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NEURAL NETWORKS

Empowering olive cultivation with artificial intelligence: a systematic literature review on advancements and prospects

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Abstract

This study provides a Systematic Literature Review on the application of Artificial Intelligence algorithms in the primary sector of olive cultivation. It compiles and analyses a collection of studies that leverage AI to enhance the efficiency and sustainability of olive production, maintenance, and harvesting processes. In this study, 43 papers were reviewed from the databases IEEE, Scopus, and Web of Science through the Preferred Reporting Items for Systematic Reviews and Meta-Analyses method. This research aims to identify AI applications in the primary olive growing sector. The findings highlight a significant trend toward adopting advanced AI techniques, particularly Deep Learning algorithms such as Convolutional Neural Networks, for many tasks ranging from cultivar identification and foliar disease classification to crop yield forecasting with high accuracies.

Keywords Artificial intelligence · Olive farming · Agriculture · Systematic review

1 Introduction

This section introduces the context, relevance, and challenges of olive cultivation, and sets the foundation for this systematic literature review by presenting its objectives and research questions. Contributing not only economically but also culturally, agriculture is a fundamental part of the essence of many countries around the world. Its impact is evident in both developed and developing nations (Gollin 2010). It is an extremely important sector for global economies, directly linked to the livelihoods of millions of people. However, agriculture faces significant challenges in an ever-changing landscape, especially in developed countries. The modernization of this sector has become imperative (Sales et al. 2022), driven not only by the desire to increase productivity and reduce costs, but also by the need to solve issues that threaten its sustainability, such as labor shortages and the increasing incidence of pests, diseases and adverse weather conditions.

Among the most significant agricultural sectors, olive farming stands out especially in Mediterranean countries, playing a crucial role in the economy and culture of these regions (Besnard et al. 2017). Since ancient times, the olive has sparked human interest, having its geographic and demographic origins linked to the ancient civilizations of the Mediterranean, such as the Sumerians, Egyptians, Greeks and Romans (Breton et al. 2012). Over the centuries, olive farming has undergone several transformations, always aiming for sustainability in the face of challenges such as pests and diseases, in addition to meeting the growing demand for its products.

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In the nineteenth and twentieth centuries, there was a notable advance in scientific research related to olive growing, with institutions and researchers dedicating themselves to systematic studies on genetic improvement, pest management, irrigation techniques and harvesting methods (Lo Bianco et al. 2021). However, it was in the twentieth century that olive farming significantly increased the number of scientific studies covering everything from agronomic aspects to socioeconomic and environmental sustainability (Maesano et al. 2021; De Gennaro et al. 2012).

In recent years, the field of olive farming has witnessed a significant transformation with the emergence of disruptive technologies such as artificial intelligence (AI), the Internet of Things (IoT) and cloud computing (Messina and Modica 2022). These innovations provide new opportunities and pose challenges that demand more advanced and integrated approaches. The olive farming research paradigm is rapidly evolving in response to these changes, with a substantial increase in research focusing on the development and application of AI algorithms. A fact that can be easily proven with a quick search for the main database terms, with the number of scientific papers published in the area increasing exponentially from 2018 onwards as its possible to check in the Fig. 1.

This growth reflects a renewed interest and recognition of AI's ability to revolutionize traditional agricultural processes. In this context, the concept of Agriculture 4.0 and Precision Agriculture gain relevance, outlining a new era in which technology plays a fundamental role in optimizing production, from intelligent resource management to the personalization of agricultural practices. In this way, this work proposes to compile and analyze these recent innovations and technological applications in olive farming, with special emphasis on the implementation of AI algorithms in the olive sector.

With the aim of not only identifying emerging trends, but also exploring the potential of these technologies to transform and elevate olive farming to new levels of efficiency, sustainability and quality. A systematic review aims to collect all empirical evidence that fits pre-specified eligibility criteria to answer a specific research question. This implies the use of explicit and systematic methods selected to minimize bias, which emerges in more reliable results from which conclusions can be drawn and informed decisions made (Ferreira et al. 2023; Booth et al. 2012). Given the rapid expansion of the topic, a systematic review is crucial to provide a comprehensive and unbiased analysis of the applications of AI in this sector, enabling a deeper understanding of the current state of research and identifying gaps that require further research.

This study proposes to carry out a systematic review to elucidate the role of AI in the context of olive farming, using the Scopus, IEEE and Web of Science databases. The main objective is to answer the following research question: What are the applications of AI in the primary olive growing sector? Following the guidelines established by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al. 2021), a total of 218 papers were examined, of which 124 were identified in the SCOPUS database, 22 in IEEE and 72 in Web of Science. After careful exclusion and filtering of papers that did not align with the research objectives, 43 papers were considered relevant for the analysis. From the review and analysis of these selected papers, the objective is not only to answer the research question but also to understand current research trends and identify possible directions for future studies.

This paper is structured into four main sections. Initially, Sect. 2 delineates the methodology employed in the study. The Sect. 3, elucidates the results garnered in response to the predefined research inquiries. Section 4 offers an in-depth discussion of these findings. Concluding the study, Sect. 5 summarizes the outcomes of the work and outlines potential directions for future research endeavors.

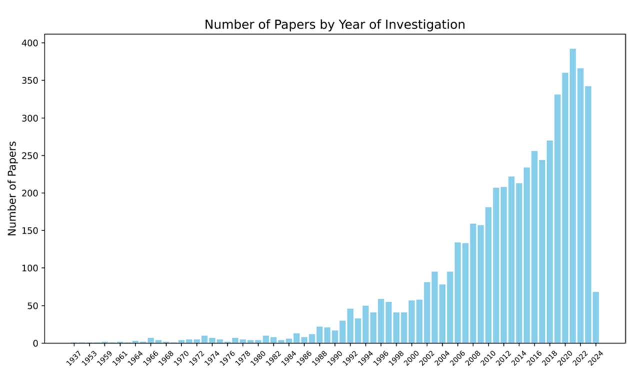

Fig. 1 Yearly distribution of published papers since the start of record-keeping

2 Methodology

This section describes the systematic review methodology adopted, detailing the search strategy, inclusion/exclusion criteria, and data extraction process to ensure transparency and reproducibility. In the current digital era, the abundance of available data has significantly enhanced the acquisition of knowledge in several areas, including agriculture and food production. In the context of this study, which seeks to elucidate the contemporary applications of AI in the olive sector, a systematic literature review methodology was adopted, as recommended by experts in the field of scientific methodology.

