Harnessing AI in Precision Agriculture for Sustainable Kiwifruit Farming

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Original scientific article

***Abstract*—Sustainable green kiwifruit production is related to enhanced fruit quality and decreased farming costs. As kiwifruit farming becomes more popular and commercialized, precision agriculture (PA) practices are adopted towards its digital and green transformation. In this work, the application of artificial intelligence (AI) in PA of kiwifruit farming is investigated, by analyzing existing applications, current research and digital innovations. This work aims to identify on a practical level all current implementations of AI in kiwifruit farming and provide a feasibility analysis for the practical application of the most current and promising AI innovations on site. Research findings are analyzed towards capturing the broad range of current status and perspectives of AI in kiwifruit farming, as well as to identify research gaps, so as to guide further beyond the green and digital transformation of the kiwifruit industry.**

***Index terms*—kiwifruit, artificial intelligence, precision agriculture, sustainable farming, green transformation, digital transformation, harvesting, pollination, agrobots.**

I. Introduction

Kiwifruit's global popularity is due to its close relation to health and well-being, since it is low-fat, free from sodium and cholesterol, high in fiber and potassium, and packed with antioxidants. Benefits related to the consumption of kiwifruit include prevention of chronic diseases like heart disease and cancer, increased immunity and digestive health [1].

Due to these benefits, kiwifruit is highly valued in the Food and Beverages industry and is used as the main ingredient in various products. Note that the kiwifruit global market size is estimated at USD 9.45 billion in 2024, expecting a compound annual growth rate (CAGR) of 4.60% during the following 5 years, reaching USD 11.80 billion by 2029 [2], as illustrated in Fig.1. As the popularity and demand for kiwifruit increase, producers are looking for innovative technological approaches towards transforming traditional time-consuming labor- and cost-intensive practices into more sustainable and efficient ones.

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PA mainly guides automation in the agricultural domain [3], including kiwifruit farming [4]. PA uses sensors and algorithms to monitor crop growth and environmental conditions, aiming to retrieve real data, extract useful information, and provide data-driven insights to help increase yield quality and quantity by providing less input resources, i.e., optimizing sustainability and productivity [5].

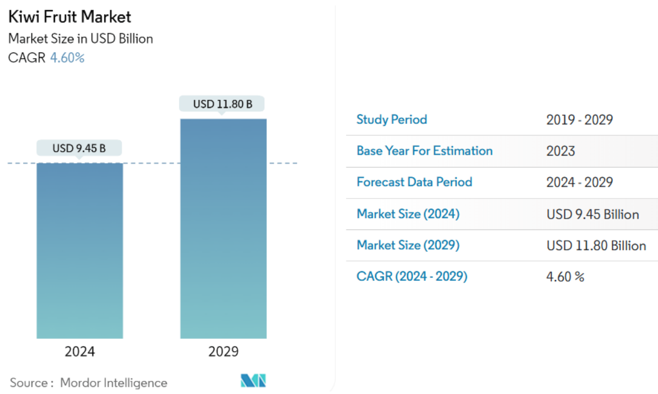


Fig. 1. The global kiwifruit market in USD [2]

PA and AI are closely related through the integration of advanced technologies to enhance farming practices [6]. The latter is achieved through highly developed digital sensors, drones and Internet of Things (IoT) devices to monitor soil, weather conditions, crop health, etc., in real-time. AI algorithms such as machine learning models process this data toward identifying patterns, aiming to deliver data-driven insights regarding crop yield, irrigation, fertilization, pest control, and more [7]. In general, AI supports PA through the developed decision supporting systems, for predictive analytics and automated decision-making. AI is also applied in PA through automated machinery and robotics, namely agrobots, for planting, spraying, monitoring, etc., resulting in enhanced precision of operations, reduced human labor costs, optimization of resources, minimum wastes and maximum efficiency [8]. AI algorithms are also used to forecast future market demand and guide farmers' decisions, as well as to improve the efficiency of the supply chain, from farm to shelves [9], [10].

Recently, PA and AI approaches have been adopted in kiwifruit cultivation towards its green and digital transformation [11]. However, for the kiwifruit, which is a relatively new crop of ever-increasing economic value, the integration of digital technologies is still in its early stages. Note that AI-based approaches in PA are in line with the

Sustainable Development Goals (SDGs) provided in the 2030 Agenda for Sustainable Development [12] adopted by all United Nations (UN) Member States, related to SDG 2 (zero hunger), SDG3 (good health and well-being), SDG 6 (clean water and sanitation), SDG 9 (industry, innovation and infrastructure), SDG 11 (sustainable cities and communities), SDG 12 (responsible consumption and production), SDG 13 (climate action), and SDG 17 (partnerships for the goals). Therefore, it can be foreseen that by fully integrating AI in PA, kiwifruit farming can significantly contribute to these SDGs, promoting a sustainable, efficient, and more resilient agricultural sector.

