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RECENT DEVELOPMENTS OF ARTIFICIAL INTELLIGENCE FOR BANANA: APPLICATION AREAS, LEARNING ALGORITHMS, AND FUTURE CHALLENGES

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KEYWORDS

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ABSTRACT

Bananas are the world's most traded fruits. Several analytical models using artificial intelligence (AI) have been developed to resolve challenges facing the banana supply chain. The number of publications in this field has steadily increased each year. However, a literature review regarding the trends of recent AI developments is not available. Thus, this study reviews the current scenario of scientific research involving AI in the stages of the banana supply chain (pre-harvest, harvest, post-harvest, processing and retail). This review covers literature published between 2015 and 2020 from online databases. Fifty-two relevant studies were retrieved from 23 countries. Consequently, we propose an AI-performance framework based on real applications implemented for bananas: the application domain, learning algorithms, performance metrics, and reported impacts. This paper discovers 11 AI-application areas for bananas, such as ripeness, leaf diseases, quality grading, crop type, crop yield, and soil control. Moreover, this review summarizes the main functionality of learning algorithms found in the literature (ANN, CNN, SVM, and K-NN). Finally, the future challenges are discussed. This comprehensive review will help researchers understand AI applications in the banana sector and analyze the knowledge gap for future studies.

INTRODUCTION

Technological advances in artificial intelligence (AI) in the field of agriculture have intensified in recent years (Benos et al., 2021; Jha et al., 2019; Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018; Meshram et al., 2021; Sharma et al., 2020). Predictive models and applications using AI have been developed to increase the competitiveness and efficiency of agricultural production processes (Elavarasan et al., 2018; Pathan et al., 2020). Thus, the agricultural supply chain has been considered a subject of AI research (Meshram et al., 2021; Sharma et al., 2020), and the findings have been published to increase current understanding in agricultural management (Handayati et al., 2015; Pathan et al., 2020; Pereira et al., 2018; Zhao et al., 2019). According to Meshram et al. (2021), agricultural tasks are categorized into three major areas: pre-harvest, harvest, and post-harvest.

Siddiq et al. (2020) and FAO (2020) announce that the banana supply chain (BSC) faces several challenges and opportunities. Some studies have examined challenges, such as post-harvest losses (Priyadarshi et al., 2021), management (Hiranphaet, 2018), and environmental impacts (Rattanapan & Ounsaneha, 2020) in developing a sustainable supply chain for bananas. So, Tinzaara et al. (2018) proposed the principal challenges in the BSC, as shown in Figure 1. Thus, the most common challenges in the pre-harvest stage are soil-nutrient control, irrigation or water management, and pest and disease control. In terms of harvest, maturity, ripening process, and handling are significant issues. In the next stage, the key challenges are post-harvest losses, shelf life, and fruit grading. Finally, in the processing stage, the major research areas are product-quality control and the value addition of bananas (products or by-products).

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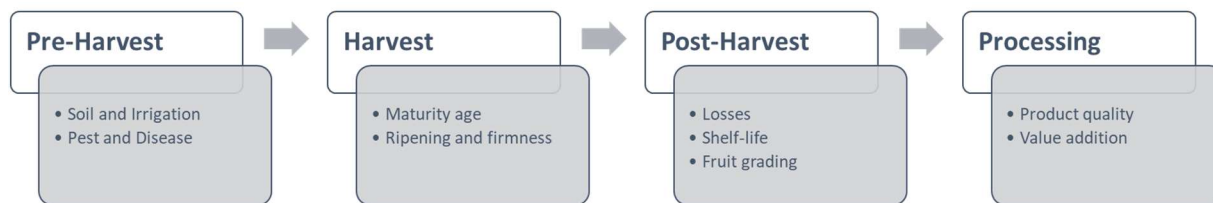


FIGURE 1. Challenges in each stage of the banana supply chain (adopted from Meshram et al., 2021; Tinzaara et al., 2018).

The BSC has emerged as a recent research area of machine learning (ML) and deep learning (DL) (Benos et al., 2021; Kamilaris & Prenafeta-Boldú, 2018; Meshram et al., 2021; Pathan et al., 2020; Rehman et al., 2019). Thus, studies on solving banana issues and improving the agricultural processes of the BSC using AI technology have increased in recent years. Given this scenario, the volume of scientific articles from different countries, regarding this research area, has increased. However, no survey study has presented the main trends in predictive AI-based models that have been implemented. Consequently, a review work must be considered.

This paper presents a comprehensive review of AI applications for bananas to explain the current scientific scenario. This review was conducted to examine the findings and trends regarding AI-application areas, the implementation of machine learning (ML) and deep learning (DL) algorithms, performance metrics, and future challenges regarding AI for bananas. The systematic review consists of collecting ML and DL techniques that have been implemented on predictive AI-based models across the BSC (pre-harvest, harvest, post-harvest, processing, and retail). The main contributions of this review are as follows: (a) to provide an empirical analysis of AI approaches, to recognize the performance of ML and DL approaches in the BSC, and (b) to put forward an AI framework based on real applications implemented along the stages of the BSC.

REVIEW

The review process followed the guidelines for systematic studies on software engineering (Wohlin, 2014). This review covers recent literature published between 2015

and 2020 from digital databases (Web of Science, Science Direct, Scopus, Springer Link, IEEE Xplore, Wiley, Taylor & Francis, and Google Scholar). This study used the search keywords such as banana, machine learning, deep learning, prediction, estimation, and forecast. Different strings were defined for each database using search terms. The search for articles began in January 2021. The final database search was conducted in February 2021. The lists of references of the manuscripts selected for full-text reading were manually examined by the authors for potentially relevant studies, which was completed in June 2021. Fifty-two relevant papers from 23 countries were retrieved from all databases. The dataset of selected publications for this study is available for download and replication at this link: <https://cutt.ly/VniXv2H>.

AI applications

The review findings emphasize that researchers have developed and tested AI-based predictive models to contribute to banana challenges. For clustering into application areas, challenges in the BSC (Figure 1) were considered. As a result, an overview of the AI approaches in the BSC is shown in Figure 2. Eleven application areas were discovered in the 52 reviewed publications, as shown in Table 1. The application areas according to their number of publications found are the following (in decreasing order): ripeness (13 publications), diseases (11 publications), quality (5 publications), crop-type (5 publications), crop yield (5 publications), soil (4 publications), fruit recognition (4 publications), process parameters (2 publications), production for consumers (1 publication), age bunch (1 publication), and pest (1 publication).