The systematic review methodological approach adopted in this study emphasizes the importance of impartiality and

Table 1 Summary table of the use of the PICO method

Criteria	Description
Problem	Researchers and software developers who use or create systems/processes related to artificial intelligence applied to the olive sector respectively
Intervention	Studies that document the implementation of emerging techniques and technologies in the olive growing sector
Comparison	Papers with effective use of traditional methods or ancient techniques
Outcome	What is being applied, where is it being applied, and how is it being applied?

Table 2 Summary table of terms and synonyms included in the search

Terms	Synonymous
Artificial intelligence	Deep learning, Machine earning, Artificial intelligence, Neural networks, Computer vision, Image recognition, Convolutional neural networks
Agriculture	Precision agriculture, Smart farming, Crop management, Diseases, Leaf
Olive farming	Olive farming, Olive oil, Olive mills, Olive harvesting

exhaustiveness in the identification, evaluation and integration of relevant studies. Efforts were made to ensure that all materials potentially significant for the analysis were considered. The process begins with the preliminary collection of information and progresses to a detailed evaluation of the selected papers.

The essence of a systematic review lies in its ability to follow a logical and clear flow, standing out for its meticulous organization and the sequence in which the evidence is examined and synthesized (Booth et al. 2012).

To carry out this systematic review, the PRISMA method was used (Page et al. 2021), following the most common steps, starting with defining the research question. This was defined using the PICO (population, intervention, control, and outcomes) method (Mamédio et al. 2007), as represented in Table 1.

Drawing upon the terminology presented in the table, the primary research question for this Systematic Literature Review was formulated as follows:

- What are the applications of AI in the primary olive growing sector today?

Following the formulation of the primary research question, three additional questions emerged:

- What are the algorithms and techniques applied?
- How are Datasets formed and what data are extracted?
- What are the principal findings derived from the studies, and what is their current stage of progression?

Once the research questions were defined, the selection of the most influential databases for the relevant sector was initiated. At this stage, three significant academic databases were utilized: Scopus, IEEE Xplore, and Web of Science. These platforms were chosen for their extensive interdisciplinary coverage and academic relevance, providing a comprehensive spectrum of scientific literature.

To initiate the search in the databases, search terms as well as key synonyms were defined. The generic search string appeared through Table 2, highlighting that it was adapted for each database. The specific equations are exposed in detail in Table 3 of the study, allowing the paper selection process to be transparent and replicable by other researchers interested in the topic.

As can be seen from Table 3, some of the terms/synonyms were changed, this process was carried out with the synonyms of the term Olive since, given the number of possible endings, some important papers for the study were missing. Some restrictions were also applied to the search, such as the language searching only for papers in English and the years of research, covering only the years 2018 up to and including 2024. After the first analysis of the papers obtained, some restrictions were also added regarding the type of papers, with only the types “papers, early access or proceeding or review paper” being used. Despite employing specific search criteria, the retrieval process yielded numerous papers spanning beyond our targeted scope, notably within medicine, nutrition, and chemistry, among others. Concurrently, the domains of agriculture, engineering, and computer science were subject to constraints, necessitating adjustments in line with each database’s limitation criteria. The search culminated in the identification of 218 papers, the distribution of which is detailed in the accompanying Fig. 2.

After extracting the papers and considering the research questions as well as the search terms, the inclusion and exclusion criteria (EC) for the study were drawn up. As inclusion criteria (IC) for the study, only two criteria were defined:

- IC1—Works that used some type of algorithm or AI procedure applied to the primary olive growing sector;
- IC2—Works that used or reference the use of computer vision algorithms applied to the sector.

Table 3 Summary table of strings used for each database

Database	Adapted/Used String
IEEE	"All Metadata":"Artificial intelligence" OR "All Metadata":"machine learning" OR "All Metadata":"deep learning" OR "All Metadata":"neural networks" OR "All Metadata":"computer vision" OR "All Metadata":"image recognition" OR "All Metadata":"CNNs" OR "All Metadata":"CNN" OR "All Metadata": "Convolutional Networks" OR "All Metadata":"Convolutional Neural Networks" OR "All Metadata":"Deep Convolutional Models") AND ("All Metadata" :Agricult* OR "All Metadata":Farming OR "All Metadata":agricultural practices OR "All Metadata":precision agriculture OR "All Metadata":smart farming OR "All Metadata":crop management OR "All Metadata":disease* OR "All Metadata":leaves OR "All Metadata":leaf*) AND ("Document Title":"Olive*")
Scopus	ALL ("Artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks" OR "computer vision" OR "image recognition" OR "CNNs" OR "CNN" OR "Convolutional Networks" OR "Convolutional Neural Networks" OR "Deep Convolutional Models")) AND TITLE ("Olive*") AND ALL (agricult* OR farming OR agricultural AND practices OR precision AND agriculture OR smart AND farming OR crop AND management OR disease* OR leaf*) AND PUBYEAR < 2017 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (SUBJAREA, "AGRI") OR LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (LANGUAGE, "English")
Web Of Science	("Artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks" OR "computer vision" OR "image recognition" OR "CNNs" OR "CNN" OR "Convolutional Networks" OR "Convolutional Neural Networks" OR "Deep Convolutional Models") (All Fields) AND ("Olive*") (Title) AND (Agricult* OR Farming OR agricultural practices OR precision agriculture OR smart farming OR crop management OR disease* OR leaves OR leaf*) (All Fields) and 2024 or 2023 or 2022 or 2021 or 2020 or 2019 or 2018 (Publication Years) and English (Languages) and Article or Early Access or Proceeding Paper or Review Article (Document Types) and Engineering Electrical Electronic or Agriculture Multidisciplinary or Computer Science Interdisciplinary Applications or Agronomy or Computer Science Theory Methods or Engineering Multidisciplinary or Imaging Science Photographic Technology or Agricultural Engineering or Computer Science Artificial Intelligence or Computer Science Information Systems or Computer Science Software Engineering or Plant Sciences or Agriculture Dairy Animal Science or Horticulture (Web of Science Categories)