To this end, this work comes as a follow up of a recent narrative review [11] focused on PA techniques in kiwifruit farming towards unraveling the potential of AI for the digital and green transformation of kiwifruit farming. In the current work, additional aspects are further considered so as to enhance our previous work and make it more complete. The contributions of this work can be summarized in the following distinct points:

1. A complete review of the most recent status of AI in PA kiwifruit farming, including:
    i. involved agricultural practices,
    ii. specific commercial and research in-field applications,
    iii. kiwifruit image datasets public and private,
    iv. identified research gaps.
2. A complete guide for the current trends of AI in kiwifruit farming including multiple technologies such as drones, IoT devices, blockchain and robotics, which have already begun to appear and implemented in practice, and
3. The foreseen future of AI regarding technologies that have been recently introduced but have not yet been incorporated into the cultivation of kiwifruit, providing a feasibility study towards their future integration.

Therefore, this work aims to cover the past, the presence, and the future of all related aspects regarding the involvement of AI in kiwifruit farming. It should be noted that related works on the subject are not available in the academic literature, as far as the authors' knowledge, apart from our previous work [11], which is an introductory work to the extensive and enriched present work. Therefore, this work is an original contribution and there are no prior reviews of direct relevant studies for comparison. The novelty of this work is to establish a review baseline on the subject and set the foundations of future works, aiming to serve as a starting point for new researchers, to uncover research gaps and overlooked areas, and inspire innovative thinking.

The rest of the paper is structured as follows. Materials and methods are included in Section II. Research results are presented in Section III and are discussed in Section IV, covering past and current trends. Section V unravels the potential of AI in kiwifruit farming, while Section VI concludes the paper.

II. Materials and Methods

The main objective of this work is to reveal the potential of AI novel trends in kiwifruit farming and conduct a feasibility study towards its full adaptation. Therefore, a narrative review is conducted [13]. Narrative reviews aim to provide comprehensive, qualitative synthesis of previous research on specific topics, without using predefined criteria, research questions, specific research strategies or statistical methods to evaluate and summarize studies. Narrative reviews offer a more flexible and interpretive approach towards identifying key themes, insights, and perspectives that could guide future research. Key features of a narrative review include their broader scope, covering a wide range of studies, their thematic organization and subjective analysis based on the authors' expertise and perspective to interpret research findings and draw conclusions, and their contextual insights aiming to provide a deeper understanding of the general context of the research theme.

To this end, research for relevant articles in academic literature has been conducted in Scopus and Google Scholar databases by using terms such as "artificial intelligence" and "kiwifruit farming". The goal is to synthesize and describe information from the available literature on the topic and provide valuable conclusions, interpretations and critiques from the gathered evidence, so as for the reader to gain a holistic understanding of this specific research field. Therefore, the steps to conduct our narrative review were as follows: the purpose of the paper was first clearly stated, and after selecting a context of relevant articles to overview, the findings were synthesized to interpret the literature, define gaps and set the stage of future research.

III. Results

In this section, the current status of AI-powered systems in kiwifruit farming is stated. This is the first step, followed by discussion on the identified AI trends, and concluding on the foreseen potentials of AI and its overall adoption in kiwifruit farming industry.

All related works regarding AI applications in kiwifruit cultivation are included in Table I. The selected taxonomy for the presentation of the results of Table I is based on the intended application. More specifically, eight applications have been identified, including Crop management analysis, Defects detection, Disease detection, Image analysis, Kiwifruit detection, Flower detection, Quality control, and Yield estimation. For each application, the specific type of application, the corresponding results, its scope, and its use, i.e., whether it is commercial or research work, as well as whether it is integrated into a robotic system, and other useful information are summarized in Table I.

Regarding crop management analysis, identified works focus on theoretical research aspects, including data analysis towards optimal fertilize and irrigation management, classification of kiwifruit based on their origin, and prediction of properties of fruits under different load and storage conditions.