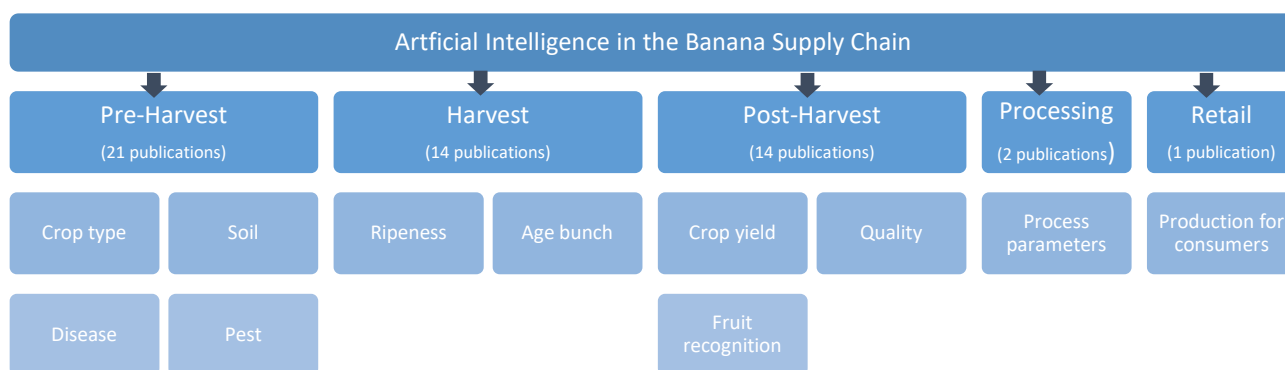


FIGURE 2. Clustering of selected publication by AI-application area.

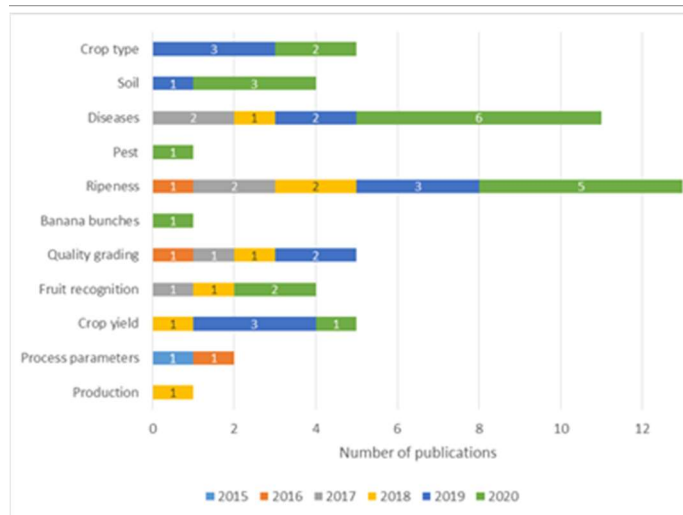


FIGURE 3. Yearly publication according to application area.

Figure 3 depicts the number of publications per year for the 11 application areas. The number of these types of publications has steadily increased each year. The annual growth rate was 66.10% (from 2015 to 2020). Additionally, there was an annual increase of 50% between 2019 and 2020. Similarly, analyzing the evolution of the application areas, both ripening and diseases have been considered the most active AI-application areas in BSC in the last five years. Eight of the 11 (73%) domain areas had publications in 2020, while six of the 11 (55%) had publications in 2019. Thus, process parameters, ripening, and quality were the first research works published between 2015 and 2016. Studies on leaf diseases and fruit recognition were published in 2017. During 2018 and 2019, predictive models for crop yield, crop type, and soil were indexed. Recently, banana-age bunches and pests have been developed as application areas for bananas in the BSC.

Figure 4 introduces the distribution of publications to identify the most popular application area in BVC. Therefore, only ripeness and disease (two of 11 application areas) accounted for 46% of the selected publications. Additionally, ripeness, disease, crop type, quality grading, crop yield, and fruit recognition (6 application areas) accounted for 83% of the total publications (Figure 4). Thus, the classification of banana ripeness levels (13 publications) and diseased banana leaves (11 publications) are considered the most popular application areas. In this manner, we can conclude that reviewed publications belong to the stages at the beginning of the BSC (pre-harvest, harvest, and post-harvest), more than the latest stages (processing and retail), as shown Figure 2 and Figure 4.

The review findings determine that the 52 selected publications were from 23 countries worldwide, as shown in Table 2. Thus, India and China are active countries that developed AI models related to seven and six application areas, respectively. Asian countries (India, China, Philippines, Taiwan, Thailand, Malaysia, and Indonesia) tend to research ripeness, soil, fruit recognition, and crop type. Countries such as Malaysia and Indonesia only have AI applications in terms of ripeness. Conversely, Latin

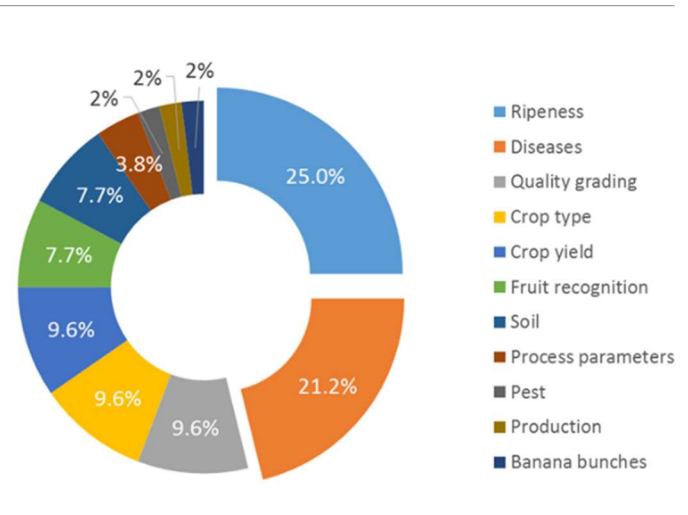


FIGURE 4. Distribution of publications by application area.

American countries (Brazil, Peru, Ecuador, and Colombia) have published studies regarding diseases, pests, soil, and crop yield.

Individual summary of selected publications by application area

This section presents a brief description of the 52 selected publications of the 11 AI-application areas implemented for bananas (Table 1).

1) Classification of crop type:

Crop management is considered an essential activity in pre-harvest practices such as food security and healthy crop assessment (Benos et al., 2021). Image processing and DL algorithms help in crop diagnosis in earlier stages (Kamilaris & Prenafeta-Boldú, 2018).

Ringland et al. (2019) developed a DL tools for crop identification and applied them to Google Street View (GSV) imagery (street level) to characterize food cultivation practices along roadside transects at very high spatial resolution. The model used a CNN architecture, called Inception V3, and transfer learning to classify six major commodity field crops: banana, cassava, maize, eucalyptus, rice, scrub, and sugarcane.

Neupane et al. (2019) proposed a DL model for banana plant, detection and counting, using high-resolution RGB images collected from an unmanned aerial vehicle (UAV). The CNN architecture, called Faster-RCNN, detects and counts the number of banana plants on an orchard. This application detects banana plants through yellow, red, and black markers, representing correct, incorrect, and missed detections, respectively.