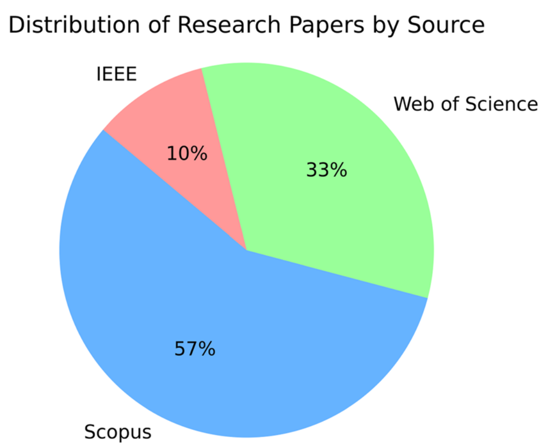

Fig. 2 Distribution of papers across the respective databases

Since IC1 requires that papers use some type of algorithm or AI procedure applied to the primary olive growing sector, this criterion is intended to select only works that have direct application in the agricultural sector, excluding other areas related to olives and olives. olive oil such as chemical/sensory analysis, transport, sales, etc. In this way, only activities such as production, maintenance and harvesting were considered as the primary sector. IC2, on the other hand, also intends to include works that, even if they do not use AI, use computer vision systems in order to be analyzed in more detail, to address it in the future.

The exclusion criteria were also defined in order to facilitate the process of selecting and extracting papers. In this case, five criteria were outlined:

- EC1—Work that does not make use of algorithms or AI systems.
- EC2—Work that does not apply to the primary olive growing sector.
- EC3—Work on other areas such as chemical analysis or medical applications.
- EC4—Systematic review works.
- EC5—Works not available in full on the scientific bases used.

EC1 ensures that selected works must make use of algorithms or AI systems, discarding works that only use emerging technologies such as IoT or UAVs. Similar to the inclusion criteria, activities such as production, maintenance, harvesting and transformation of the product are also considered as a primary sector in the exclusion criteria). Taking into account the predominance of areas such as chemistry, medicine and nutrition, the third exclusion criterion was created in order to exclude possible studies that had escaped the search string restrictions. It was also decided not to use systematic review papers so as not to cause bias in the proposed review, thus, the fourth exclusion criterion emerged. Finally, EC5 was created, which refers to papers that are not available in the scientific databases used.

Once the inclusion and exclusion criteria have been defined, papers will be selected based on them. To this end, the papers resulting from the search strings were evaluated using the StArt (Fabbri et al. 2016) software. At this stage, they were listed, and their titles, keywords, and abstracts

Table 4 Quality criteria used to evaluate papers

Criteria	Description of the quality criteria	List to choose from
QC1	Was the paper written with coherence and textual cohesion?	Yes/No
QC2	Were the methods or techniques reported objectively?	Yes/No
QC3	Was the use of AI in the context of olive growing explicitly mentioned?	Yes/No
QC4	Are there practical applications and have they been described in detail?	Yes/No

Table 5 Data to be extracted from papers

Field	Type	Content
What sector does it apply to?	Pick on list	Production, maintenance, harvest
What stage is the work at?	Pick on list	Theoretical, Experimental, Prototyped, on the market
What challenges does the project seek to solve?	Text	
Solution applied?	Text	
How is dataset acquired into the systems?	Pick on list	Dataset Online, Own dataset (real data)
Data augmentation?	Pick on list	Yes/No
Dataset typology?	Text	
Parameters extracted from the dataset?	Text	
Specific algorithms?	Text	
Type of algorithms used?	Pick on list	Segmentation, Regression, Classification, Mix
Results?	Text	

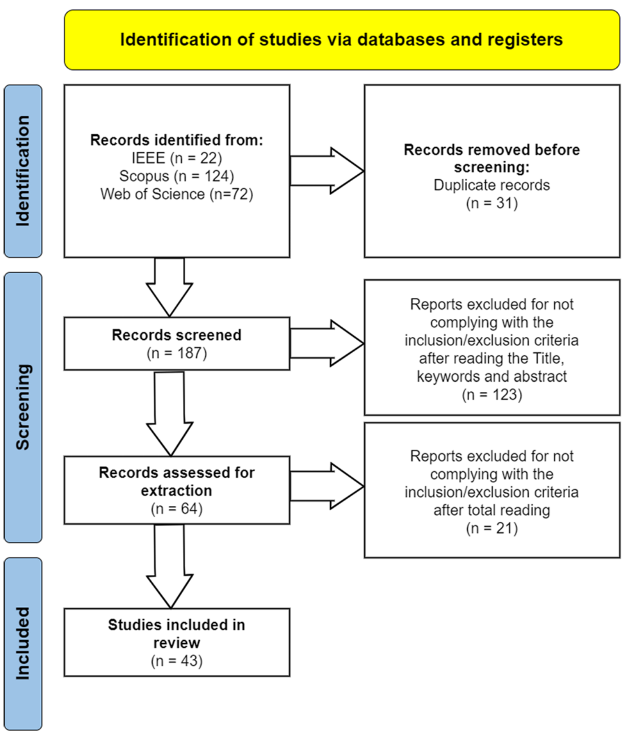

Fig. 3 Summary diagram of the PRISMA report

were analyzed to check their suitability for the selected inclusion and exclusion criteria. If they meet the proposed requirements, they will be selected and go to the next phase, information extraction. In order to also systematize the extraction part, the quality criteria were defined as the first article filter.