TABLE I
GENERAL INFORMATION OF AI-POWERED APPLICATIONS IN KIWIFRUIT CULTIVATION

Crop Management Analysis						
Ref.	*Type*	*Scope*			*Use*	*Robotics*
[14]	Data analysis	Fertilize and irrigation management			Research	-
[15]	Data classification	Distinguishing the Kiwifruit geographical origin			Research	-
[16]	Data regression	Prediction of physical properties of kiwifruit during different loadings and storage			Research	-
Defects Detection						
Ref.	*Type*	*Defect type*	*Results*		*Use*	*Robotics*
[17]	Object detection	External surface defects	95.00% R^2		Research	-
[18]	Classification	External surface defects	99.60% acc.		Research	-
[19]	Object detection	CPPU treated kiwifruits	90.00% acc.		Research	-
[20]	Classification	Invisible damages	98.27% acc.		Research	-
Disease Detection						
Ref.	*Type*	*Disease*	*Plant part*	*Results*	*Use*	*Robotics*
[21]	Classification	Black spot	Fruit	86.71% prec.	Research	-
[22]	Classification	Powdery mildew	Fruit	95.91% acc.	Research	-
[23]	Classification	Bacterial canker	Leaves	71.00% acc.	Research	-
[24]	Classification	Brown spot, Bleeding Canker, Anthracnose, Mosaic	Leaves	83.34% acc.	Research	-
[25]	Classification	Bacterial canker	Fruit/Leaves	85.00% acc.	Research	-
[26]	Classification	Brown spot, Anthracnose, Mosaic	Leaves	98.54% acc.	Research	-
[27]	Classification	Armillaria root, Bacterial blight, Bleeding canker, Botrytis fruit rot, Phytophthora root, Water staining, Juice blotch, Sooty mold, Collar rot, Crown rot	Leaves	85.64% acc.	Research	-
[28]	Classification	Lower rot, Ephemeral nightshade moth, Anthrax, Gray mold, Brown spot, Ulcer	Leaves	94.43% acc.	Research	-
[29]	Classification	Brown spot, Anthracnose, Mosaic, Black spot, Yellow leaf, Ulcer	Trunk/Leaves	98.78% acc.	Research	-
Image Analysis						
Ref.	*Type*	*Scope*			*Use*	*Robotics*
[30]	Generative AI	Image generation to reconstruct the incomplete surface of kiwifruit			Research	-
Kiwifruit Detection						
Ref.	*Type*	*Objective*		*Results*	*Use*	*Robotics*
[31]	Object detection	Kiwifruit detection		93.10% prec.	Research	✓
[32]	Segmentation	Cluster separation		86.40% acc.	Research	-
[33]	Segmentation	Kiwifruit detection		0.19% ME	Research	✓
[34]	Object detection	Kiwifruit detection		98.00% prec.	Research	✓
[35]	Object detection	Image fusion for kiwifruit detection		90.50% prec.	Research	✓
[36]	Segmentation	Smartphone images for kiwifruit detection		98.48% prec.	Research	-
[37]	Object detection	Kiwifruit detection in challenging lightings		97.00% acc.	Research	-
[38]	Object detection	Kiwifruit detection		87.61% prec.	Research	-
[39]	Object detection	Kiwifruit detection		92.30% acc.	Research	-
[40]	Object detection	Kiwifruit picking platform		82.60% prec.	Research	✓
[41]	Object detection	Kiwifruit detection		96.70% acc.	Research	-
[42]	Object detection	Kiwifruit feature point coordinates extraction		-	Research	✓
[43]	Segmentation	Development of a robotic harvester		89.60% acc.	Research	✓
[44]	Object detection	Development of a robotic harvester		90.07% acc.	Research	✓
[45]	Segmentation	Kiwifruit detection		88.30% acc.	Research	-
Flower Detection						
Ref.	**Type**	*Objective*		*Results*	*Use*	*Robotics*
[46]	Classification	Flower detection for robotic pollinator		89.10% prec.	Research	✓
[4]	Object detection	Flower detection for robotic pollinator		91.00% prec.	Research	✓
[47]	Classification	Selection of suitable flower for pollination		91.60% prec.	Research	-
[48]	Object detection	Simultaneous detection of flower and bud		97.60% prec.	Research	✓
[49]	Object detection	Green flower detection for robotic pollination		97.00% prec.	Research	✓

TABLE I
CONT.

Quality Control					
Ref.	*Type*	*Objective*	*Results*	*Use*	*Robotics*
[50]	Regression	Hardness estimation	97.00% acc.	Research	-
[51]	Classification	Variety classification	97.79% acc.	Research	-
[52]	Remote sensing	Phenology observations for an e-learning interactive platform	-	Kiwi Platform	-
[53]	Regression	Sugar content prediction	100% acc.	Research	-
[54]	Classification	Solid content prediction	37.00% R^2	Research	-
[55]	Regression	Soluble solids content (SSC) prediction	41.00% R^2	Research	-
[56]	Classification	Quality grading	98.30% acc.	Research	-
[57]	Classification	Quality grading	97.50% acc.	Research	-
Yield Estimation					
Ref.	*Type*	*Objective*	*Results*	*Use*	*Robotics*
[58]	Segmentation	Robot for yield prediction	96.00% R^2	Research	✓
[59]	Segmentation	Yield estimation using Android phone	76.40% prec.	Jingold	-
[60]	Segmentation	Fruit counting and yield prediction prototype mounted on a microtractor	20.00% av. error	Research	-

TABLE II
INFORMATION OF THE USED DATASETS

Crop Management Analysis									
Ref.	*App.*	*Data type*	*Dataset access*	*Synthetic data*	*Augmented data*	*Num. of data*	*Num. of objects*	*Targets*	*Sensor type*
[14]	Aerial	Tabular	Private	-	-	-	11 Features	1 Value (soil quality)	-
[15]	Indoor	Tabular	Private	-	-	100	10 Features	3 Classes (Geographic Regions)	-
[16]	Indoor	Tabular	Private	-	-	150	11 Features	3 Values (Weight, Density, Volume)	-
Defects Detection									
Ref.	*App.*	*Data type*	*Dataset access*	*Synthetic data*	*Augmented data*	*Num. of data*	*Num. of objects*	*Targets*	*Sensor type*
[17]	Indoor	NIR	Private	-	-	115	11 Features	3 Values (Weight, Density, Volume)	-
[18]	Indoor	RGB	Private	-	-	268	-	-	
[19]	Indoor	RGB	Private	-	-	4663	4663	2 Classes (Defective, Healthy)	MV-EM200C camera
[20]	Indoor	Hyperspectral	Private	-	-	237	-	-	-
Disease Detection									
Ref.	*App.*	*Data type*	*Dataset access*	*Synthetic data*	*Augmented data*	*Num. of data*	*Num. of objects*	*Targets*	*Sensor type*
[21]	Outdoor	RGB	Private	-	-	7404	-	10 classes Disease Severity	Canon Camera
[22]	Outdoor	RGB	Public	-	-	12000	12000	4 severity levels	-
[23]	Outdoor	Hyperspectral	Private	-	-	504	-	2 Classes (Symptomatic, non-symptomatic	spectroradiometer (ASD FieldSpec® HandHeld 2)
[24]	Indoor/ Outdoor	RGB	Private	-	6500	2101	-	5 classes Diseases	Nikon D7500
[25]	Outdoor	RGB	Private	-	-	504	504	2 Classes (Symptomatic, non-symptomatic	-
[26]	Outdoor	RGB	Private	-	11322	666	666 leaves	3 Classes (Disease)	BM-500GE/BB-500GE
[27]	Outdoor	RGB	Private	-	-	29951	29951	10 Classes (Diseases)	-
[28]	Outdoor	RGB	Private	-	3600000	17820	360000 Leaves	6 Classes (Disease)	Nikon DSLR
[29]	Outdoor	RGB	Public	-	25168	2115	2115 leaves	6 Classes (Disease)	-