Zhao et al. (2019) implemented CNN and RNN models for early-crop classification using imagery time series (satellite images). The model learned the phenological information of five crops: paddy, sugarcane, banana, pineapple, and eucalyptus. Thus, this model combines spatial and temporal patterns for crop classification.

Mandal et al. (2020) implemented an SVM classifier for six labels: rice, sugarcane, cotton, bananas, bare fields, and mixed classes. The predictive model used images of satellite multitemporal crop classification. The image dataset described the geometric features of the crop from a 4-month interval covering the critical crop-growth stages.

TABLE 1. Overview of AI approaches for bananas.

	Application area	Description	Number of studies (n=52)	References
Pre-Harvest	Crop type	Crop type detection. Identifying banana plantations among other crops.	5	(Ringland et al., 2019), (Neupane et al., 2019), (Zhao et al., 2019), (Mandal et al., 2020), (Sinha et al., 2020)
	Soil	Soil quality classification. Classifying the type or quality of soil in banana cultivation.	4	(David & Guico, 2019), (Vite Cevallos et al., 2020), (Yuan et al., 2020), (Vigneswaran & Selvaganesh, 2020)
	Diseases	Disease detection and classification. Detecting diseased banana leaves or classifying the type of disease that affect leaves.	11	(Singh & Misra, 2017), (Amara et al., 2017), (Ferentinos, 2018), (Aruraj et al., 2019), (Liao et al., 2019), (Tsai et al., 2019), (Campos Calou et al., 2020), (Athiraja & Vijayakumar, 2021), (Chaudhari & Patil, 2020), (Gomez Selvaraj et al., 2020), (Criollo et al., 2020)
	Pest	Classification of pest incidence. Estimating the level of pest incidence in banana plantations.	1	(Almeyda et al., 2020)
Harvest	Ripeness	Classification of ripeness level. Analyzing the ripeness of the fruit and classifying the stage of ripeness.	13	(Adebayo et al., 2016), (Adebayo et al., 2017), (Mohapatra et al., 2017), (Zhang et al., 2018), (Chen et al., 2018), (Mazen & Nashat, 2019), (Pu et al., 2019), (Sabilla et al., 2019), (Vetrekar et al., 2019a), (Vetrekar et al., 2019b), (Saad et al., 2019), (Zhu & Spachos, 2020), (Ni et al., 2020)
	Age bunch	Classification of banana age bunches. Detecting and classifying the level of maturity or shape of bunches on the banana plant.	1	(Fu et al., 2020)
Post-Harvest	Quality grading	Banana grade classification. Classifying the quality of banana fruit at post-harvest.	5	(Sanaeifar et al., 2016), (Olaniyi et al., 2017), (Piedad et al., 2018), (Le et al., 2019), (Ucat & Cruz, 2019)
	Fruit recognition	Recognition of the fruit-shape. Classifying types of banana cultivars or detecting banana among other fruits.	4	(Dittakan et al., 2017), (Mureşan & Oltean, 2018), (Xue et al., 2020), (Sugadev et al., 2020)
	Crop yield	Crop yield forecasting. Classifying the yield level of the banana crop (tons/hectare) or estimating the harvest period (days).	5	(Rathod & Mishra, 2018), (Rebortera & Fajardo, 2019b), (Rebortera & Fajardo, 2019a), (de Souza et al., 2019), (de Lima Neto et al., 2020)
Processing	Process parameters	Estimation of process parameters. Predicting output parameters in the culinary banana drying process.	2	(Guiné et al., 2015), (Khawas et al., 2016)
Retail	Production for consumers	Forecasting of banana production. From the total production (country) for the last years, forecasting production for the following years.	1	(Rehman et al., 2018)

TABLE 2. AI applications developed by country.

Stage	Application area	India	China	Philippines	Taiwan	Thailand	Malaysia	Brazil	Peru	Ecuador	Germany	Greece, Belgium, and Colombia	Romania	Portugal	USA and Australia	Iran and Turkey	Egypt, Ireland, Indonesia, and Canada
Pre-Harvest	Crop type	✓	✓			✓									✓		
	Soil	✓	✓	✓						✓							
	Diseases	✓			✓			✓	✓		✓	✓					
	Pest								✓								
Harvest	Ripeness	✓	✓		✓		✓				✓						✓
	Age bunch		✓														
Post-Harvest	Quality grading			✓	✓											✓	
	Fruit recognition	✓	✓			✓							✓				
	Crop yield	✓		✓				✓									
Processing	Process parameters	✓												✓			
Retail	Production		✓														

Sinha et al. (2020) developed a predictive model using the hyperspectral reflectance properties of individual banana leaves to differentiate 12 banana genotypes. Moreover, the study extrapolated ground-based hyperspectral measures from high-resolution WorldView-3 (WV3) satellite imagery. The study assessed two classification models: the CPPLS classification algorithm and RF-based classification.

2) Prediction of soil features:

Monitoring of soil properties is essential for agricultural management (Benos et al., 2021). Banana crops have essential soil-nutritional requirements such as N, P, and K (Alves et al., 2015; de Andrade Neto et al., 2017; Rajput et al., 2017). Furthermore, the decrease of banana crop yield can be caused by a lack of soil nutrients or weak soil management (Cevallos et al., 2020). Thus, healthy soil is associated with a low incidence of plant pathogens and diseases (David and Guico, 2019). ML techniques help farmers in the decision-making process to improve the quality of soil and banana fruit.

David and Guico (2019) developed a predictive model to classify the type of soil properties (suppressive and conducive soil) in a banana crop that can cause diseases (*Panama*). The model considered the following soil features as input of the model: dielectric properties, moisture, temperature, and sunlight. The study compared four ML models (GBC, KNN, SVM, and ANN) and selected the best algorithms with the best performance. This served as an early diagnosis of soil infections in banana crops.

Cevallos et al. (2020) introduced an ML model to estimate soil quality (classifying into 3 labels: optimal, acceptable, and not acceptable). The study used soil-nutritional compounds (N, P, K, Ca, Mg, Fe, Mn, Cu, and Zn) as samples that were extracted from 0 to 30 cm deep from the soil of the banana crop. The author used seven ML algorithms (MLP, BN, LGR, DT, RF, SVM, and KNN) to compare their performances and chose the best predictive model.

Yuan et al. (2020) focused on the classification of soils. The authors developed classification models for diseased and healthy soils using features such as bacterial and fungal samples. The study employed metadata from multiple independent sources (soil samples from different countries). It analyzed the soil of four crops (banana, cucumber, watermelon, and lily). Their proposal was based on detecting models of microbial disease patterns (fusarium wilt) and identifying microbial community characteristics used to predict soil health. The authors compared the performances of three ML algorithms: RF, SVM, and LGR.