The quality criteria, as can be seen in Table 4, emphasize the quality of the writing and the adequacy of the paper in the proposed research. The fact that there are practical applications is also addressed, in this case practical applications being understood as any software application or application outside the presented dataset, with external feedback. Following the quality criteria, the parameters and information that would be extracted from the papers were defined.

In this second step, the summaries and conclusions of each study are analyzed. From this analysis, the inclusion, exclusion and quality criteria are reassessed. As a result, a complete list of studies that met all criteria will be obtained. At this stage, the selected studies will be read in full, to extract parameters of interest for the study. These parameters are defined in the Table 5, as it's possible to notice there are two distinct types: selection from a list of options and free writing. They, together with the data collected throughout the process, will allow the answer to the main research questions of this study.

After detailing the entire review process and the criteria adopted, as recommended by several authors, the summary diagram of the PRISMA report is presented below.

Observing Fig. 3 makes it easier to understand the selection process, the research on scientific bases resulted in 218 papers for selection. Of these, 31 duplicate papers were excluded using the biblometrix software in the Rstudio program. Of the 187 papers that passed the selection phase, 123 papers were excluded for not meeting the inclusion/exclusion criteria after the first reading (Title, Keywords and abstract) 64 papers passed the extraction phase, of which one was excluded for being a duplicate and 20 were rejected for not meeting the inclusion/exclusion criteria after the second reading (total reading). Therefore, 43 papers were used in this systematic review, of which 3 papers were obtained from IEEE, 19 from Scopus and the remaining 21 papers were obtained from Web of Science.

3 Results

This section will present the results obtained through the Systematic Literature Review, trying to answer the research questions succinctly and objectively. Quantitative and qualitative data extracted from the evaluation of the papers will be used. Starting with the main research question (RQ).

3.1 What are the applications of AI in the primary olive growing sector?

In order to reach the answer to the main research question, it is imperative to carry out both a quantitative and qualitative analysis of the selected papers. Starting with quantitative analysis and using the data obtained from the question “What sector does it apply to?”, a graph was created with the three possible answers.

The area graph in Fig. 4 shows the distribution of papers by area and year, from 2018 to 2024. In this case, the areas were divided into three categories, production in blue, maintenance in orange and harvest in green. The papers were classified within each of the areas according to similar criteria. In the production part, all papers that have some connection with the plantation and identification of varieties, whether through fruit or leaf, were associated. In the maintenance part, papers relating to the health of the olive trees were allocated, whether in terms of water stress, pests or diseases. Finally, in the harvest sector, there are papers relating to harvest forecasting, fruit calibration and maturation stages.

As can be seen, in terms of production, publications per year show little variation, between one and two papers per year, with the exception of 2021, where no papers were published. In the total time chosen for the review, this area presents a total of eight papers out of the forty-three selected, corresponding to a percentage of 19%.

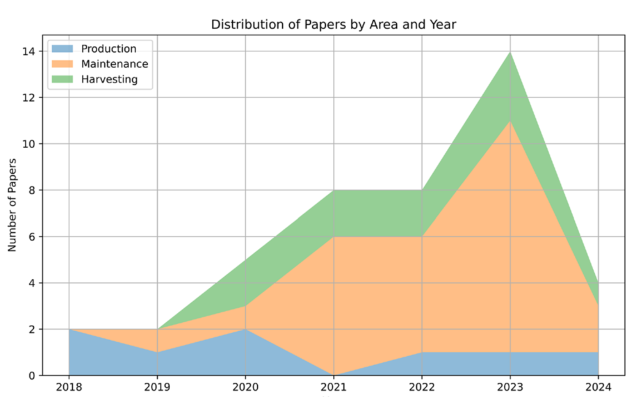

Fig. 4 Distribution of papers by area and year

Observing the area of Olive Tree Maintenance, there is a noticeable lack of publications in the first year of the study, with a marked growth then manifesting itself until the year 2023 with the publication of ten papers, publications that tend to remain high in the year 2024 as it already has two papers published by the review closing date (end of February). In terms of total contribution to the primary olive growing sector, the maintenance area has twenty-five papers, around 58% of the total.

Finally, in the papers related to harvesting, there is a similarity with the maintenance area with no study included in the review, but in this case, it is the first two years. From 2020 to 2022, two papers were published per year, increasing this number to three papers in 2023. In the current year, one article has been published in the area. Overall, this area covers ten papers out of the total, corresponding to approximately 23%.

Overall, quantitatively it can be stated that the papers refer to three main areas of activity in the primary sector, with a cycle of interest that has varied significantly over the years. The peak in 2023 for the maintenance area stands out as an anomalous event or a year of intensive focus on that topic, which is probably connected to a greater availability of online datasets related to the topic. Qualitative data from the papers referring to each of the areas will then be presented, in order to answer the main RQ.

Starting with production, where it is possible to demonstrate the growing importance of AI in the primary sector, it has proven to be a valuable tool in tasks such as identifying cultivars. Analyzing the eight selected papers, it is possible to identify that they are all linked to the identification of varieties, whether through the fruits (olive) (Hayajneh et al. 2023; Ponce et al. 2019; Luna et al. 2020; Pariente et al. 2018), the endocarp (Miho et al. 2024; Satorres Martínez et al. 2018) of the leaves (Mendes et al. 2022) or the set of the three (Beyaz 2020). To carry out this identification, the authors also use different techniques ranging from Electrical Impedance Spectroscopy (Luna et al. 2020) to capturing videos (Beyaz 2020) or images (Miho et al. 2024; Hayajneh et al. 2023; Satorres Martínez et al. 2018; Ponce et al. 2019; Mendes et al. 2022; Luna et al. 2020). This type of data, combined with advanced techniques, such as Convolutional Neural Networks (CNNs) and machine learning algorithms, guarantees accurate recognition of olive tree varieties, allowing easy and reliable identification that is crucial to maintaining varietal purity.