TABLE II
CONT.

Image Analysis									
Ref.	*App.*	*Data type*	*Dataset access*	*Synthetic data*	*Augmented data*	*Num. of data*	*Num. of objects*	*Targets*	*Sensor type*
[30]	3D scan	RGB	Private	Yes	3000	480	-	1 Class (Kiwi)	-
Kiwifruit Detection									
Ref.	*App.*	*Data type*	*Dataset access*	*Synthetic data*	*Augmented data*	*Num. of data*	*Num. of objects*	*Targets*	*Sensor type*
[31]	Outdoor	RGB	Private	-	-	117	7114 kiwis	1 Class (Kiwi)	-
[32]	Outdoor	RGB	Private	-	-	487	-	-	-
[33]	Outdoor	RGB	Private	-	-	223	-	-	-
[34]	Outdoor	RGB	Private	-	-	4175	37720 kiwis	1 Class (Kiwi)	-
[35]	Outdoor	RGB, NIR	Public	-	-	1000	39678 kiwis	4 Classes (kiwi, overlap, adjutancy, separated)	Kinect V2
[36]	Outdoor	RGB	Private	-	-	66	5361 (poly), 2925 (rect)	1 Class (Kiwi)	Smartphone
[37]	Outdoor	RGB	Public	-	-	48	11760 Kiwi	1 Class (Kiwi)	Basler ac1920-40uc
[38]	Outdoor	RGB	Private	-	20160	2400	-	1 Class (Kiwi)	Canon S110
[39]	Outdoor	RGB	Private	-	-	700	2100	1 Class (Kiwi)	(Canon S110
[40]	Outdoor	RGB	Public	-	-	1500	41168 kiwis	1 Class (Kiwi)	-
[41]	Outdoor	RGB	Private	-	-	100	300 kiwis	1 Class (Kiwi)	-
[42]	Outdoor	RGB	Private	-	-	0	-	1 Class (Kiwi)	Kinect
[43]	Outdoor	RGB	Private	-	-	63	-	-	-
[44]	Outdoor	RGB	Private	-	-	1936	-	-	-
[45]	Outdoor	RGB	Private	-	-	103	-	-	-
Flower Detection									
Ref.	*App.*	*Data type*	*Dataset access*	*Synthetic data*	*Augmented data*	*Num. of data*	*Num. of objects*	*Targets*	*Sensor type*
[46]	Outdoor	RGB	Private	-	3344	880	7000 Flowers	1 Class (Kiwi-Flower), 1 Class (Flower Center)	Intel RealSenseD415 camera
[4]	Outdoor	RGB	Private	-	-	1451	-	-	-
[47]	Outdoor	RGB	Private	-	1704	355	-	7 Classes (Kiwi Flower Stage)	-
[48]	Outdoor	RGB	Public	-	0	740	-	2 Classes (Kiwi Flower, Kiwi Bud)	-
[49]	Outdoor	RGB	Private	-	0	1451	-	1 Class (Kiwi-Flower), 1 Class (Flower Center)	-
Quality Control									
Ref.	*App.*	*Data type*	*Dataset access*	*Synthetic data*	*Augmented data*	*Num. of data*	*Num. of objects*	*Targets*	*Sensor type*
[50]	Indoor	NIR	Private	-	0	400	400	1 Value (Hardness)	-
[51]	Indoor	RGB	Private	-	0	2056	2056	4 Classes kiwi varieties	Raspberry Pi Camera
[52]	Outdoor	Multimo dal data	Private	-	0	0	-	Phenology Observations	IoT Device
[53]	Indoor	NIR	Private	-	0	140	-	3 Classes (Sugar Level)	Spectral Camera
[54]	Indoor	Hypersp ectral	Private	-	0	495	495	1 Value (Solid Content)	Hyspex-VNIR-1800 camera
[55]	Indoor	Hypersp ectral	Private	-	0	495	495	1 Value (Soluble Solids Content)	Hyspex-VNIR-1800 camera
[56]	Indoor	RGB	Private	-	0	490	10 Features	4 Classes kiwi quality	-
[57]	Indoor	RGB	Private	-	0	326	326 kiwis	3 Class of kiwi quality	-
Yield Estimation									
Ref.	*App.*	*Data type*	*Dataset access*	*Synthetic data*	*Augmented data*	*Num. of data*	*Num. of objects*	*Targets*	*Sensor type*
[58]	Outdoor	RGB	Private	-	-	-	-	-	-
[59]	Outdoor	RGB	Private	-	-	-	-	-	-
[60]	Outdoor	RGB	Private	-	0	50	-	1 Class (Kiwi)	Sony Alpha 5100

