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A Review of AI Techniques in Fruit Detection and Classification: Analyzing Data, Features and AI Models Used in Agricultural Industry

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Abstract. Artificial Intelligence (AI) techniques are used in agricultural industry for detecting, classifying, and assessing the quality of fruits. The primary focus of the discussed fruits pertains to oil palm fresh fruit bunches (FFB), which have been a significant contributor to Malaysia's economy. The quantity of research concerning oil palm FFB is limited and has not received extensive attention in the literature. A clear guide regarding the most useful types of data and features in the field is absent. Different concerns also persist regarding the ability of AI models to perform agricultural tasks with sufficient accuracy. Therefore, this review aims to explore the significant data, features, and AI models used, ascertain the performance level in the domain, and contribute an informative analysis of agricultural and oil palm fields. In this context, various types of data, capturing devices, public datasets, features, and diverse AI models used in agricultural industry are subjected to analysis. Most of the analyzed research achieved above 90% performance in terms of accuracy, coefficient of determination (R2), as well as sensitivity and mean average precision (mAP). The results show that there is a high capability of AI to perform agricultural tasks with high accuracy. In this context, the literature is thoroughly examined to provide a comprehensive understanding of the different elements of AI in agricultural industry.

Keywords: Agriculture; Artificial intelligence; Computer vision; Palm oil FFB; Ripeness

1. Introduction

Agriculture is one of the oldest and most important practices of human civilization. The first occurrence was estimated to have happened about 12,000 years ago (National Geographic Society, 2022). Subsequently, agricultural technologies and practices have been subjected to significant evolution. The massive and expanding industry is responsible for the production of goods intended for human consumption. Oil palm FFB, tomatoes, mangoes, bananas, and berries are some of the analyzed agricultural products. In addition, 9 out of 16 of the reviewed research are related to oil palm, which is one of the biggest sources of revenue for Malaysia, contributing to 2.7% of the gross domestic product (GDP) (Hirschmann, 2022). According to the Food and Agriculture Organization of the United Nations, the production of vegetable oils has doubled from 2000 - 2019 due to the massive increase in palm oil production (FAO, 2021).

The objective of agricultural industry is to produce and harvest healthy fruits and distribute to customers. The accurate detection and counting of the crops or trees,

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classification of ripeness level, determination of quality, yield estimation, and disease detection are important to produce healthy fruits. Meanwhile, the tasks are usually performed manually by the staff or farmers present on the premises. This conventional technique presents some problems, namely 1. time-related issues; a slow and tiresome process (Thakur *et al.*, 2020) 2. The general unreliability of the technique includes human errors and subjectivity in the technique (Makky and Cherie, 2021) 3. Labor intensiveness (Fadilah *et al.*, 2012) and 4. Associated costs (Fadilah *et al.*, 2012). Therefore, there is a need to use modern technologies and tools such as Artificial Intelligence (AI) to tackle these issues and challenges. Some of the applications of AI include earthquake occurrence estimation (Nugroho, Subiantoro, and Kusumoputro, 2023), online learning enhancement (Neo *et al.*, 2022), and GDP forecasting (Lomakin *et al.*, 2022).

AI leverages computers and machines to mimic the problem-solving and decision-making capabilities of the human mind. Machine learning (ML) is a branch of AI and computer science that focuses on the use of data and algorithms to imitate the way humans learn, gradually improving accuracy. Deep learning (DL) is a sub-field of machine learning with a neural network comprising more than three layers (IBM Cloud Education, 2020a).

(Xu *et al.*, 2021) proposed a machine learning technique, using a Random Forest (RF) algorithm based on improved grid search optimization (IGSO-RF) to detect oil palm plantations. Meanwhile, fruit quality detection has been performed with deep learning when a successful cross was achieved (Dhiman, Kumar, and Hu, 2021).

This review aims to present a thorough review of AI techniques used in agricultural industry, analyzing all the necessary stages by introducing the types of data and features to provide insights into the future trajectory and prospects of the field. The main contributions of the literature review are:

- Introducing and discussing the devices used in the literature and the type of data produced.
- Providing a list of useful datasets in the literature.
- Presenting the different data types in the literature and the respective capturing tools.
- Discussing the prevalent features and attributes used to develop AI models and providing a table showing the popularity and prevalence in the literature.
- Showing the huge variety of available AI models in the literature.