In the case of olive grove maintenance, the number of papers is already more extensive, as are the applications covered. The studies focus on innovative solutions for the early diagnosis and management of diseases and pests, which are crucial challenges for the health and productivity of olive trees. After analyzing the papers, it is possible to divide them into two main groups:

- Detection of diseases and pests with 88% of papers.
- Other factors with 12%.

In the disease and pest detection group, authors work in different ways, some make a binary classification between sick/healthy (Diker et al. 2023; Navrozidis et al. 2023; Mamalis et al. 2023; Bocca et al. 2023) using different datasets, as will be demonstrated below. A large number of authors classify three categories: healthy, the fungus *Aculus olearius* and the disease known as "peacock eye" which is caused by the fungal pathogen Spilocaea oleagínea (Alshammari et al. 2022, 2023; Alshammari and Alzahrani 2023; El Akhal et al. 2023; Uğuz and Uysal 2021; Mamdouh and Khattab 2022; Bruno et al. 2023). Another fungus that attracts the attention of the authors is Verticillium wilt, is a soilborne fungus disease caused by the organism (*Verticillium dahliae*), in this field the authors present work ranging from the prediction of the risk of developing this fungus (López-Escudero et al. 2023), the classification binary between this and the bacterium *Xylella fastidiosa* (Poblete et al. 2021) or the classification between various classes of diseases/fungi (Raouhi et al. 2024; Sehree and Khidhir 2022; Osco-Mamani and Chaparro-Cruz 2023; Navrozidis et al. 2022; Raouhi et al. 2022). Another fungus that caught the attention of studies was *Colletotrichum acutatum*, which is the main cause of anthracnose in olive trees. In this regard, the authors again used the binary classifications that distinguish the presence of anthracnose and water stress (Fazari et al. 2021). Also the classification among several other diseases/fungi including anthracnose is presented in the study (Alruwaili et al. 2019). The authors also focus on the detection of pests, mainly the Olive Fly (*Bactrocera oleae*), which is responsible for direct damage to the harvest as it lays its eggs in the olives. Regarding this pest, there are two works, namely on its detection (Mamdouh and Khattab 2021) and prediction (Chacón-Maldonado et al. 2023).

In the group of other factors, there are a small number of works that explore the estimation of the bio-volume of olive trees (Safonova et al. 2021), the assessment of the nutritional status of olive cultivation (Noguera et al. 2021), and the detection of the Phenophase of olive tree flowering (Milicevic et al. 2020).

The authors use different parts of the tree to classify the olive tree's health status. As can be seen, leaf classification (Diker et al. 2023; Alshammari et al. 2022, 2023; Alshammari and Alzahrani 2023; El Akhal et al. 2023; Uğuz and Uysal 2021; Osco-Mamani and Chaparro-Cruz 2023; Bocca et al. 2023; Raouhi et al. 2022; Mamdouh and Khattab 2022; Bruno et al. 2023), corresponding to approximately 44% of the identified papers. Also, a significant percentage of authors (32%) use the tree canopy as a whole to carry out the classification (Poblete et al. 2021; Raouhi et al. 2024; Safonova et al. 2021; Sehree and Khidhir 2022; Milicevic et al. 2020; Navrozidis et al. 2023; Mamalis et al. 2023; Navrozidis et al. 2022), use leaves, fruits and branches (Alruwaili et al. 2019) and only fruit (Fazari et al. 2021). The remaining studies use external factors to the olive tree, such as meteorology (Chacón-Maldonado et al. 2023; López-Escudero et al. 2023), fly traps (Mamdouh and Khattab 2021), and aerial photography of olive groves (Noguera et al. 2021). An interesting fact about the study is that, of the studies that use images, 30% use images from UAV/satellite. This type of advanced applications allows quick and reliable diagnosis, essential for making informed decisions about crop management, and contributes to the optimization of maintenance practices, reducing costs and increasing the sustainability of olive production.

In relation to the harvest, the group consists of ten of the forty-three papers, within these, despite all being broadly linked to the olive harvest, it is possible to highlight some research subgroups. One of them is the ripening stage of the olives, where in this subgroup the authors use RGB (Ortenzi et al. 2021; Khosravi et al. 2021; Macías-Macías et al. 2023; Hassan et al. 2024) and multispectral (Noguera et al. 2022) images to classify the olives at different stages of ripeness and acidity or fat contain. Another approach is to identify the fruits, using RGB images of the entire canopy (Aljaafreh et al. 2023; Aquino et al. 2020), also using images of the entire canopy, the publication (Aquino et al. 2023) makes a harvest prediction based on these images and the number of olives identified. Still in the field of harvest forecasts, the paper (Cubillas et al. 2022) forecasts the harvest based on meteorological data. Within the harvest group, an on-site fruit calibration system is also presented for table olives (Sola-Guirado et al. 2020).

Regarding the material used to make these applications, it is possible to verify that the majority used RGB/multispectral images, whether of the fruit or the tree itself, with one of the works using meteorological data.

Answering the main RQ, AI is demonstrating its capabilities to revolutionize the primary olive growing sector, with applications that extend to production, maintenance, and harvesting. In production, AI assists in the precise identification of olive tree varieties, using advanced techniques to analyze fruits, leaves and endocarps. With regard to maintenance, it offers innovative solutions for the early diagnosis and effective management of diseases and pests, contributing significantly to the health and productivity of olive trees. Finally, at harvest, AI improves the efficiency of operations by predicting harvests and classifying the ripening stages of

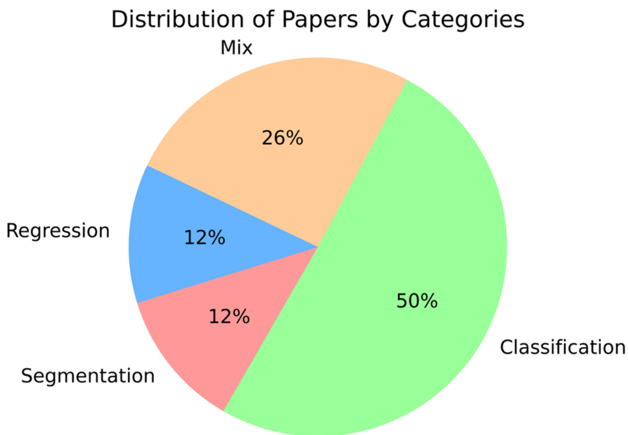

Fig. 5 Distribution of papers by categories

olives, proving to be an essential tool for optimizing processes, reducing costs and increasing the sustainability of olive production. This set of applications highlights the fundamental role of AI in modernizing and optimizing the olive farming sector, facing its contemporary challenges with advanced technology.