A more comprehensive analysis of crop management could include additional dimensions, such as environmental sustainability and economic analysis studies, as well as impact analysis of the integration of technological interventions. Defects detection focus mainly on external abnormalities on the fruit surface, since appearance significantly influences consumer appeal, and defines the economic value of fruits. Identified research works manage to detect defects reporting accuracies of more than 90% in all cases. Studies on disease detection focus on the analysis of defects on leaves and fruits towards identifying specific diseases that are common on kiwifruit cultivations, such as black and brown spot.

Regarding image analysis, only one work has been identified for the reconstruction of the incomplete surface of kiwifruit images based on generative artificial intelligence techniques. Generative AI has been extensively used for synthetic dataset generation in the agricultural sector, aiming to address the challenge of data scarcity and enhance precision agriculture. Both fruit and flower detection are among the most popular tasks in the literature, and the ones that have been extensively integrated in robotic automations, either for yield estimation, harvesting or automatic pollination, reporting efficient detection accuracies.

Studies on quality control mainly focus on fruits grading based on specific objectives such as phenology observations. Note that quality control and defect detection for fruits are closely related but not exactly the same; defects detection is a specific process within quality control towards identifying external or internal defects, while quality control is a broader process that involves additional aspects such as size, hardness, ripeness, sugar content, compliance with standards for packing, storage and transportation and more. More insights regarding the eight AI applications that have been identified are included in the discussion section.

Table II is a supplementary table that includes information regarding the used datasets in each one of the previously referenced works of Table I. Details on the used datasets, such as their type, accessibility, number of data, synthetic data, features, and targets, as well as the acquisition sensor type, are summarized in Table II, and discussed in the discussion section.

Note that all information included in both Tables has a meaningful reflection on the results, which are further analyzed and discussed thoroughly in the upcoming section.

IV. Discussion

In this section, the current status of AI in kiwifruit farming is presented, as a result of the information included in Tables I and II. Applications, datasets and research gaps are also identified.

A. *Current Status*

The current status of AI in kiwifruit farming is depicted in Tables I and II. Research works included in both tables verify that agricultural digitalization has significantly advanced kiwifruit production during recent years, for multiple applications, however, leaving room for a greater involvement in the future, as discussed in the following subsections.

A.1 Applications

The studied works propose various applications using AI approaches. More specifically, eight applications have been identified, and are included in Table III.

From Table III, it can be concluded that most applications focus on post-harvest stages of kiwifruits (application numbers: 1, 3, 4, 5, 6, and 8), while quality control and manufacturing phases are less popular (application numbers: 2, 7). Table III also includes the amount of AI applications for kiwifruits, i.e., number of relevant papers.

Observation of the results reveals that detecting kiwifruit and plant diseases from images captured in outdoor environments are the most common applications, followed by quality control.

TABLE III
Distinct Applications in Kiwifruit Farming

ID	*Application name*	*No. of papers*
1	Crop management analysis	3
2	Defects detection	4
3	Disease detection	9
4	Image analysis	1
5	Kiwifruit detection	15
6	Flower detection	5
7	Quality control	8
8	Yield estimation	4

Indeed, fruit detection is a fundamental task in PA, and it is the first step towards several other applications, such as precision robotic harvesting, accurate yield estimation, detecting defects for quality control, growth tracking, application of pesticides, disease detection, and ripeness estimation. Computer vision and AI algorithms are therefore developed, aiming to detect and localize fruits under challenging environmental conditions, such as lighting and shadowing variations, occlusions, overlaps, etc.

Intact early disease detection from images can provide an easy way to analyze the infection of kiwi plants, towards applying pesticides more efficiently, thus, reducing waste and limiting environmental impact, ensuring optimal use of resources and sustainable farming management.

Significant research can also be observed in the quality control of kiwifruits, primarily focusing on indoor applications, therefore, after harvest time. The reviewed methods evaluate the concentration of sugar towards ripeness estimation, defects, and geometrical attributes of the harvested fruits through images to ensure compliance with quality market standards.

Table I also indicates a tendency towards integrating algorithms for kiwifruit detection into robotic systems. Most robotic systems found in the literature provide kiwifruit detection for automatic harvesting tasks or kiwi flower detection for automatic pollination. Therefore, our work located two functional autonomous robotic harvesting systems [43], [44] as well as robotic pollinators [4], [46], [49].

Pollination is essential for the fertilization process leading to the setting of kiwifruits, therefore directly influencing yield production. Moreover, efficient pollination ensures the optimal size and shape of the produced fruits. Yet, pollinator populations of bees, which are vital for the ecosystem, are ever decreasing. Supporting pollinators, other than natural, are therefore required. Manual pollination techniques are common, while in recent years, artificial pollination based on robotics and computer vision detection techniques has emerged as a novel trend. Advancements in computer vision algorithms can lead to high detection accuracies, as seen from the results included in Table I, increasing the efficiency of automated systems.