Vigneswaran & Selvaganesh (2020) proposed modeling soil nutrients for crop rotation such as banana, rice, corn, and turmeric to search for better crops yield for farmers. The authors introduced a model to predict suitable crops for cultivation and crop rotation by measuring the soil quality. Regarding the features of the model, they considered soil samples with five nutrient values: urea, K, Mg, pH, and N. The study used neuro-fuzzy logic and RBF algorithms to develop the ML model.

3) Detection and classification of leaf diseases:

Banana crops are treated for a variety of diseases (Amara et al., 2017; Aruraj et al., 2019), which cause injury to leaves and impact production loss to the farmers (Siddiq et al., 2020). Therefore, detecting diseases at an earlier stage and thus taking preventive action to maintain healthy banana crops is challenging for farmers (Athiraja & Vijayakumar, 2021). Moreover, detection and classification of leaf disease by using AI technology allow reducing a large work of monitoring in bigger crops (Singh and Misra, 2017). According to the literature, image processing and ML classifiers assist in disease diagnosis.

Singh and Misra (2017) presented a model that includes an image segmentation technique and a genetic algorithm for automatic detection as well as classification of

plant leaves disease. Samples of banana leaf with early scorch disease, rose with bacterial disease, lemon leaf with Sun burn disease, and fungal disease in beans leaf are considered for input data. To classify the leaf disease, the authors proposed a new algorithm, then compared the performance of different ML methods such as MDC and SVM.

Amara et al. (2017) introduced a deep learning-based approach that automated the classification of banana leaves: healthy leaf, diseased leaf by *black sigatoka*, and diseased leaf by *black speckle*. The model learns the color and texture features of images (RGB and grayscale) using the LeNet89 architecture as a CNN to classify banana-leaf diseases.

Ferentinos (2018) proposed a CNN architecture for the identification of plant diseases using simple leaf images (healthy or diseased). The study has three classifications: healthy banana leaves, *black sigatoka*, and *black speckle* (the last ones are leaf diseases). The study used five CNN architecture to compare the results.

Aruraj et al. (2019) proposed texture-pattern techniques for identifying and classifying diseases in banana leaves. The study implemented SVM and KNN algorithms and compared the performances of two study cases: healthy vs. *black sigatoka*, and healthy vs. *cordana leaf spot*.

Liao et al. (2019) used labeled samples of late-stage banana-leaf disease to train the predictive model. In the study, banana-leaf disease was detected using spectral-spatial information through morphological profiles. The PCA and SVM algorithms were used to classify the three stages: early, middle, and late.

Tsai et al. (2019) developed a real-life image-recognition method for *panama* disease using a DL approach. The study compared the performance of five CNN architectures (LeNet-5, VGG16, VGG-19, ResNet-34, and ResNet-50) with different activation functions. CNN models were used to extract original color images to identify two labels of banana leaves: normal banana and leaves infected by *panama* disease.

Campos et al. (2020) applied ML techniques and digital image processing to monitor the severity of a *yellow sigatoka* attack on banana crops. In the study, RGB aerial images by UAV were used. The study developed a predictive model in two stages: (1) classification to identify abnormal leaves using SVM and ANN, and (2) classification to identify scene elements, such as a healthy leaf, central vein, abnormal leaf, and soil, using the SVM technique.

Athiraja and Vijayakumar (2021) proposed a ML model to (1) classify banana plants diseases such as *panama* wilt, leaf spot, virus diseases, crown rot, anthracnose, tip rot, and (2) recognize the disease cells into six labels: initial, very tiny, tiny, medium, high, and very high. Moreover, for that purpose the authors trained and compared the result of ML algorithms such as MDC, KNN, SVM, CBR, and ANFIS (a mixture of the technique of ANN and fuzzy logic). The ANFIS algorithm attained excellent results for all labels.

Chaudhari and Patil (2020) introduced an automated system to identify banana-leaf diseases by extracting color, shape, and texture features. The authors used K-means clustering to segment images in diseased leaves and the SVM algorithm to classify diseases such as *sigatoka*, *cucumber mosaic virus*, *banana bacterial wilt*, and *panama* disease.

Selvaraj et al. (2020) combined high-resolution satellite imagery data with advanced ML models to detect and

classify banana plants and provide information regarding their overall health status. The model used image processing, then VGG-16 and Retina-Net (CNN architecture) to classify healthy and infected plants.

Criollo et al. (2020) implemented a CNN to detect banana-leaf diseases using RGB images. The predictive model was trained to classify three labels of banana-leaf diseases: *black sigatoka*, *bacterial wilt*, and health status.

4) Prediction of pest incidence:

Pests and diseases damage banana crops; therefore, they must be controlled to minimize post-harvest losses and ensure fruit quality (Siddiq et al., 2020). After the review, only one study discussed pests in banana crops. Almeyda (2020) developed an ML model to predict the level of *thrips* pest incidence in banana crops. The author used two supervised learning algorithms: LGR and SVM. Climatological and soil data were used as features and the level of incidence (low and medium) as labels. To obtain climatological and soil data, a weather station and network of IoT sensors were implemented.

5) Classification of ripeness stages:

Ripeness is a significant topic in banana harvest because of its impact on fruit quality and price (Mazen & Nashat, 2019). Farmers must identify banana ripeness levels to reduce losses during the post-harvest process and extend storage life due to bananas have a high rate of deterioration (Siddiq et al., 2020). According to the literature, AI and computer vision help to detect efficiently banana ripeness.

Adebayo et al. (2016) (2017) presented a classification system for predicting six banana ripening stages. Thus, the quality attributes of bananas, such as chlorophyll, elasticity, and soluble solids content were assessed for input data. The authors implemented an ANN classifier (using multilayer-perceptron).

Mohopatra et al. (2017) proposed a non-destructive assessment method to measure ripening stages of red banana (7 labels). The study analyzed dielectric properties as features for the prediction of seven labels of banana ripeness. It used three combination of ML algorithms for image processing: CLBP, LBP, NRLBP and FCM. For classification at different ripening, FCM clustering method gave far better results.

Zhang et al. (2018) proposed a novel CNN classifier for bananas at seven ripening stages. The algorithm learned a set of fine-grained image features. Additionally, the study compared the performance of the CNN model with other ML algorithms such as SVM.

Chen et al. (2018) developed a method to monitor fruit maturity: unripe, half-ripe, fully ripe, and over-ripe. Their proposal focused on monitoring variations in the volatile organic compounds produced by the fruit during the maturation process. The predictive model used the SVM and KNN algorithms combined with PCA and LDA.