3.2 What are the algorithms and techniques applied?

After an initial review of all selected papers, it was decided to cluster the papers into four distinct categories: those that employed segmentation, regression, classification, and mixed algorithms that combine more than one of these tasks (e.g., segmentation and classification).

As can be seen by analyzing Fig. 5, the distribution of papers by categories is mostly represented by classification algorithms, with an absolute value of 22 papers.

Analyzing the categories of algorithms used for classification, it is easily noticeable that they are largely composed of deep learning algorithms, more precisely, CNNs. Around 59% of the papers correspond to CNNs, within this group several adapted structures are suggested (Miho et al. 2024; Uğuz and Uysal 2021; Fazari et al. 2021; Milicevic et al. 2020; Alruwaili et al. 2019; Khosravi et al. 2021; Mamdouh and Khattab 2022) or well-known structures from the literature are used, such as VGG16/19 (Osco-Mamani and Chaparro-Cruz 2023), Mobilenets (Raouhi et al. 2022), among others (Raouhi et al. 2024; Sehree and Khidhir 2022; Aquino et al. 2020; Ponce et al. 2019). Of the remaining 41% of the papers, approximately 14% combine machine learning with CNNs (El Akhal et al. 2023; Alshammari et al. 2022). Around 19% propose modifications, such as restructuring models or integrating multiple ML algorithms (Poblete et al. 2021; Alshammari et al. 2023; Navrozidis et al. 2023; Hassan et al. 2024). Lastly, the remaining 8% use established ML models that have been specifically adapted to address the problem under studying (Mendes et al. 2022; Navrozidis et al. 2022; Pariente et al. 2018).

The set of cluster algorithms (Mix) uses deep learning and machine learning techniques more diversified and balanced than the previous group. Starting with the use of algorithms such as partial least squares regression (PLSR), artificial neural networks (ANN), support vector regression (SVR), and gaussian process regression (GPR) to assess the nutritional status of crops (Noguera et al. 2021), and partial least squares discriminant analysis to identify olive cultivars (Satorres Martínez et al. 2018). Techniques such as Naive Bayes and Random Forest are applied to automatically evaluate the visual quality of green olives (Sola-Guirado et al. 2020). The general trend is the adoption of models adjusted to the specificities of the tasks, demonstrating the adaptability and effectiveness of these technologies in the agricultural sector. CNNs continue to be applied with ML algorithms such as Random Forest and Support Vector Machines (SVM) (Diker et al. 2023). Deep learning algorithms are also used in this set, either through techniques such as explainable hybrid deep learning (Chacón-Maldonado et al. 2023), or represented through a hybrid approach that integrates evolutionary algorithms for recognizing and classifying diseases in olive leaves (Alshammari and Alzahrani 2023). Another type of algorithm within deep learning is the YOLO algorithm for real-time detection of olive fruits (Aljaafreh et al. 2023) and for pest identification (Mamdouh and Khattab 2021; Mamalis et al. 2023). Also making use of convolutional layers, R-CNN is highlighted for quality control of table olives (Macías-Macías et al. 2023), and is also combined with other CNNs such as inceptionV3 for detecting leaf diseases (Bocca et al. 2023).

In the field of regression, despite the small number of papers, the applications presented is to evaluate and predict agricultural conditions and characteristics of olive trees. From crop yield prediction through Generalized Linear Models and SVM (Cubillas et al. 2022), to olive quality assessment using low-cost spectral data, and ANNs (Noguera et al. 2022). The identification of cultivars is also addressed, whether through video analysis using computer vision algorithms (Beyaz 2020) or Electrical Impedance Spectroscopy techniques combined with neural networks and IoT (Luna et al. 2020). Also in the field of diseases, regression is used, in this case, through fuzzy logic in a system to predict the risk of Verticillium wilt in olive groves (López-Escudero et al. 2023).

Finally, concerning segmentation algorithms, which also have a similar representation to the previous group, the algorithms used again tend towards CNNs. Whether to calculate biovolume by segmenting aerial images using the Mask R-CNN algorithm (Safonova et al. 2021), or for classifying olives (Hayajneh et al. 2023) or classifying diseases using algorithms such as EfficientNet-b0 (Bruno et al. 2023). Not only are big CNNs used, but simpler machine learning algorithms are also used. One of them uses the k-nearest neighbors (KNN) technique in images to quickly determine the degree of ripeness of batches of olives (Ortenzi et al. 2021). The other estimates olive production through perceptual visual characteristics, where a neural network with connected multilayer perceptron is the essence of the proposed method, organized into specific layers for processing image descriptors (Aquino et al. 2023).

Observing Fig. 5 it is possible to understand the predominance and diversity of algorithms and techniques applied in the field of olive growing. It is evident that classification is an area of intensive interest, with most studies focusing on the use of Deep Learning algorithms, specifically CNNs, for a variety of applications. CNNs, especially through adapted and recognized structures, have been the backbone for most studies, highlighting their versatility and adaptability to different tasks. While studies range from disease identification, to fruit quality assessment, and crop yield prediction, it is undeniable that the trend is towards increasingly more adjusted models, incorporating optimization techniques as well as combinations between several models. Although regression and segmentation represent a smaller percentage, innovative applications of these algorithms demonstrate an expanding field, applying techniques from computer vision, on-device machine learning, and IoT to tackle complex agricultural problems.

