Intelligent Systems with Applications 16 (2022) 200102

Contents lists available at ScienceDirect

Intelligent Systems with Applications

journal homepage: www.journals.elsevier.com/intelligent-systems-with-applications

Review

Deep learning for precision agriculture: A bibliometric analysis

Solemane Coulibaly [a,b,1,*], Bernard Kamsu-Foguem [b,2], Dantouma Kamissoko [a], Daouda Traore [a,3]

[a] Université de Ségou, sis à Sebougou. BP: 24 Ségou, Mali
[b] Laboratoire Génie de Production de l'ENI de Tarbes, 47, avenue d'Azereix - BP 1629 - 65016 Tarbes CEDEX, Tarbes 65000, France

ARTICLE INFO

Keywords:
Bibliometrics
Deep learning
Precision agriculture
Environment

ABSTRACT

Recent advances in communication technologies with the emergence of connected objects have changed the agricultural area. In this new digital age, the development of artificial intelligence, particularly deep learning, has allowed for acceleration and improvement in the processing of collected data. To highlight the evolution and advances observed in deep learning in agriculture, we conducted a bibliometric study on more than 400 recent research studies. The analyses carried out on recent research works suggest that deep learning is widely involved in the digitization of agriculture areas with high accuracy exceeding the standard image processing techniques. Most of the works focus on crop classification problems, weed, and pest identification. Their methods are mainly based on convolutional neural network architecture. From the cases study, we have identified three key challenges that are essential in the deep learning methods applied in agriculture: (i) the need to consider the perception of the domain actors, their appropriation or interaction with the existing tools; (ii) the requirement to perform statistical tests to analyze the performance of the classifiers resulting from the learning process; and (iii) the need to perform statistical cross-validations with the training data. In the end, we summarized the agricultural data processing process consisting of several parts, for a better consideration of the expectations resulting from the challenges addressed. We consider that this study can serve as a guideline of research for the scientist and practician in the application of deep learning methodology in agriculture.

1. Introduction

Agriculture is the practice of growing food. Given the increase in population, this sector must meet many requests for food while considering societal (such as labor), environmental (water scarcity, loss of biodiversity, land degradation, etc.), and economic issues. The constraints of its development have become numerous given the seasonal variability and extreme climate. It is more necessary than ever to find innovative practices for the development of the agricultural sector.

Digital integration has significantly changed farmers' knowledge of field management with innovative technologies like intelligent computing, robotics, drones, or sensors onboard farm machinery. Using these technologies is encouraging data scientists and agronomists to design analytical tools and techniques to accurately organize field management and address the new challenges at hand (fungal attack detection, crop yield prediction, advanced spraying, etc.). These novel practices require farmers' technical assistance to support their needs and help them maximize their crop yields based on data and task automation.

Recent advances in artificial intelligence (AI) based applications have had a strong impact in this area. They have contributed to a significant advancement of computer vision, machine learning, and deep learning solutions in the development of automated and robust systems. According to Research and Markets (2017), the AI market in agriculture was valued at US$ 518.7 million in 2017. With a growth rate of 32.7%, it will reach US$ 312.4 billion by 2027. With the increasing use of computer vision, agricultural applications have transformed traditional farming practices into something amazingly more productive. Their uses have been successful in having an impact on the production and economics of the sector. These benefits in agriculture include optimized and

* Corresponding author.
E-mail address: solemane.coulibaly@enit.fr (S. Coulibaly).
[1] Solemane COULIBALY: https://orcid.org/0000–0003–2037–4539.
[2] Bernard KAMSU-FOGUEM: https://orcid.org/0000–0003–3617–3184.
[3] Daouda TRAORE: https://orcid.org/0000–0001–7587–2813.

https://doi.org/10.1016/j.iswa.2022.200102
Received 16 April 2022; Received in revised form 8 July 2022; Accepted 21 July 2022
Available online 28 July 2022

accurate use of chemicals (pesticides, insecticides, and fertilizers), planning of farmers' work, recognition of plant images, online monitoring and analysis of crop health, and reduction of environmental degradation. Thus, agriculture can cope with new constraints, encouraging agronomists (or experts) to find new tools within the agricultural value chain that offer better prospects.