Mazen and Nashat (2019) developed an automatic computer-vision system to identify the ripening stages of bananas between four labels: green, yellowish green, mid-ripen, and overripen. The proposed system is based on extracting texture features of the banana fruit, which used HSV color space, and development of brown spots. The model implemented numerous ML techniques such as ANN,

SVM, NB, KNN, DT, and DAC. Consequently, ANN-based framework performed the best results.

Pu et al. (2019) demonstrated hyperspectral imaging for accurate and non-destructive ripeness classification of *bananito* fruit (tree maturity stages). The model is based on the visible peel spectra, considering features such as fruit firmness, soluble solids content, and color parameters. The study compared the experimental results of three algorithms: SVM, SIMCA, and PLSDA.

Sabilla et al. (2019) determined ripeness levels of bananas based on banana peels and RGB images. Thus, the ripeness levels were assessed: unripe, ripe, and overripe. The model was trained using separately ML techniques such as SVM, KNN, and DT.

Vetrekar et al. (2019a) presented a multispectral imaging approach to acquire the eight spatial and spectral narrow spectrum bands across the VIS and NIR wavelength range to detect artificially ripened bananas using SVM classifier. Subsequently, the authors (Vetrekar et al., 2019b) presented another study on the detection of the artificial ripening of bananas using six different feature-extraction methods independently, complemented with SVM and ProCRC algorithms.

Saad et al. (2019) developed a banana-peeling machine for ripeness classification to reject bananas at a supermarket. The automatic system classified tree levels of maturity: unripe, ripe and overripe bananas. To reach that purpose, the authors developed a CNN architecture and used RGB images, which were captured by the banana-peeling machine.

Zhu and Spachos (2020) implemented a two-layer image-processing system based on AI for banana grading. In the first stage, the model used an SVM algorithm regarding color and texture features to classify the ripening stages of bananas (unripened, ripened, and over-ripened). In the second stage, the model uses a CNN architecture known as YOLO v3 to classify specific ripeness stages: mid-ripened and well-ripened.

Ni et al. (2020) analyzed the banana-freshness changing process. The samples of banana appearance were gotten by the number of days it has been stored: one, three, five, seven, nine, and eleven days (seven labels in total). The predictive model used the GoogLeNet architecture (CNN) to classify banana freshness at different time intervals. Moreover, the results improved their accuracy after applying data augmentation for the dataset and transfer learning.

6) Prediction of age bunch:

Age-bunch control is an important practice during the harvest stage (Siddiq et al., 2020). The maturity indices of banana bunches (immature, mature, and over-mature) is noticed through changes in color, size, shape, length, and volume. In this review, we discovered a unique study on the detection of banana-age bunches. Fu et al. (2020) introduced a tele-detection method for banana detection in natural environments under different illumination and occlusion conditions. The study used a regular RGB color camera to obtain banana-age bunch images at different growing stages (immature or mature) and shapes of bunches. The YOLOv4 architecture was trained and tested in different illumination environments (sunny front-light, sunny back-light, and cloudy conditions) to detect banana age-bunch.

7) Prediction of quality grading:

Although banana crops face several challenges, the international banana market has high-quality standards, according to FAO (2019). Farmers need to identify the levels of banana quality in an efficient way. Moreover, quality grading is essential to place sale prices of fruit in order to maximize their economic income. However, the morphological and physiological characteristics of bananas can be influenced by several aspects such as type of cultivar (Dittakan et al., 2017), irrigation system (Arantes et al., 2018), fertigation (de Andrade Neto et al., 2017), among others. Thus, DL algorithms and computer-vision techniques work together to recognize banana quality fruit.

Sanaeifar et al. (2016) implemented a computer-vision system with ML algorithms to evaluate banana color features during the shelf life. The color features in different color spaces, including RGB, HSV, and $L^*a^*b^*$, were selected as the inputs for the predictive models. Meanwhile, the quality indices, including firmness, total soluble solids, and pH, were chosen as outputs. The regression model compared the performance of SVR and the back-propagation MLP algorithm.

Olaniyi et al. (2017) developed an automatic system for the classification of healthy and defective bananas. The study implemented RBF, SVM and an ANN with back-propagation optimization and compared their performance models. The identification system used GLCM (gray level co-matrix) texture features such as contrast, energy, homogeneity, and entropy for training and testing the ML model classifier.

Piedad et al. (2018) introduced an ML model for estimating banana quality attributes. RGB color images and the length of the top middle finger of the banana tier were considered features for classifying banana tiers into four classes: extra class (export-quality fruit), class I (high-value domestic fruit), class II (local trade and consumption), and reject class (local trade with low cost). The authors used ML methods, such as MLP, SVM, and RF, and compared their classification accuracy.

Le et al. (2019) developed a model to classify banana fruit tiers into two labels: normal and reject for sale. The study implemented a mask region-based CNN, called Mask R-CNN. This algorithm offers to detect banana images while at the same time generating a mask separating the fruit from its background. The model improved its performance after data augmentation was applied.

Ucat & Cruz (2019) presented a CNN model for grading the classification of post-harvest bananas. The banana was graded into four classes (size of a banana hand) according to the finger-size requirements (number of defects, diameter of the finger, and finger length). The study proposed image processing for physical-feature extraction from images (color and grayscale) and the HSV color space. The model was more effective for finger-size value extraction than for surface-defect value extraction.

8) Fruit recognition:

In recent years, human visual perception has been simulated using DL models to separate different fruits or vegetables in order to reduce cost and error (Sugadev et al., 2020). According to (Xue et al., 2020), an accurate fruit classification is considered of interest in the fresh supply chain, factories, and supermarkets. This domain area covers

publications that introduced predictive models for object recognition of fruits (shape, texture, color, and other features) using deep neural networks, image processing, and computer vision.

Diattakan et al. (2017) presented a classifier for three banana cultivars using the morphological profile as a scale-invariant shape analysis. The authors developed the model using separately seven ML algorithms: SVM, DT, NB, AODE, BN, LGR, and ANN. The BN was the best classifier.

Mureşan and Oltean (2018) developed a CNN architecture for fruit recognition. The authors used a large dataset containing images of a wide variety of fruits. The CNN classified 60 labels of fruits in total; however, only two labels belong to type of bananas: green and red banana.

Xue et al. (2020) presented a hybrid deep-learning-based fruit image classification approach. The authors developed a CNN model (CAE-ADN) to classify fruits. The model was tested using datasets with labels of fruit such as apple, banana, carambola, guava, kiwi, mango, etc.

Sugadev et al. (2020) introduced a predictive model for identifying fruits such as Granny Smith apples, papaya, and banana. A CNN architecture was used in the study. Thus, the authors developed a real-time prototype to automate the billing process in fruit shops to reduce billing time compared to conventional billing techniques.