The combination of traditional ML methods with emerging DL approaches and the integration of systems like TinyML and IoT illustrate an ever-evolving technology landscape, pointing to a future where decentralized processing and in-situ data analysis.

3.3 How are datasets formed and what data are extracted?

As the proper functioning of AI algorithms is closely linked to the dataset on which they are trained, this is undoubtedly a question that this study needs to address. To organize the data in a facilitated manner, a response field was created regarding the origin of the datasets. Three main themes were addressed: whether the authors created the dataset, its extracted parameters, and the use or non-use of data augmentation. Since two of these questions involve limited-choice answers, their analysis will be conducted quantitatively, followed by a more qualitative approach to the open-response question.

The reviewed studies reveal diverse practices in this analysis of dataset origins and the application of data augmentation techniques. Approximately 30% of the studies utilized publicly available datasets, while the remaining developed their own. Among those that relied on available datasets, the application of data augmentation techniques was limited, only 38% of these studies employed data augmentation. Similarly, within the group that developed their own datasets, 40% applied data augmentation techniques.

Among the authors who used publicly available datasets, six of the thirteen papers in this subgroup (Alshammari et al. 2022, 2023; Alshammari and Alzahrani 2023; Uğuz and Uysal 2021; Mamdouh and Khattab 2022; Bruno et al. 2023) relied on the same dataset to identify diseases in olive leaves. These studies not only refined techniques and optimized results but also highlighted the critical role that publicly shared datasets play in fostering collaboration and advancing research in the olive sector. Analyzing now the papers that developed their own dataset, it's noticeable that many were collected and assembled specifically for each study. The creation of datasets involves everything from capturing images of olive leaves in various health conditions (Diker et al. 2023; El Akhal et al. 2023; Alshammari et al. 2022; Bocca et al. 2023; Raouhi et al. 2022) to using images of olive groves captured by drones (Raouhi et al. 2024; Sehree and Khidhir 2022), emphasizing the importance of computer vision in diagnosis and classification in olive farming. Furthermore, meteorological data (Cubillas et al. 2022), spectroscopy data (Noguera et al. 2022; Navrozidis et al. 2023) and images of various olive ripening stages (Khosravi et al. 2021) are examples of extracted parameters, showing the use of environmental and phenological data to predict yields and diseases. The parameters extracted from the datasets cover a range from simple visual characteristics, such as color and size (Sola-Guirado et al. 2020), to more complex information, such as water stress (Poblete et al. 2021) and spectral (Noguera et al. 2022; Navrozidis et al. 2023) indices. After extracting the parameters, the use of AI algorithms is used to process this data, demonstrating an effort to translate raw data into actionable insights that can inform agricultural practices and management decisions.

3.4 What are the principal findings derived from the studies, and what is their current stage of progression?

Grounded on the quantitative data acquired, it becomes apparent that the predominant portion of studies is situated within the experimental phase. These studies are characterized by having a well-structured methodology and are in the testing process. The proportion of studies in the experimental phase reaches 98% of the total papers analyzed. Only one paper stands out (Sola-Guirado et al. 2020), which is in the prototyping phase.

Regarding the principal findings, the high accuracy achieved in classification and prediction tasks is notable.

For example, the study (Diker et al. 2023) achieved an accuracy of 98.63% in classifying foliar diseases, showing the effectiveness of feature extraction in the early identification of adverse conditions in olive trees. Similarly, the study (Poblete et al. 2021) achieved an accuracy of 98% and a kappa coefficient of 0.7 using a three-stage method to identify infections, emphasizing the ability of AI to discriminate between distinct pathogens with high reliability.

Yield estimation is another area that has benefited considerably from AI techniques. The work (Aquino et al. 2023) highlights a robust method, with a mean squared error of just 0.9914 kg per sample point, indicating the viability of visual modeling in harvest prediction. In contrast, the study (Ortenzi et al. 2021) showed an accuracy of 60% in identifying the maturity of olives, suggesting that, despite advances, there is still room for refinement of methods in certain aspects of production.

The study (Chacón-Maldonado et al. 2023) provides a comprehensive insight into pest prognosis, with the lowest mean absolute error (MAE) of 2.909 using the XENADL algorithm, highlighting the potential of explainable AI. In parallel, the identification of olive tree varieties has also shown promise, with study (Miho et al. 2024) reporting an accuracy of 86% in correctly predicting olive tree varieties.

On the optimization area, study (Alshammari et al. 2023) achieved an impressive 98.9% accuracy using the WOA-ANN technique, outperforming other methods such as KNN, SVM and Naive Bayes, demonstrating the strength of fine-tuned deep learning methods. Similarly, the study (Raouhi et al. 2024) achieved 99% accuracy in disease classification, confirming the positive impact of transferred learning on images captured by unmanned aerial vehicles.

Harvest prediction benefits from models based on historical and meteorological data, as demonstrated by the study (Cubillas et al. 2022), where forecast models generated in early crop yield prediction absolute errors better than 20%. Image segmentation is also advanced, as shown in the study (Safonova et al. 2021), where the estimated biovolume of olive trees had an average accuracy of 82% when compared to ground truth measurements.

In pest detection, the study (Mamdouh and Khattab 2021) achieved an accuracy of 84% and an mAP of 96.68%, showing the success of the YOLO framework in counting and detecting pests. The study (Alruwaili et al. 2019) achieved an overall accuracy of 99.11%, with precision, recall and F1 measures above 99%, demonstrating the effectiveness of deep learning models in disease detection. This is corroborated by the study (Luna et al. 2020), which achieved correct detection in 100% of cases when classifying olive varieties using electrical impedance spectroscopy.

Finally, the application of AI in quality control and classification under field conditions is evidenced by the study (Hassan et al. 2024), which performed fruit classification with an efficiency of 99.26% against a white background and 97.25% on a conveyor belt, highlighting the AI's ability to operate effectively in dynamic environments.

These studies highlight the significant impact and applicability of AI in various phases of olive production, from disease management to harvest optimization, showing the power of AI in transforming contemporary agriculture and its untapped potential for future innovations.