The selection process in this literature review was conducted by limiting the publication dates to the 2012 - 2023 period. The papers covered the applications of AI in agriculture and were found through Multimedia University Library Integrated Access (MULiA) on EBSCO. Additionally, the terms “fruit ripeness detection”, “fruit ripeness classification”, “oil palm ripeness detection” and “oil palm ripeness classification” were used in the search engine**.** After specifying the publication date (2012 - 2023), as well as selecting academic journals and conference materials for the publication type, 4472, 3490, 396, and 419 results appeared for each of the search queries, respectively. To reduce the large number of results, a subject filter under the “computer vision” tag was used to obtain 136, 148, 20, and 21 papers, respectively. After the filter application, the selection of papers became very easy and manageable.

A total of 41 papers using AI techniques for agricultural purposes were analyzed in the literature review. However, the contents of 16 papers were discussed to maintain conciseness and avoid redundancy. These papers adequately present applications of AI in agricultural industry and cover topics about oil palm fresh fruit bunches (FFB), tomatoes, mangoes, bananas, and berries. Table 1 shows the databases of the reviewed papers and specifies the publication type.

Table 1 Publication details of the reviewed papers

Database	Source Type	No. of Papers	References
Scopus	Journal	7	(Worasawate, Sakunasinha, and Chiangga, 2022; Dhiman, Kumar, and Hu, 2021; Aghilinategh, Dalvand, and Anvar, 2020; Wan and Goudos, 2020; Mubin, *et al.*, 2019; Mazen and Nashat, 2019; Ibrahim, Sabri, and Isa, 2018)
ScienceDirect	Journal	1	(Lee *et al.*, 2022)
SwePub	Journal	1	(Xu *et al.*, 2021)
Directory of Open Access Journals	Journal	1	(Mansour, Dambul, and Choo, 2022)
IEEE Xplore Digital Library	Conference Journal	2 1	(Huang, Wang, and Basanta, 2022; Thakur *et al.*, 2020; Septiarini *et al.*, 2019)
IOPscience	Conference	2	(Makky and Cherie, 2021; Iqbal, Herodian, and Widodo, 2019)
Nature	Journal	1	(Raj *et al.*, 2021)

This review is comprised of six sections and the different types of data used to feed AI models for agricultural applications are discussed in section 2. Meanwhile, section 3 has a more in-depth analysis of AI techniques used in the relevant literature. In Section 4, the results of different techniques are stated and compared. Section 5 analyzes the results and detects the present trends, research problem(s), and the future direction of AI techniques in agricultural industry. Finally, section 6 offers a conclusion, featuring the main points of the review.

2. Inputs

In this section, the tools used to capture the relevant data and features used in AI models in the context of agriculture are discussed. This provides insights into tools suitable for capturing data, as well as the attributes to be selected or extracted.

2.1. Data

The data used can be divided into camera-based and sensor-based categories. Camera-based data are acquired using cameras and smartphones, while sensor-based data are detected by more complicated sensors. The two categories are distinguished by the complexity and availability, where camera-based data are easier to capture, due to the ubiquity of smartphones and digital cameras. In this context, RGB images are more frequently used than other types of images in the day to day life (Neglia Design, 2015). Sensor-based data include hyperspectral (Lee *et al.*, 2022), biochemical, physical, and electrical data (Worasawate, Sakunasinha, and Chiangga, 2022).

2.2. Data Capturing Devices

There are many options for data-capturing devices in agricultural industry. The selection of the device is dependent on the purpose of the project and the required data.

2.2.1. NIR Camera

NIR (Near-Infrared) is a part of the electromagnetic spectrum invisible to the naked eye. Due to an intense beam of infrared rays, any object can be visualized with high precision. A familiar example of the technology is MRI scans which are most common in hospitals. (Iqbal, Herodian, and Widodo, 2019) captured NIR spectral data with the help of NIR camera for oil palm FFB ripeness detection.