Another interesting conclusion from the summarized findings of Table I is regarding the use of each application, i.e., their distribution as final products or plain research.

It is evident that most of the studies are intended primarily for research purposes, with only two published works presenting a more comprehensive solution for end users and the market in general. The first one [52] introduces a platform that collects data from weather stations, cameras, and soil sensors to predict and analyze phenology in kiwi fields. Additionally, a complete platform is provided to end-users towards monitoring crops. The second one [59], refers to a web service combined with a computer vision methodology for detecting and counting kiwi fruits in the field. The counting results are correlated with harvest metrics, such as kiwi weight, for yield estimation.

A.2 Datasets

The existence of quality data is crucial for the development of AI methods in general, as well as for kiwifruit farming applications. Efficient AI models, especially machine and deep learning models require large amounts of high-quality data. In the case of crops, such as in our case, diverse conditions need to be captured in datasets, so as to endure generalization of models under varying conditions, since farming involves outdoor conditions subjected to noises, occlusions and dynamic environmental conditions, resulting in lighting variations and shadowing. On top of these, different climates, soil types and evolving farming practices may lead to several different scenarios, that would be useful towards adaptable, robust, and models that generalize well. To this end, while Table I includes more general information, Table II is focused on the used datasets in each referenced work due to their underlined importance.

From the analyzed papers, certain characteristics of the used datasets have been collected, such as data type (image, tabular data or multimodal), the number of data, if they used augmentation or synthetic images, the targets for each study and whether the dataset is publicly available or not.

It is evident that in most cases image data are preferable. Of the analyzed papers, 45 use image data, while only four works use other types such as tabular data from sensors or chemical indicators. Images are preferable for AI algorithms and particularly for farming tasks related to computer vision and pattern recognition. Images can capture a wide range of complex data such as textures, shapes, colours, spatial relations, etc., that can be used to fully interpret the world, while they provide an intuitive representation for humans that can be visually explainable and naturally perceived. Note that deep learning models work by analyzing image data, therefore advancements in AI and machine learning need image data to be tested.

Therefore, it is clear that image data have high value and information density which gives an advancement in computer vision for agricultural tasks. This emphasis points out that future research may continue prioritizing visual data.

Figure 2 summarizes the number of images used in the works for the three most common target applications, as identified from our research: kiwifruit detection (Fig. 2(a)), disease detection (Fig. 2(b)), and quality control (Fig. 2(c)). From Fig. 2, it can be observed that most of the proposed works use a relatively small amount of image data for all three applications. Additionally, kiwi disease recognition datasets contain more images than kiwi fruit detection datasets. This difference can be attributed to the fact that most kiwi fruit diseases are identified on leaves, which have diverse shapes and positions within images. Furthermore, kiwi disease recognition involves a greater number of classes compared to kiwifruit detection. These findings highlight the need for rich image datasets that could cover a wider range of visual detection tasks.

Figure 3 visually shows the availability of the used datasets in all selected works. Most of the used datasets, in 44 of the studies, are not public, while there are only five open access datasets. Of these five public datasets studies, three are for kiwifruit detection, one for kiwi flower detection, and one for disease detection. Note that this one dataset for disease detection is not specified on kiwifruit diseases; it is designed for various crops diseases on leaves also including kiwi leaves.

A.3 Research Gaps

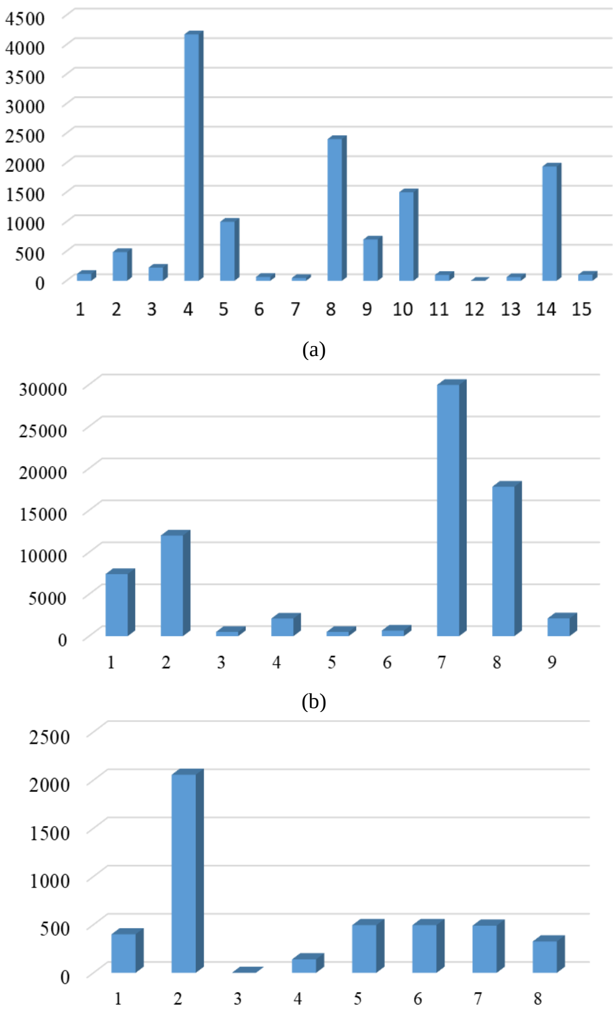
Based on the previous analysis, several research gaps have been identified.