4 Discussion

This section discusses the main findings in relation to existing literature, analyzes the strengths and gaps of current research, and outlines the implications for the future development of AI in olive farming. The results of this Systematic Literature Review elucidate the significant impact and applications of AI in the primary olive growing sector. The explicit mention of the use of AI in the context of olive farming reinforces the relevance of the topic and the alignment of studies with current technological trends in the agricultural sector. However, a significant opportunity is identified to expand the practical applicability of this research. The absence of a detailed description of practical applications in almost all papers signals a potential disconnect between theoretical research and its actual implementations in the field. This indicates the need for greater emphasis on translating experimental results into best practices and tangible applications that farmers and olive grove managers can adopt.

Regarding the information extracted from the papers, it was possible to notice a considerable dispersion in AI applications that range from production to harvesting, with a particular interest in the maintenance of olive trees. The amount of papers in the maintenance area, which corresponds to around 58.1% of the total, highlights the growing importance given to the detection of diseases and pests, a crucial element for the sustainability and viability of olive farming.

In the production area, the AI techniques applied focus on identifying olive tree cultivars, with a clear favoritism for methods that use images of fruits, leaves and endocarps. This trend in the selection of visual data highlights the preponderant role of computer vision in the characterization and classification of varieties, an essential step to guarantee the quality and authenticity of olive oil. It is also notable that, despite the smaller amount of research focused on harvesting, there is a continuous development of techniques to improve the accuracy of predicting and classifying the ripening stages of olives.

A wide range of algorithms are applied, but CNNs dominate classification. CNNs are favored for their efficiency in handling complex image data, which is critical for disease classification and pattern recognition. Traditional machine learning models, although fewer in number of works, demonstrate robustness, especially when combined with CNNs or applied to specific regression and segmentation tasks.

The cycle of interest in studies varies over the years, with specific peaks that may be associated with the availability of publicly available datasets or emerging issues in the sector that require immediate attention. AI, with its data processing and learning capabilities, provides the necessary tools to adapt quickly to these new demands.

Regarding the datasets, the preference for developing data over using publicly available data suggests a targeted effort by researchers to capture specific nuances and local conditions that generic datasets may not reflect. This choice indicates the desire to align closely with olive trees' actual conditions and each region's specific challenges. The lower prevalence of data augmentation in studies with proprietary datasets may indicate the capture of sufficient natural variability that obviates the need for synthetic data augmentation techniques.

Finally, regarding the results obtained, there is a clear trend towards excellence and precision in diagnoses and predictions. In most of the studies evaluated, they all present high accuracies achieved in critical tasks such as classifying diseases, cultivars and estimating production. Such results highlight the success of AI techniques applied to well-structured data, with direct implications for decision-making in olive farming. Discussion of these results in existing literature highlights AI as a dynamic field with transformative potential for olive farming. AI applications in agriculture are not only improving existing operations but also covering the way for disruptive innovations that could define future agricultural practices. As technology advances, anticipate growth in adopting even more sophisticated AI techniques that will continue to push the frontiers of efficiency and sustainability in the primary sector.

Despite the comprehensive nature of this systematic literature review, some limitations should be acknowledged. First, the review included only papers published in English and indexed in Scopus, IEEE Xplore, and Web of Science, potentially introducing language and publication bias. Additionally, the inclusion and exclusion criteria focused strictly on the primary olive sector (production, maintenance, and harvesting), which may have excluded relevant findings from adjacent stages such as processing or distribution.

Moreover, most of the studies analyzed are still at an experimental stage, lacking large-scale field validation and real-world implementation, which limits the generalizability of the results. The strong reliance on proprietary datasets also indicates potential challenges in reproducibility and limits broader cross-region applications.

Future research should prioritize transferring these promising AI approaches from controlled experimental environments to practical, on-field scenarios, enabling broader adoption by farmers and agronomists. Furthermore, many of the AI techniques discussed, especially those involving advanced image analysis and predictive modeling, hold potential for application in other perennial crops such as vineyards and orchards, which share similar disease detection and yield forecasting challenges.

5 Conclusion and future works

This section summarizes the key contributions of the review, highlights the current limitations, and proposes directions for future research and practical applications in the field. This systematic literature review offered a comprehensive overview of the impact of AI in olive farming, a sector that traditionally follows centuries-old practices. The results of the review indicated a significant growth in the use of AI, especially in olive tree maintenance, where early detection of diseases and pests plays a preponderant role. The growth trend in research focused on this type of problems, evidenced by the sharp increase in publications in the year 2023, signals a growing awareness of the importance of sustainable management practices.

Furthermore, cultivar classification and identification, as well as harvest prediction and optimization, have proven to be promising areas for the application of advanced algorithms. CNNs emerge as the backbone of AI methodologies, given their effectiveness in analyzing images for accurate classification of diseases, varieties and ripening stages of olives. Although the use of custom datasets is predominant, reflecting the need for specific and contextualized data, the availability of online datasets fosters broader collaboration and accelerates innovation in the field.

In terms of practical implications, this study highlighted the potential of AI to revolutionize traditional methods in olive farming, pointing to a future where management practices are informed by accurate, real-time insights derived from data. With the integration of AI, producers, and scientists can not only improve crop quality and yield while implementing more sustainable and efficient management methods.

It can be concluded that AI holds a vital position as a catalyst for innovation in the primary olive sector, with the promise of contributing significantly to the sustainability and resilience of the sector. While this study provides an in-depth understanding of current and future trends, it also highlights the need for ongoing studies that can further validate and refine AI applications, as well as strategies that promote the dissemination and adoption of these technologies globally.

Regarding future works, the primary gap identified during the preparation of this work predominantly revolves around the lack of real-world applications, as the research is largely confined to controlled experimental settings. Consequently, the principal focus of future efforts should entail extending the outcomes derived from controlled environments to real-world field scenarios, thereby facilitating the adoption of this technology by farmers or crop managers.

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Declarations

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Ethics approval This article does not contain any studies with human participants or animals performed by any of the authors.

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