2.2.2. Hyperspectral Camera

Hyperspectral imaging collects and processes information from across the electromagnetic spectrum for each pixel of a scene, to find objects, identify materials, or detect processes. In addition, (Lee *et al.*, 2022) used a hyperspectral camera for early detection of BSR disease in oil palm trees using hyperspectral images.

2.2.3. Other Devices

Worasawate, Sakunasinha, and Chiangga (2022) used an electronic balance, a digital refractometer, and a capacitor sensor to measure the physical, biochemical properties, and electrical properties of mangoes to classify the ripeness. Furthermore, (Raj *et al.*, 2021) used a Raman spectrometer to collect the Raman spectra of oil palm FFB to classify the ripeness. (Aliteh *et al.*, 2020) determined oil palm FFB ripeness using an augmented reality (AR) marker to capture photos and moisture content was determined using the infrared moisture analyzer.

2.3. Public Datasets

The size of a dataset is an important factor in determining the accuracy of AI models and the results obtained are improved with increased data availability. A small dataset also introduces the risk of not providing concise and general data, representing the related field broadly. These datasets do not provide high accuracies on new data but the construction can be challenging due to the time required to capture all the images available public datasets are a viable solution, as presented in Table 2 (Quintanilla Warren, and Schonning, 2022).

Papers using satellite data adopt only a fraction of the available dataset annually. Satellite imagery covers large areas of land from the point of view and is not suitable for the detection of small fruits. Table 2 shows that datasets including close-up images of fruits are a more popular option for detection.

Table 2 Datasets used in the literature and the applications

Name	Type	Size	Agricultural Application
LANDSAT	Satellite images of the surface of the earth	3000 data points (Xu *et al.*, 2021)	Detecting the oil palm plantations (Xu *et al.*, 2021)
WorldView-3 (WV-3)	Satellite images of the surface of the earth	24 tiles (Mubin, *et al.*, 2019)	Oil palm maturity detection and oil palm counting (Mubin *et al.*, 2019)
FIDS30	Images of common fruits. The images are classified into 30 different fruit classes. Every fruit class contains about 32 different images.	971 images	General purpose fruit quality assessment (Dhiman, Kumar, and Hu, 2021)
Fruits-360	Images of three fruit varieties: apples, oranges, and mangoes.	4000 images	Multi-class fruit detection (Wan and Goudos, 2020)
Date Fruit Dataset for Automated Harvesting and Visual Yield Estimation	Images of date fruits	8231 images	Estimating Date Fruits Type, Maturity Level, and Weight (Faisal *et al.*, 2020)

2.4. Features

The features and attributes selected to be fed to AI models must be relevant to agricultural task at hand and be selected appropriately. For instance, color features are selected in the ripeness classification of fruits, showing that the color can signify the level of ripeness.

Feature extraction in deep learning techniques is conducted automatically and no hand-selected feature is required. The images are simply given as inputs to the deep learning model to create a feature map of all the detected features. However, not all AI models can automatically extract features and in this context, the features must be selected manually. Table 3 shows the type of features used for agricultural purposes.

Table 3 Main features selected and the respective application

Used Features	Agricultural Application
Color features	Oil palm FFB ripeness classification (Mansour, Dambul, and Choo, 2022; Thakur *et al.*, 2020; Septiarini *et al.*, 2019; Ibrahim, Sabri, and Isa, 2018) Banana ripeness classification (Mazen and Nashat, 2019) Tomato ripeness detection (Huang, Wang, and Basanta, 2022)
Spectral features	Detecting oil palm plantations (Xu *et al.*, 2021) Oil palm FFB ripeness classification (Raj *et al.*, 2021; Iqbal, Herodian, and Widodo, 2019) BSR disease detection in oil palm trees (Lee *et al.*, 2022)
Physical features e.g. size, shape, etc.	Mango ripeness classification (Worasawate, Sakunasinha, and Chiangga, 2022) Fruit ripeness classification (Thakur *et al.*, 2020)
Temperature	Oil palm FFB quality assessment (Makky and Cherie, 2021)
Aromatic volatiles emitted by fruits	Berries ripeness classification (Aghilinategh, Dalvand, and Anvar, 2020)

3. AI Techniques

AI techniques in agricultural context can be divided into two groups, namely conventional and deep learning techniques. The commonly used conventional techniques include support vector machines (SVM) and k-nearest neighbor (KNN). Meanwhile, deep learning is a subset of machine learning and the models include convolutional neural networks (CNN) and recurrent neural networks (RNN).