Visual observation of plants by experts was usually conducted through diagnosis when needed. Nevertheless, this unprofitable method takes mostly time (R. Li et al., 2019) while affecting the precision of the task executed. To address these issues, technologies like image processing, the internet of things, machine learning, and deep learning can be used to get data and process it. Classical algorithms (support vector machine, random drill, k-nearest neighbor) of machine learning have been applied in many studies to extract image features such as color, shape, or texture (Liakos, Busato, Moshou, Pearson & Bochtis, 2018). These algorithms require designing features of objects manually and are highly dependent on the data acquisition methods, preprocessing, and feature extraction performance.

With the upgrading of computational performance and large volume datasets, the algorithms of deep learning have been effective in many areas. Due to their expressive capabilities on the data, they have been able to avoid the disadvantages of traditional extraction methods. This allows the machine to perform complex processing on big data, providing predictions with promising results. In recent years, thanks to the deep neural network approach (LeCun, Kavukcuoglu & Farabet, 2010, 2015; Szegedy et al., 2014; Zeiler & Fergus, 2013), many applications of computer vision (Mavridou et al., 2019; Tian et al., 2020) are being employed in many tasks in agriculture to achieve this aim. Therefore, they have received more attention from researchers and experts in the agricultural field (Affouard, Lombardo, Goëau, Bonnet & Joly, 2019; Liakos et al., 2018; N. Zhu, Song, Jiang & Song, 2018). However, this precision agriculture also raises many issues and challenges related to the ecological transition of the agricultural system, such as reducing energy consumption, achieving higher quality production by minimizing the use of intrants, and the place of humans in decision-making systems.

Deep learning has made many technical advances today. Nevertheless, the interpretation of the results of the training models on the data has generated long debates in the scientific and end-user communities. With these new trends, the future of digital agriculture was discussed through the main challenges and opportunities to overcome the major shortcomings of deep learning in the face of sustainable and explainable agriculture. We conducted a literature review based on bibliometrics that summarizes, evaluate different publications, and then revealed the trends and hotspots of the current research. Indeed, we have defined keywords or search terms and variants related to precision agriculture with deep learning. Two main research questions have been selected: (a) what are the strategic themes related to digital agriculture? (b) what are the main challenges and opportunities of digital agriculture? The answers to these questions are analyzed and discussed with bibliometric tools. This work, therefore, provides a basis for further research with the following contributions:

1 Analysis of the most influential publications and the contributions that stand out in precision agriculture.
2 Analyzing co-citations and citations to identify potential research directions.
3 Identification of hot topics in agriculture and deep learning for future research.

The rest of the paper is structured as follows: Section 2 introduces precision agriculture. Section 3 contains the bibliometric methodology used. Analysis and results presented in Section 4, while Section 5 focuses on the discussion of the main challenges related to using deep learning in agriculture. Finally, Section 6 concludes this paper.

2. Precision agriculture

Agriculture, which appeared thousands of years ago, consists of making use of an environment to produce food. In most countries, it is considered the main source of employment. Lack of knowledge about soil types, yields, crops, and weather conditions, inappropriate use of intrants, irrigation problems, and crop failures led farmers to make intuitive farm adjustments. However, this was possible because the parcels were small and there were technical and economic shortages. Now, a failure to monitor this information could well cause new problems and additional costs for production. This state needs to be changed when the farms were extended and divided into several units of hectares. The opportunities offered by the latest digital technologies have strongly boosted agriculture's progress towards industrialization. The mechanization has turned agriculture into a new era, Agriculture 4.0, where intensive agriculture is now a major contributor to the efficiency of agricultural production processes. This includes the global positioning system, big data, the internet of things, cloud computing, and image feature extraction. For example, based on geographic coordinates, we can conduct modular interventions on farms. From image features, it is possible to determine the crop disease. This kind of thinking is at the origin of the precision agriculture concept, which translates into the right intervention at the right place and at the right time (Zimmerman, 2008; Zwaenepoel & Le Bars, 1997).