9) Forecasting of crop yield:

Estimating a future scenario by considering the behavior of past events is the based idea of forecasting (Rathod and Mishra, 2018). If farmers know in advance their crop yield, they will make planning more effectively and efficiently for storing, pricing and marketing (de Souza et al., 2019). In that context, ML models using regression techniques or statistical models are trained for estimating yield of banana harvest.

Rathod and Mishra (2018) proposed a hybrid model using time-series data to forecast the yields of bananas and mangoes. This model employed ARIMA (statistical analysis model) and TDNN, and nonlinear SVR was used for nonlinear modeling. Thus, the experimental results attained better performance with a hybrid model that considered both ARIMA and non-linear SVR algorithms.

Rebortera and Fajardo (2019b) introduced a DL-based model to forecast banana harvest yield. The model employed time-series data for the number of bunches cuts. The experimental results demonstrated that the AI technique, RNN-LSTM, had better performance compared to conventional models such as ARIMA. In another study, Rebortera and Fajardo (2019a) proposed a multiple LSTM model for forecasting banana harvest yields. The study compared the experimental results from three LSTM-based models: simple layer, multiple layers, and an enhanced LSTM layer. For forecasting, the enhanced model outperformed single-and multiple-layer models.

de Souza et al. (2019) used an MLP to estimate the banana harvest period (number of days) in subtropical regions. The authors analyzed the relationship between climatic variables during the banana bunch gestation period to predict the time of banana harvest.

de Lima Neto et al. (2020) implemented an ML model to classify banana crop yields (high or low) at a local scale. Soil nutrients diagnosis was fundamental in the study. The classifier used information about the type of banana cultivar, soil-nutrient composition, and time of harvest as features. The study compared the performance of two ML classifier: ANN and RF algorithms.

10) Estimation of drying process parameters:

Optimization of the outcome parameters is considered relevant in the culinary banana drying process (Siddiq et al., 2020). Particularly, phenolic compounds (Vu et al., 2018) and their antioxidant properties (Segundo et al., 2017) have been the most studied. Thus, ML models can conduct to model and forecast a future phenomenon based on factors which influence it, using regression technique and correlation analysis.

Guiné et al. (2015) presented a model to estimate two output parameters, antioxidant activity, and phenolic compound content, for the banana drying process. The banana variety, dryness state, and order of extraction were considered as input variables. In the study, a regression model was developed for each parameter using an ANN algorithm.

Khawas et al. (2016) estimated the quality of the overcome process evaluated using four output parameters for vacuum drying of culinary bananas: rehydration ratio, scavenging activity, non-enzymatic browning (color), and hardness (texture). The researchers considered only three input features for the regression model: drying temperature, sample slice thickness, and pretreatment. The study compared the performance of the predictive model using the MLP algorithm, which was optimized using GA.

11) Forecasting of banana production:

Forecasting banana harvest yield is a valuable mechanism for planning future production in the agricultural sector (Rebortera & Fajardo, 2019a). Thus, forecasting production offers assistance in planning the future and decision-making process for sustainable growth of a country (Rathod and Mishra, 2018). A study on forecasting of banana production has been reported in the literature (Rehman et al. 2018). This study from an Asian country introduced a regression model to estimate fruit production such as banana, apple, citrus, pears, and grapes. The researchers employed annual time-series data and implemented MLReg to forecast banana production (in tons).

ML and DL algorithms

AI has been implemented in agriculture in recent years (Benos et al., 2021; Jha et al., 2019; Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018; Sharma et al., 2020). Numerous ML and DL algorithms exist (Mohri et al., 2018). These techniques are categorized by learning methods, such as supervised, unsupervised, and reinforcement (Elavarasan et al., 2018; Mohri et al., 2018; Rehman et al., 2019). Some of these require a powerful computing environment, such as DL learning techniques (Patrício & Rieder, 2018; Zhou et al., 2017).

TABLE 3. ML & DL algorithms implemented along the BSC.

Stages	Domain area	Algorithm		Metrics reported
		Supervised	Unsupervised	
Pre-Harvest	Crop type	CNN, LSTM, GRU, RF, SVM, CPPLS	PCA	Accuracy: 64%–97%
	Soil	ANN, SVM, GBC, MLP, BN, LGR, DT, RF, NFL	KNN	Accuracy: 87%–98%
	Diseases	CNN, MDC, GA, SVM, ANN, ANFIS, CRB, RF	KNN, KM, PCA	Accuracy: 85%–99%
	Pest	LGR, SVM	PCA	Accuracy: 79%
Harvest	Ripeness	CNN, ANN, FCM, NB, DT, DAC, SIMCA, PLSDA, ProCRC	KNN, PCA	Accuracy: 94%–100% RMSE: 0.0308–1.1170
	Age bunch	CNN, SVM	-	Accuracy: 99%
Post-Harvest	Quality grading	CNN, ANN, SVR, RBF, SVM, RF	-	Accuracy: 94%–100% RMSE: 0.0218–4.910
	Fruit recognition	CNN, ANN, SVM, DT, NB, AODE, BN, LGR	KNN	Accuracy: 84%–99%
	Crop yield	ANN, RF, LSTM, NLSVR	-	Accuracy: 75% RMSE:34.8–46.69 MSE: 0.00397
Processing	Process parameters	ANN, GA	-	MSE: 57.85–721.06
Retail	Production	OLSR, MLReg	-	Accuracy: 60%

TABLE 4. Top 5 most-used techniques.

Top	Technique	Learning Task	No. papers where appear
1	SVM	Classification, and imagen pre-processing	22
2	CNN	Object Classification	18
3	KNN	Clustering, and imagen pre-processing	9
4	ANN	Regression and classification	8
5	RF	Regression	6

After the review, we identified more than 30 algorithms that belong to supervised and unsupervised learning, as listed in Table 3. Researchers and practitioners have applied supervised algorithms, such as ANN, SVM, RF, and CNN, and unsupervised algorithms, such as KNN, KM, and PCA. Moreover, we discovered only a few models that used unsupervised learning techniques. However, reinforcement learning was not found during the review process.

Table 4 lists the most commonly used AI techniques in the reviewed publications along the BSC. On the one hand, ML algorithms, SVM appeared in 22 publications (42% of all publications), while KNN, ANN (for classification), and RF were used in nine, eight, and six publications, respectively. Moreover, ML algorithms such as ANN (for regression), MLP, LGR, LSTM, and RBF appeared in three publications on average. The top-2 most popular AI-application areas (Figure 4) have implemented object recognition or classification tasks (46% of total publications).

On the other hand, DL algorithms have been frequently implemented by researchers. CNN appeared in 18 publications (35%). Popular CNN architectures (such as AlexNet, GoogLeNet, VGG16, VGG-19, ResNet-34, ResNet-50, LeNet89, LeNet-5, Retina-Net, Yolov3, Yolov4, CAE-AND, and Mask R-CNN) were used to train the predictive model in the BVC domain. These studies typically used a large dataset of images (GRB, multispectral and hyperspectral).