The main processes, comprising four stages to implement AI techniques are shown in Figure 1. The first stage is capturing or collecting data as inputs and this stage is represented in section 2. The second stage includes the pre-processing techniques that prepare the data for AI models, namely cropping, resizing, and blurring images. According to previous results, feature extraction in deep learning techniques is automated unlike in conventional techniques. A significant portion of the image's pixels are efficiently represented through feature extraction, enabling the effective capture of the relevant details in the image (Bhagat, Choudhary, and Singh, 2019). Additionally, feature-extracting processes include filtering, texture analysis, and color histograms.

Depending on AI techniques, classification or regression is carried out to produce the intended results. The main distinction is that while classification aids in the prediction of discrete class labels, regression assists in the prediction of continuous quantities. For instance, (Aghilinategh, Dalvand, and Anvar, 2020) and (Thakur *et al.*, 2020) used linear discriminant analysis (LDA) and CNN for berries and strawberry ripeness detection, respectively. The majority of the reviewed papers are in the classification category, and these stages are explored through the introduction of five popular AI frameworks in the literature.

Figure 1 Main processes included in implementing AI techniques

3.1. Conventional Models

3.1.1. SVM

SVM are supervised machine learning models used for classification, regression, and outliers detection. In SVM algorithm, each data item is plotted as a point in an n-dimensional space with the value of each feature representing the coordinate. Subsequently, classification is performed by finding the hyperplane differentiating the two classes (Ray, 2023). Some of the applications of SVM include face recognition, handwriting recognition, protein fold, and remote homology spotting (bioinformatics) (GeeksforGeeks, 2023). For oil palm FFB ripeness classification, (Septiarini *et al.*, 2019) achieved a 92.5% accuracy with SVM. Similarly, (Aliteh *et al.*, 2020) achieved a 94.2% accuracy using a modified SVM. (Worasawate, Sakunasinha, and Chiangga, 2022) used SVM for mango ripeness classification and obtained 91.1% accuracy.

3.1.2. KNN

The k-nearest neighbors (KNN or k-NN) algorithm was developed by statisticians Evelyn Fix and Joseph Hodges in 1951 for regression or classification problems. KNN uses proximity to conduct classifications or predictions about the grouping of an individual data point. Additionally, the algorithm is used in recommendation systems, pattern recognition, data mining, financial market predictions, and intrusion detection (IBM, n.d.). In this context, (Raj *et al.*, 2021) used KNN for palm oil FFB ripeness classification based on the carotene content with 100% accuracy.

3.2. Deep Learning Models

3.2.1. CNN

Convolutional neural network (CNN or ConvNet) was first developed and used around the 1980s (Mandal, 2021). CNN is a class of deep neural networks that use a mathematical operation known as convolution in at least one of the layers. These networks are most commonly applied to image, speech, or audio signal inputs. Furthermore, CNN has three main types of layers, namely convolutional, pooling, and fully-connected (FC) layers. Firstly, the data is fed to the convolutional layer and the maps are generated after the filters or kennels are applied to detect the features. The reduction is reported in the pooling layer dimension and the fully connected layer classification is achieved based on the features extracted through the previous layers (IBM Cloud Education, 2020b). CNN is used in facial recognition, medical imaging, and autonomous driving systems (Gandharv, 2022). Additionally, (Thakur *et al.*, 2020) and (Ibrahim, Sabri, and Isa, 2018) developed an oil palm FFB and strawberry ripeness classification system with 92% and 91.6% accuracies, respectively.