In practice, precision agriculture is based on the integration of information and communication technologies in a parcel's management. It aims to modulate the farming practices according to the intra-parcel variability (soil texture, slope value, vegetation cover, etc.) to correctly control the agricultural production process and optimize the farming interventions. As the world's population grows, the current challenge is to improve the quality and quantity of agri-food products while respecting human health and the environment. Precision agriculture, therefore, addresses the needs of farmers as an integrated agricultural system focused on information and production. Precision agriculture addresses the needs of farmers as an integrated agricultural system built on information and production. Its aims to increase the efficiency, productivity, and profitability of production in the long term, both on a site-specific and farm-wide basis, while minimizing unintended impacts on wildlife and the environment (Tran & Nguyen, 2007). According to Gandonou, (2005), precision agriculture is a set of technologies that have contributed to launching agriculture into the information-driven world, and which is designed to help farmers gain more control in managing agricultural operations. In effect, precision agriculture is an upgrade to the conventional decision support system for crop production.

In addition, precision agriculture is characterized by several agronomic, technological, and economic challenges to respond appropriately to agribusiness needs. The technological challenge is characterized by using embedded tools (biomass or chlorophyll sensors), airborne systems (drones or satellites), and mapping systems. The agronomic challenge is to improve the input-yield ratio and the selection of crop varieties adapted to phytosanitary contexts. The environmental issue is related to the limitation of soil erosion and nitric nitrogen losses through leaching. Therefore, the aim is to encourage optimal fertilization while preserving human health and the environment. The economic aspect contributes to securing the farm's business profits by reducing the cost of production and limiting the excessive use of intrants while safeguarding the quality and yield of the crops.

Precision agriculture generates a lot of information from data collected on plots by land, by connected objects, or by satellite tools. There is therefore a real need to develop tools and methods to store, analyze, interpret, visualize, and disseminate the data collected to derive new value from it (Fig. 1). These agricultural applications represent the means of producing knowledge pertinent to decision support systems (Wolfert, Ge, Verdouw & Bogaardt, 2017) that can accompany farmers and public or private decision makers. In the

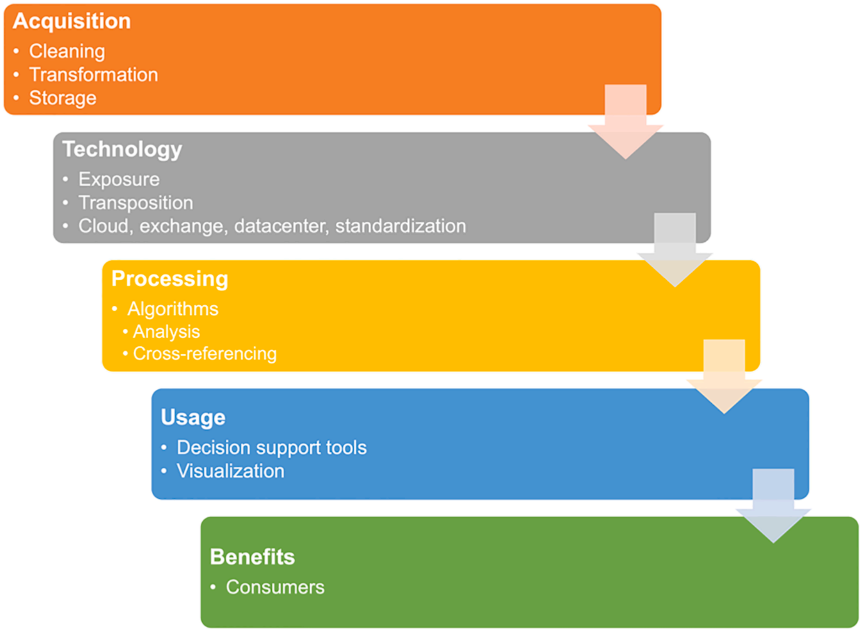

Fig. 1. Agricultural data processing.

industrial revolution era, artificial intelligence, machine learning, and deep learning have become very popular in scientific research with many applications in natural language processing, image classification, disease diagnosis, text mining, etc. Today, deep learning has many example cases applied to crop and soil management (Liakos et al., 2018). For these reasons, deep learning becomes a relevant answer that extends the traditional agronomic models to better help farmers in their position in the agricultural value chain.