There is a profound lack of open datasets for kiwi-related AI methodologies. This lack creates several issues, such as limitations in benchmarking and comparability between the developed methodologies, as there is no common base for comparing various proposed methods.

Additionally, when many methods rely on private, in-house datasets, there is a high risk that these methods may be biased and lack generalization to broader scenarios. Another issue arising from the lack of open datasets is the limited reproducibility. Researchers and commercial product developers are unable to test and replicate the performance of published methods, which hinders scientific progress and the development of reliable solutions.

Another important research gap is the lack of studies that consider applicability and end-user experience in methodology design. This approach keeps many proposed studies at an academic level, without presenting or testing their methodologies from an end-user perspective. As a result, scalability and practicality are limited, particularly regarding user-friendliness and performance with larger, more diverse datasets.

In a real agricultural scenario, consider for example 30 farmers that grow kiwifruits. If each farmer captures 20 photos of kiwi plants daily, this will return up to 600 images per day, which is a significant volume of data with high diversity in content. Note that current methods are trained on datasets of around 2,000 images. The latter scenario highlights the potential limitations of such methods to handle both the diversity and volume of images existing in real-world conditions since most studies are tested on limited data from controlled datasets, raising concerns about whether research-focused methods are robust enough to handle the challenges and variability of real-world conditions.



(c)
Fig. 2. Number of data used for (a) kiwifruit detection, (b) disease detection, (c) quality control

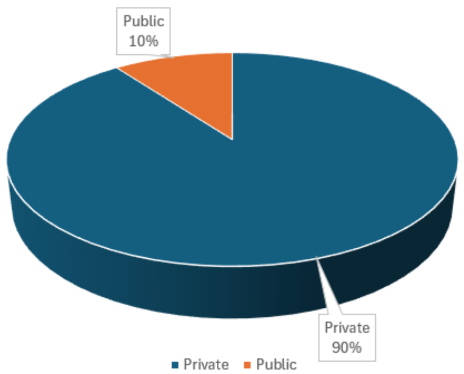


Fig. 3. Availability of datasets

Moreover, there is a gap in kiwifruit quality estimation directly in the field. Most quality estimation methods are designed for indoor environments, which limits options for managing fruits that do not meet market quality standards. Developing more computer vision methods for in-field quality estimation could offer better strategies for managing kiwi crops and optimizing harvest practices.

A research gap in multimodal methodologies that combine sensory data (such as soil or weather information) with images of kiwi plants and chemical indicators has also been identified. Integrating these data types could lead to more accurate estimations of fruit quality or improved probability predictions for diseases' occurrence.

Therefore, image enhancement methods are crucial to improve the performance and reliability of detection algorithms, particularly for yield estimation applications, which remain relatively underexplored. Unfortunately, the lack of available public datasets obstructs the development of sophisticated methods capable of distinguishing between diseases with similar symptoms or detecting diseases at early stages.

Nonetheless, there is a gap between indoor and outdoor applications around the agricultural digitalization of kiwifruits. Integrating these approaches into unified systems could greatly enhance yield management strategies.

B. Future Potential

The identification of both current status and research gaps can guide research and clarify the future potential of AI in kiwifruit farming. Therefore, the adoption of the following technological advancements has the potential to further revolutionize kiwifruit production contributing to the efficiency, sustainability, and profitability of future kiwifruit farming practices.

B.1 Internet of Things Devices

The Internet of Things (IoT) is an emerging trend in intelligent PA. The use of IoT devices and advanced sensors within kiwifruit orchards can enable the real-time collection of multiple agricultural information and monitoring of essential variables related to both the environment and crops' health. IoT sensors are used in agriculture usually measuring temperature, humidity, pH, weather data, illuminance, etc.

Even though IoT technologies are nowadays advanced and widely used in agriculture, their efficient application in the kiwifruit orchards is still under study [61].

B.2 Drones

Drones are used extensively in PA due to their ability for aerial monitoring and surveillance on a farm scale, which is useful to timely identify pests and disease outbreaks. Drone systems in kiwifruit farming are mainly used for pollination; however, only limited real-world trials have been reported [62], while some researchers argue that robotic pollinators could not efficiently replace natural ones [63]. Therefore, the challenges related to aerial pollination, such as precision and consistency due to dense foliage and weather conditions, and related acquisition and maintenance costs or technical complexities for farmers, could be further investigated.

B.3 Blockchain

Blockchain technologies combined with AI, IoT and big-data analytics, have become very prominent in recent years. Blockchain can create records throughout the kiwifruit supply chain, enabling traceability, transparency and security of data [64]. The latter is important to build trust with consumers who would be able to validate the origins, quality, and organic certification of products [11].

There are several open source blockchain environments that are currently available, such as Ethereum, that could be employed in kiwifruit farming in several innovative ways, towards enhanced traceability, automated transactions, data integrity, real-time monitoring of kiwifruit conditions during transportation and storage, and more, ultimately leading towards more sustainable agricultural practices.