In this manner, SVM, CNN, KNN, ANN, and RF, were frequently selected for the machine-training process. SVM (ML method) and CNN (DL method) were the most implemented methods used to solve prediction banana tasks. These two methods appeared in 22 and 18 publications, respectively. SVM was used in the learning process of the classification or detection of crop type, soil quality, leaf diseases, pest incidence, bunch maturity, quality grading, and fruit recognition. Several CNN architectures have been implemented in predictive models for classifying crop type, leaf diseases, ripeness stages, age bunch, and fruit recognition.

Additionally, the hybrid approach has expanded over the last five years (Abiodun et al., 2018; Elavarasan et al., 2018; Zhou et al., 2017). Hybrid models combine two or more learning algorithms to achieve better performance (effectiveness and efficiency), compared to the conventional ML or DL techniques. Thus, hybrid AI-based models were discovered for banana-outcome variables, with optimal results: CNN and CAE-ADN (Xue et al., 2020); nonlinear SVR and ARIMA (Rathod & Mishra, 2018); ANN, and GA (Khawas et al., 2016).

Performance metrics

Regarding the performance of the learning process, metrics are essential to evaluate the model. For classification models, researchers usually reported accuracy and precision as the performance metrics. Meanwhile, for regression

models, studies reported the RMSE and MSE in the majority of publications.

The review findings show that AI-based models for BSC have reported a wide range of performance results. Due to researchers have trained more than two algorithms, even hybrid algorithms, and have selected the best performance. In this study, we have presented the best performance models reported (metrics and their values) by each selected publication.

Table 3 shows that some ML algorithms obtained an average accuracy close to 90% along the BSC. Classification models for soil, disease, and fruit recognition have reported accuracies between 84% and 90%. Meanwhile, predictive models for ripeness and quality grading have attained over 94% of accuracy. For the classification task, the CNN and SVM algorithms performed better than other algorithms. Conversely, the regression models reported numerous error values. Some models obtained error values close to zero, whereas others reported high error values. Thus, an efficient learning algorithm depends on large amounts of data (Zhou et al., 2017), feature engineering techniques used (Van Klompenburg et al., 2020), among others.

Proposed framework and future challenges

AI-BSC performance framework

The review findings confirmed that AI-driven technologies improved BSC challenges. We recapitulated all findings from the literature to develop an AI-BSC performance application framework. Thus, it is useful to propose a framework and define future challenges to be considered by researchers, practitioners, policymakers, and other decision-makers in the BSC. Figure 5 presents the proposed framework of AI-based models for bananas which covers four components: stages of the BSC, application areas, ML and DL algorithms, and impacts.

The first component of this framework is the BSC stage. It represents the major agricultural task along the BSC: pre-harvest, harvest, post-harvest, processing, and retail. The review revealed that diverse challenges were addressed at each stage. Thus, the second component covered the challenges faced in the 11 application areas. For example, data on crop type, soil, disease, and pest are used to improve the decision-making process in pre-harvest using ML and DL

models. The generated data are fundamental factors considered in AI-based models. In the pre-harvest stage, IoT sensor networks, weather stations, and digital cameras are used to generate data. Furthermore, a computer-vision system is required to capture and store data (such as RGB, multispectral, and hyperspectral images) in the harvest and post-harvest stages. Conversely, time-series data collected from sources including plantations, food processing, and macro-economic reports are used to forecast crop yield, process parameters, and production, respectively.

The third component is related to the learning algorithms. The study discovered that supervised, unsupervised, and hybrid learning techniques were used to train and test AI-based models to address challenges and improve the BSC performance. Although reinforcement learning was not presented in the literature, it represents an opportunity to begin research.

The last component addresses the impacts and benefits of the BSC performance. From this survey, we identified the contributions of ML and DL models to solving complex problems and achieving sustainable performance in all stages of the BSC. In the pre-harvest stage, specifically in crop and soil monitoring and management, research provides a beneficial solution for automating the tracking of productivity by remote sensing monitoring (Neupane et al., 2019; Ringland et al., 2019), accurate information on food security (Sinha et al., 2020; Zhao et al., 2019), sustainability of agricultural land use (David & Guico, 2019; Yuan et al., 2020), and integrated nutrient management (Cevallos et al., 2020; Vigneswaran & Selvaganesh, 2020; Yuan et al., 2020). The literature on the detection and classification of banana diseases has positive impact on automatic disease detection (Amara et al., 2017; Aruraj et al., 2019; Ferentinos, 2018; Singh & Misra, 2017; Tsai et al., 2019), increasing productive efficiency (Campos Calou et al., 2020), healthy production (Athiraja & Vijayakumar, 2021), enhancement of crop yield, reduction of losses (Almeyda et al., 2020; Chaudhari & Patil, 2020; Criollo et al., 2020), and prevention of revenue losses for farmers (Liao et al., 2019). Additionally, researchers declare that intelligence models help to save time and human effort toward manual monitoring (Aruraj et al., 2019) and provide valuable assistance to agronomists (Ferentinos, 2018), which contributes to operational flexibility in crop monitoring (Selvaraj et al., 2020).

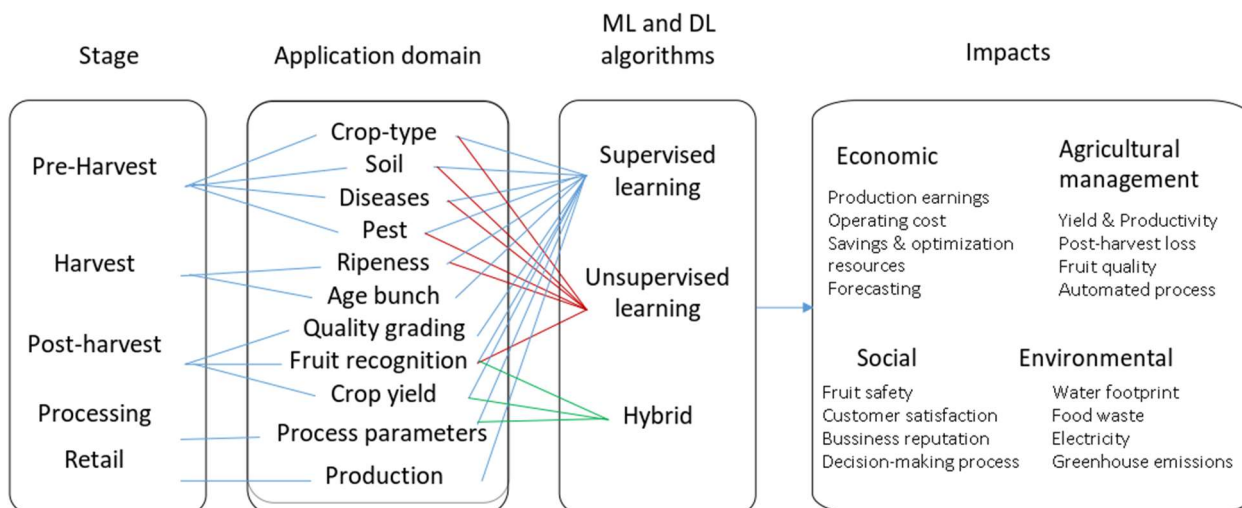


FIGURE 5. Proposed framework: AI for bananas.