The digital transformation of agriculture supported by deep learning is a new card of scientific and technical progress. It is starting to change the vision of farmers by providing many benefits to manage frequent changes in external conditions. The solutions developed have complemented the technologies (agronomic and computers) already in play to increase production and modernize certain stages of precision agriculture. However, their use requires technical assistance for farmers to achieve sustainable agriculture. Thus, deep learning has become a driving force for the transformation and development of agriculture.

The benefits of digital agriculture are very strong. The applications of artificial intelligence and deep learning offer many opportunities to reinforce the various stages of agriculture to face the different difficulties and achieve the goals (Gupta, 2019; N. Zhu et al., 2018):

1 Agricultural information processing: Monitoring the condition of plants and animals is vital for agricultural production.
2 Models make disease detection a feasible process, increasing the production potential of healthy crops.
3 Optimal control of agricultural production systems: Control strategies for agricultural production systems are often dependent on the farmer’s experience or expert knowledge, which does not consider the physiological condition of the plants.
4 Crop management practices have reached new heights, and it has become quite practical for farmers to manage crops with minimal effort.
5 Intelligent farm machinery equipment: agricultural production involves many types of tasks.
6 Deep learning models to make accurate predictions efficiently analyze agricultural data.
7 Management of the agricultural economic system: Agricultural output alone is not enough. Many other factors must be included, such as prices and the quality of agricultural products. It is very important to forecast the prices of agricultural products.
8 AI has significantly revolutionized the weather forecasting system, which plays a key role in agriculture.

The agricultural sector has been reshaped by deep learning techniques. Many agricultural practices have been impacted by technological developments. However, humans must be the main actor in this change to control the risks emitted by the various technological integrations and information interpretation.

3. Methodology

3.1. Bibliometric analysis: overview

Literature analysis or bibliometrics is the quantitative analysis of scientific production and the analysis of the networks of this production (Aria & Cuccurullo, 2017; G. Chen & Xiao, 2016; De Bellis, 2009, 2009; Koskinen et al., 2008). Based on a query related to a given subject or field, it makes it possible to identify studies, authors as well as their relations concerning the various citations and publications. Numerous factors are considered, such as the number of citations, the number of publications per author, the keyword frequency, author, institution (affiliations), and country relationships. It mainly involves the following steps: (a) the collection of related works or bibliographic data (b) the review and detailed analysis of these works and (c) a graphical or tabular visualization of the collected results (Fig. 2).

The first step is a keyword search of conference papers or journal articles, book chapters, and other media to obtain bibliographic data. This step was performed in the IEEE Xplore digital library and the Association for Computing Machinery (ACM) digital library, as well as in scientific indexing services such as Web of Science (WoS), Elsevier Scopus, or Google Scholar. WoS seems to be widely used because of its multidisciplinary nature. Indeed, databases can be very generalist like Google Scholar or very specialized like IEEE Xplorer. On the other hand, Scopus, developed by Elsevier, clearly does not meet the criteria of open access.

Hence, in this work, we focus on WoS, which also offers advanced search features useful for selecting significant sets of articles that can be considered as an interesting basis for building our bibliometric analysis.

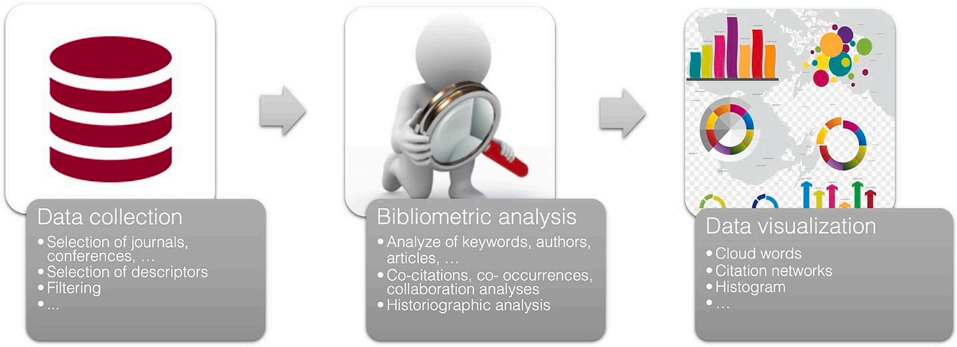

Fig. 2. Bibliometric analysis process.