B.4 Robotics

Robotics have already entered the agricultural sector and are expected to further revolutionize traditional labor-intensive, time-consuming and costly processes. In kiwifruit farming, robots have been already used for harvesting and pollination, while other manual agricultural practices such as weeding, pruning, and spaying, have not yet been automated by robots in kiwifruit farming, leaving space for future innovations in kiwi orchard management.

Robotic pollinators, either aerial or from ground platforms, are useful for the targeted spraying of kiwifruit flowers directly so as to efficiently substitute unreliable natural pollinators, aiming to improve both the quality and quantity of produced kiwifruits. Ground robotic systems have the ability to detect the targets more precisely and spray directly, reducing the costs of pollen (or herbicides in case of spraying) and related environmental impacts. Robotic harvesters can detach kiwifruits from the crops without harming their external surface, by using precise robotic vision algorithms and appropriate end-effectors.

Yet, robotic systems for kiwifruits have not yet been adequately commercialized mainly due to slow picking rates. However, the future of robotics in kiwifruit farming is deemed feasible towards addressing seasonal labor shortages, due to the consistency and productivity of robotic systems and their ever-increasing capabilities for precision tasks due to the advancements of AI, robotics and machine learning algorithms.

It should be noted that market demands are supporting robotic innovations, due to the related benefits of enhanced sustainability and high-quality products [8].

V. Unraveling the Potential of AI

The last years have been transformative for AI. Groundbreaking innovations in the field are foreseen to reshape various fields, including agriculture, and more specifically kiwifruit farming. Companies like Fruitometry [65] are already using AI for kiwifruit farming practices, towards assessing early indication of crop load, harvest estimation, and more, by using 3D imaging and AI to count buds, kiwi flowers, and kiwifruit densities. Drones equipped with AI algorithms are used by Zespri [66], the world's largest marketer of kiwifruit, to provide crop monitoring, yield prediction, irrigation, fertilization and supply chain optimization.

However, most novel and current AI innovations, such as generative AI tools and multimodal AI, have not yet been integrated into practical in-field applications.

The mass adoption of generated AI, starring ChatGPT, cannot leave agriculture intact. Generative AI tools can be efficiently integrated into feasible kiwifruit farming practices, to enhance their efficiency, by providing useful information and tailored guidance to farmers regarding kiwifruit practices. Large Language Models (LLMs) could be trained on specific input data to provide supporting tools for farmers towards efficient sensory data interpretation and optimal decision making by providing access to a huge knowledge-specific agricultural repository. By analyzing and combining complex data, such as historical plant and yield data, weather patterns, soil health, irritation and fertilization patterns, LLMs could provide data-driven estimates for yield and plant health issues, and guide farmers to manage effectively their resources. Towards the same direction, multimodal AI can integrate various data types acquired from drones, cameras, satellites, and various sensors, to provide farmers with holistic crop monitoring capabilities and enable forecasting to adapt their practices and prevent yield losses. Moreover, AI copilots, such as Microsoft's security copilot, could assist in cybersecurity issues towards detecting threats in real-time.

AI learning models could also be employed, by using digital twins integrated with AI, aiming to provide new data and create models that could learn and improve their accuracy over time, e.g., for yield prediction or anomaly detection. Therefore, AI simulations could predict possible outcomes on crops' growth, such as the results from a fertilization or irrigation strategy and help farmers to select the most effective approach. Moreover, AI simulations could be used for predictive maintenance to predict failures in equipment such as agricultural machinery or irrigation systems.

VI. Concluding Remarks

In this work, a complete review of the most recent status of AI in PA kiwifruit farming is conducted. The conducted research aims to cover the past, the presence, and the future of all related aspects regarding the involvement of AI in kiwifruit farming. These aspects include the agricultural practices involved, commercial and research in-field applications, and kiwifruit datasets. Moreover, research gaps, trends of AI in kiwifruit farming, as well as the foreseen future of AI regarding technologies that have been recently introduced in the cultivation of kiwifruit but have not yet been incorporated, have been identified, aiming to provide a feasibility study towards their future integration.

Results identified eight main applications using AI in kiwifruit farming, including crop management analysis, defects detection, disease detection, image analysis, kiwifruit detection, flower detection, quality control, and yield estimation. Our analysis labelled key research gaps in AI methodologies for kiwifruit farming, highlighting a lack of open datasets, hindering benchmarking, comparability, and reproducibility of research, as well as leading to potential bias and limited generalization of AI models. Identified methodologies often overlook scalability and real-world applicability; limited in-field applications have been reported with most approaches restrained to indoor environments. Integration of multimodal data, such as images, sensory inputs, and chemical indicators, remains underexplored. Finally, results revealed limited AI-based robotic automations, and related research leading to commercial products, leaving space for more innovations.

The potential of the kiwifruit industry is related to the integration and adoption of innovative digital technologies, such as IoT devices, drones, robotics, and blockchain, all empowered by AI algorithms. Recent advancements in generative AI are expected to play a vital role shortly, guaranteeing improved efficiency, productivity, and sustainability in cultivating kiwifruit.

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