3.2.2. Faster RCNN

Faster RCNN is more complex than a typical CNN and the model consists of the convolution network, region proposal network (RPN), region of interest (ROI) pooling, softmax classification, and bounding box regression. Faster RCNN is mainly used in the medical and traffic fields for white blood cells (Zeng *et al.*, 2023) and object detection (He, Liu, and Huang, 2023). In addition, (Wan and Goudos, 2020) constructed a multi-class fruit detection system with a mean average precision (mAP) of 90.72%.

3.2.3. RNN

RNN is a supervised deep learning neural network that allows previous outputs of sequential or time series data to be used as inputs while having hidden states. It preserves the sequence and order of events in a sequence when dealing with sequential data. Time series analysis such as stock price forecasting, speech recognition, and sentiment are some of the general use cases (Dilmegani, 2023). In the pre-processing stage, (Dhiman, Kumar, and Hu, 2021) used a contrast enhancement technique, followed by grayscale conversion to balance the unstable light in the input fruit image suppressing the object definition. Subsequently, canny edge detection was used to discover the boundaries of the fruits, and quality assessment was performed with an accuracy of 98.47% by using RNN.

4. Results

Table 4 summarizes the representative AI techniques used in agricultural industry, specific objectives, details of the data, and performance in terms of accuracy. The quantity and quality of the datasets as well as AI techniques used determine the level of accuracy and reliability of the results. In this context, small numbers of data do not produce high levels of accuracy.

Table 4 Research papers that discuss AI techniques in agricultural industry

Reference	Objective	AI Techniques	Data	Size of Data	Performance
(Xu *et al.*, 2021)	Oil palm tree detection	Random forest algorithm based on improved grid search optimization (IGSO-RF)	Spectral data; Landsat-8 top-of-atmosphere reflectance (TOA) images and Sentinel-1A data from Google Earth Engine (GEE) database	3000 data points	Overall Accuracy = 96.08%
(Mubin *et al.*, 2019)		Using two LeNet-based CNNs.	Satellite imagery from WorldView-3 (WV-3) database	3737 images	Accuracy for mature trees = 92.06% Accuracy for young trees=95.11%
(Septiarini *et al.*, 2019)	Oil palm FFB ripeness classification	SVM	RGB images of FFB	160 images	Accuracy = 92.5%
(Iqbal, Herodian, and Widodo, 2019)		Partial Least Square (PLS) Regression	NIR scans of FFB	60 samples	R2=0.93
(Raj *et al.*, 2021)		KNN	FFB spectral data	46 samples	Accuracy = 100%
(Ibrahim, Sabri, and Isa, 2018)		SVM, CNN, and AlexNet using transfer learning.	RGB images of FFB	120 images	SVM accuracy = 75% CNN accuracy = 92% AlexNet accuracy = 100%
(Mansour, Dambul, and Choo, 2022)		MobileNetV2 SSD, EfficientDet (Lite0, Lite1 and Lite2) and YOLOv5 (YOLO v5n, YOLOv5s and YOLOv5m)		304 images	MobileNetV2 SSD mAP = 0.478 EfficientDet- Lite0 mAP = 0.743 EfficientDet- Lite1 mAP = 0.803 EfficientDet- Lite2 mAP = 0.812 YOLOv5n mAP = 0.781 YOLOv5s mAP = 0.832 YOLOv5m mAP = 0.842

Table 4 Research papers that discuss AI techniques in agricultural industry (Cont.)

