and storage. The intent is to provide more clarity on the scope of work done in these areas

III. METHODOLOGY

A. Search Strategies

Firstly, the review process was initiated by searching the following repositories Researchgate, ScienceDirect, and Google Scholar. Using a search string with the keywords AI "AND/OR" Machine Learning "AND" Agricultural Post-harvest processing.

B. Inclusion and Exclusion Criteria

Secondly, after the aggregation of several publications, selection criteria were applied as follows: 1. Is the article written in English? 2. Is it a Journal paper? 3. Did it employ the use of the AI/ML model as the core of the proposed model? And finally, 4. Is the work dated between 2018 to 2023?
If the answer to all the above listed selection criteria questions is "yes" then the article is selected for the next phase, which is synthetization otherwise the article is dropped.

C. Research Questions

The research questions for the study are as follows:

- RQ1: What segment of the post-harvest processing is it applied?
- RQ2: Which AI/ML algorithm/model is most used or applied in each post-harvest segment to improve the process?
- RQ3: What parameters and/or features were used to achieve the goal of the proposed model?

D. Data Collection/Extraction

To achieve an optimal literature synthesis, we used the research questions to extract relevant taxonomies from each of the 'qualified' literature.

IV. RESULT AND DISCUSSION

The selected publications are shown in Table 1. The table shows, the source repository, reference, article title, and year of publication.
To address research question 1(RQ1) post-harvest processing segment targeted in the articles was investigated and summarized as shown in Fig 1.

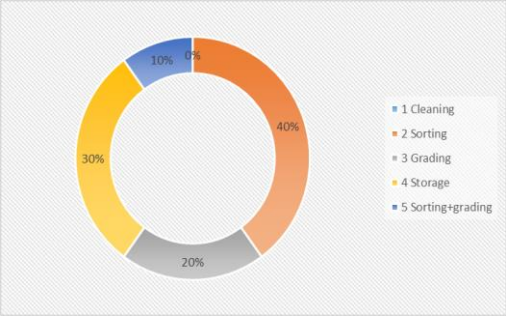

Figure 1: Articles based on Post-harvest segment

As shown in Fig.1. Artificial intelligence is most applied in the post-harvest segments of sorting closely followed by grading and then storage. In contrast, the cleaning segment comes last with a null value.
To answer the second research question (RQ2) AI/ML model was used in each post-harvest segment to improve the process. Fig. 2 shows an aggregate breakdown of used AI/ML models by selected articles.

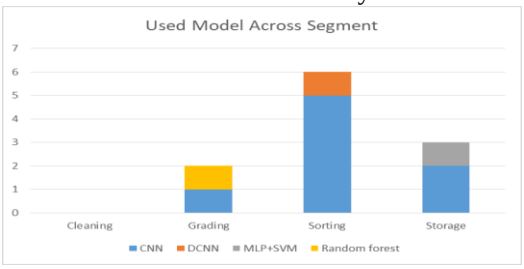

Figure 2: Used Model across Segment

Convolutional Neural Network (CNN), Deep Convolutional Neural Network (DCNN), Multi-Layer

Perceptron (MLP), Simple Vector Machine (SVM), and Random Forest are the models used in our surveyed literature. As shown in Fig. 2 the CNN model is the most used and has a wider spread as it is applied in three (3) out of the four post-harvest segments. This can be attributed to its suitability in handling complex classification problems, image and video data processing, etc. The accuracy rate of these models across the literature ranges from 92.1% to 99%. Thus, it can be adjudged as highly suitable for the purposes intended.

To address the third research question (RQ3) of identifying features and/or parameters used we extracted these data from each of the selected articles to achieve their objective. This is shown in Table 2

Table 1: Selected Publication

Source	Reference	Title	Year
Science Direct	[2]	Applications of new technologies for monitoring and predicting grain quality stored: Sensors, Internet of Things, and Artificial Intelligence	2022
Science Direct	[3]	Recent Advancement in Postharvest Loss Mitigation and Quality Management of Fruits and Vegetables Using Machine Learning Frameworks	2022
Research Gate	[4]	Postharvest Grading Classification of Cavendish Banana Using Deep Learning and Tensorflow	2019
Google Scholar	[5]	Image-based deep learning automated sorting of date fruit design of an automatic apple sorting system using machine vision	2019
Science Direct	[6]	A Deep Learning-Based Model for Date Fruit Classification	2022
Science Direct	[7]	Prediction of wheat moisture content at harvest time through ANN and SVR modeling techniques	2020
Science Direct	[8]	Maturity classification of sweet peppers using image datasets acquired in different times	2020
Google Scholar	[9]	Design and evaluation of an intelligent sorting system for bell pepper using deep convolutional neural networks	2021
Science Direct	[10]	Development of an optimally designed real-time automatic citrus fruit grading–sorting machine leveraging computer vision-based adaptive deep learning model	2023
Science Direct	[11]	Postharvest classification of banana (Musa acuminata) using tier-based machine learning	2018

We can see from Table 2 that one of the commonest features used across all the segments is the image followed by other physical properties such as size, weight then features such as moisture, CO2 concentration, wind, and humidity for mainly storage post-harvest processing segment.

TABLE 2: FEATURES AND PARAMETERS USED BY SEGMENT

Segment	Used Feature
Cleaning	NA
Grading	weight
	image
	morphological
Sorting	RGB Color,
	Length Size
	image
Storage	moisture content
	CO2 concentration
	physical properties
	image
	humidity
	wind speed

V. CONCLUSION

In conclusion, this paper conducted a systematic literature review on the application of AI in post-harvest processing and the key findings of this study includes firstly, it shows that deep learning model such as CNN as the most used algorithm and its used across the various post-harvest segment. Secondly, the physical properties of objects such as image and size are the most essential features used in the analysis. Finally, this study has shown that the sorting segment of the post-harvest processes enjoys most of the attention with little to none at all for the cleaning phase.

The application of AI in post-harvest processing is still in its early stages, but the potential benefits are significant. As AI technology continues to develop, we can expect to see even more innovative and effective AI-powered solutions for post-harvest processing, particularly in post-harvest cleaning and other sectors. Furthermore, the scope of this study can be expanded to include other repositories and wider date ranges so that more work can be considered.

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