During the harvest stage, the applications of ML and DL varied. The main benefit is automated non-destructive methods of ripening assessment with better accuracy (Chen et al., 2018; Mohapatra et al., 2017; Pu et al., 2019; Saad et al., 2019; Zhu & Spachos, 2020). Particularly, the authors confirmed that these models can minimize expenses from destructive traditional techniques (Zhang et al., 2018), reduce mistakes made with the naked eye (giving uniform results) (Sabilla et al., 2019; Vetrekar et al., 2019b, 2019a), and enhance the quality and safety of fruits for consumption (Adebayo et al., 2016, 2017; Ni et al., 2020). Thus, it ensures the productivity, competitiveness, and quality standards of small-scale farmers and firms (Mazen & Nashat, 2019). Furthermore, recent developments in the prediction of bunch age have provided efficient fruit-detection systems in the natural environment (Fu et al., 2020).

Similarly, in the post-harvest stage, overcoming the shortcomings of manual operator approaches is considered the main goal. In this manner, some impacts are listed by the authors owing to the quality and size standards of bananas for automatic grading systems: reduction of the stress of manual operators (Olaniyi et al., 2017), effective prediction of the quality indices of bananas during shelf life (Sanaeifar et al., 2016; Ucat & Cruz, 2019), and reduction of postharvest losses (Le et al., 2019) (Piedad et al., 2018). Therefore, DL algorithms and computer-vision techniques work together causing efficient fruit recognition. For example, they enhance the accuracy of the banana cultivar detection system (Dittakan et al., 2017) and automate the recognition of multi-class fruits (shape and size) (Mureşan & Oltean, 2018; Sugadev et al., 2020; Xue et al., 2020). To forecast crop yield, the review findings indicated that it provides effective decision-making for the monitoring and estimation of harvests for farmers (Lima Neto et al., 2020; de Souza et al., 2019; Rebortera & Fajardo, 2019a, 2019b) and assistance to policymakers to plan the future more efficiently (Rathod & Mishra, 2018).

Finally, food processing and retail stages have reported significant impacts, such as optimizing electricity resources and time in the drying process of culinary bananas in order to increase quality of product (Guiné et al., 2015; Khawas et al., 2016), and predicting future agricultural productivity (Rehman et al., 2018).

In summary, the review findings confirm that AI-driven technologies support improvement in the challenges of the BSC. Thus, the use of ML and DL algorithms has a positive impact in the following aspects: economic (increase of production earnings, optimized operational costs, savings and optimization of resources, and accurate forecasting), agricultural management (enhanced agricultural productivity, optimized harvest yield, reduced post-harvest losses, good eating quality, effective ripening and fruit grading, efficient monitoring of resources like water and soil, automated process, and enhanced decision-making process), social (improved safety of fruit, increased customer satisfaction, business reputation, minimized stress from manual operations, and eased decision-making processes to farmers, managers, policymakers, etc.), and environmental (reduced environmental impacts such as optimizing the water footprint in pre-harvest, reduced food waste in post-harvest, minimized electricity and greenhouse gas emissions in food processing).

Future challenges

Possible future challenges and development directions are focused on the following aspects for sustainable AI-based models:

a) **Improving the quality of data and computational resources:** Researchers must pay attention to technical challenges of data to enhance AI developments. It includes efforts to manage data security (generation, storage, data access, high-quality images, etc.), i.e., standardization of data collection from different sources. Additionally, to improve the learning process of the AI model, practitioners should have access to robust computational resources and Internet connectivity to easily and sustainably train and test ML and DL algorithms.

b) **Performing real-time data analysis in natural environments:** Predictive models have been developed to solve real problems. Real-time data modeling is a trend in the field of AI. Thus, models can be trained by considering the real environmental conditions of crops (sunny and cloud conditions, or occlusion degree) preventing controlled environments or under-laboratory conditions.

c) **Hybrid and transfer learning approaches to enhance the model:** To improve the efficiency of results, the hybrid approach is considered a trend to train the AI model. Thus, two or more learning algorithms can work together to improve the performance of the predictive model. Further, the advancements in transfer learning techniques allow a reduction in the workload of data, the model might train faster, with a small amount of data, and obtain better results. Particularly, DL models such as CNNs for image recognition are suitable for implementing transfer learning.

d) **User-friendly predictive models:** Small-holder farmers are non-experts in ML and DL techniques. Therefore, researchers should develop easy-to-use and user-friendly applications of AI so that it could be incorporated in the daily routine of agricultural practices in a sustainable way. Moreover, the device interoperability should be considered too.

CONCLUSIONS

This study presented an overview of the recent developments in AI for bananas. Thus, this review described the application areas, highlighted ML and DL algorithms that have been implemented, listed the performance metrics that have been reported in literature, and explained the positive impacts declared by the researchers.

The review findings show that 11 AI-applications areas are available for BSC. According to the reviewed publications, the most active application areas for bananas are the following: ripeness, disease, crop type, quality grading, crop yield, and fruit recognition. Thus, publications belong to the stages at the beginning of the BSC (pre-harvest, harvest, and post-harvest), more than the latest stages (processing and retail).

The review identified several AI-based models that have used a wide range of ML and DL algorithms for regression, classification, and clustering tasks. Conventional and hybrid algorithms were used to train and test the models. Deep learning approaches have been widely used to resolve challenges facing the banana supply chain. Thus, transfer learning and data augmentation were used by researchers to improve the performance of their models.

Regarding the impacts on the BSC, the review findings confirmed that AI-driven technologies support improving the sustainability of the BSC. The reviewed publications have demonstrated a positive effect for BSC on the following aspects: economic, agricultural management, social, and environmental. Afterward, this research work presents the future challenges for AI in the global banana industry.

In that manner, this study highlights several points of consideration that could be useful for users of the BSC, such as small-holder farmers, producers, processors, and decision-makers. Additionally, this review article will help researchers, practitioners, and policymakers gain an understanding of AI applications for bananas.

Therefore, we are the first to present a comprehensive overview that explains the AI-based model for the global banana industry. This framework can be used to continue developing this research area and to expand the knowledge frontier in future.

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