Reference	Objective	AI Techniques	Data	Size of Data	Performance
(Makky and Cherie, 2021)	Oil palm FFB quality assessment	Linear regression model, multiple-regression model	FFB thermal imaging	N/A	Coefficient of determination (R2) range = 0.67 – 0.83
(Lee *et al.*, 2022)	Early detection of BSR disease in oil palm trees	Multilayer perceptron (MLP)	FFB spectral data	5739 images	Overall Accuracy = 86.67%
(Wan and Goudos, 2020)	Fruit detection	A deep learning framework for multi-class fruit detection based on improved Faster R-CNN	RGB images of apples, oranges, and mangoes from the Fruits-360 dataset	4000 images	mAP = 90.72%
(Dhiman, Kumar, and Hu, 2021)	Fruit quality classification	RNN	RGB images from the FIDS30 dataset + images from Google	400 images	Overall accuracy = 98.47%
(Worasawate, Sakunasinha, and Chiangga, 2022)	Mango ripeness classification	k-Means, Gaussian Naïve Bayes (GNB), Support Vector Machine (SVM), Feed-Forward Artificial Neural Network (FANN)	Biochemical, physical, and electrical data were extracted from mangoes	120 mango samples	GNB accuracy range = 57% - 81% SVM accuracy range = 55% - 91.1% FANN accuracy range = 79% - 93.6%
(Mazen and Nashat, 2019)	Banana ripeness classification	Levenberg–Marquardt backpropagation optimization algorithm	RGB images of bananas	300 images	The overall class recognition accuracy of 100% is obtained for the green and overripe classes, while it is 97.75% for the yellowish-green and mid-ripe classes.
(Huang Wang, and Basanta, 2022)	Tomato detection and ripeness classification	A fuzzy Mask R-CNN model	RGB images of tomatoes	900 images	Accuracy for tomato detection = 98% Weighted precision for ripeness classification = 0.9614 Weighted recall for ripeness classification = 0.9591

Table 4 Research papers that discuss AI techniques in agricultural industry (Cont.)

Reference	Objective	AI Techniques	Data	Size of Data	Performance
(Aghilinategh, Dalvand, and Anvar, 2020)	Berries ripeness detection	ANN, PCA, and LDA	Aromatic data emitted by white berry and blackberry	120 samples	ANN accuracy= 100% (blackberry), 88.3% (white berry) LDA accuracy= 96.67% (blackberry), 85% (white berry) PCA analysis characterized 97% and 93% variance in the blackberry and white berry, respectively.
(Thakur *et al.*, 2020)	Strawberry ripeness classification	CNN	RGB images of strawberries	300 images	Accuracy = 91.6%

According to Table 4, 12 out of the 16 papers produced results greater than 90% in terms of accuracy, coefficient of determination (R^2), sensitivity, and mean average precision (mAP). The performances of AI models were mostly considered in terms of accuracy, which was calculated by dividing the number of correct predictions of the model by the total number of samples.

5. Discussion

The trends among the reviewed papers, research problems encountered during the literature review, and the prospects in the agricultural industry are discussed in the section. Understanding the occurring trends offers a broad knowledge of state-of-the-art developments. Conventional machine learning and statistical models, such as SVM, established for many years are widely used for agricultural applications as seen in Table 4. In contrast, newer deep learning models, such as CNN, which are structurally more complex but more time-consuming and demanding in terms of computing power, have gained popularity and widespread adoption due to superior performance, accuracy, and computational prowess.

The absence of platforms or applications catering to the needs of the target market with user-friendly interfaces, devoid of programming requirements and not reliant on high processing capabilities, represents a ripe area for exploration. The development of lightweight AI models and user-friendly AI-driven mobile or desktop applications holds promise for enhancing the accessibility of the technology and meeting market demands.

Predictions regarding AI applications in agricultural industry can be formulated by examining the focal areas of leading companies worldwide. For instance, TensorFlow which is an open-source platform for machine learning developed by Google Brain Team in 2015, has a heavy focus on developing and improving deep models such as ResNet, and EfficientNet (Tensor Flow, 2020). Big companies such as Google influence the direction of research and the market, with the development of newer deep learning models to gain more traction and popularity in the future.

6. Conclusions

In conclusion, this literature review was carried out to provide insights into AI techniques used in the agricultural industry as well as the inputs of data and features. The papers reviewed were from the recent 10 years using machine learning and deep learning models. AI models mostly used RGB data and color features of fruits as input. Conventional and deep learning models had high levels of performance for accurately performing tasks in the agricultural industry through the review. This high level of performance could tackle the problems included high time consumption, labor intensiveness, and associated costs in conventional techniques of handling fruits. In addition, AI could save time, the need for additional labor, and costs. This review discussed the different elements of AI techniques in the agricultural industry.

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