It should be noted that the data collected was processed to eliminate spuriously (such as abbreviations) information that would have hindered the subsequent stages of our study.

The analysis and visualization phase of the search queries were carried out using the Bibliometrix tool (Aria & Cuccurullo, 2017) which is easy to use with intuitive web interfaces. Bibliometrix is an R package for conducting quantitative research in scientometrics (e.g., the science of measuring and analyzing science) and bibliometrics. It permits to import of bibliographic data from several sources such as Scopus or WoS. At the same time, it offers an evaluation system based on co-citation as well as the measurement of scientific collaboration.

3.2. Citation analysis

Bibliometrics is a popular approach to identifying key research trends (Mas-Tur et al., 2021). It relies on various calculations, such as the number of citations, the number of keywords, the number of publications per author, the institution (affiliations), or country.

Citation analysis is one of the main classical techniques of bibliometrics. It shows the structure of a specific field through the different types of networks such as co-citation, direct citations, and bibliographic coupling (Aria & Cuccurullo, 2017).

The total of citations for a scientific journal indicates its importance in that field of research (Garfield, 1972). For an author, the total number of citations is a reliable measure of the attention the author receives from the scientific community i.e. the author's scientific impact (Krell, 2009).

Thus, citation analysis describes the citation frequency of articles. It helps to show the most influential authors and publications in a field that are significantly impacting (Gundolf & Filser, 2013; Vokurka, 1996). The citation analysis of publications also helps to identify relevant work on a specific topic (Rejeb et al., 2021; Sharma, Shishodia, Gunasekaran, Min & Munim, 2022).

The co-citations analysis explores the relationships between the publications that are the network (C. Chen, Paul & O'Keefe, 2001; Small, 1973). It uses journals and cited authors as the unit of analysis. It is a valuable method, which shows the intellectual structure of a field (citation). The co-citation network becomes possible to detect publications that belong to the same group because of the similarity of the topics.

Despite the critique of citation analysis (M. H. MacRoberts & MacRoberts, 2018; Ou & Kim, 2019), it is considered one of the techniques often used to analyze the literature, and identify the most influential authors, journals, or articles in a research field (M. h. MacRoberts & MacRoberts, 2010).

3.3. Data collection

The objective of this study is to map the scientific structure of deep learning research in the agriculture sector through bibliometric analysis, visualization, and network analysis. For this purpose, as the query keywords, we used the following query on 1 June 2022 in the WoS database (Web of Science Group, 2022):

("deep learning") AND ("agriculture*" OR "farming")

The question was intentionally formulated in a large way to cover more research topics. It considers the years of publication, title, abstract, and author/indexed keywords of the articles. The bibliographic data was downloaded as a BibTeX file. In a filtering process, we selected English-language documents up to 2022. As a result, 1406 documents are identified and analyzed by Biliometrix tool.

Through citation analysis, we explored the relationship between authors and papers to provide an understanding of the underlying issues in precision agriculture. We identified the most influential keywords, authors, and publications with significant contributions. An analysis of the papers on agricultural topics is performed considering certain research questions such as the deep learning models and architectures put forward, the data sources used the classes and labels of the data, and the overall performance obtained according to the adopted metrics. Finally, we analyzed the connections between countries, institutions, and journals to describe the collaborative network.

4. Analysis and result

In this section, we perform a bibliometric analysis to explore the applications of deep learning in agriculture. This quantitative approach reveals the intellectual structure of the field, frequency of citations, hot topics, or future research directions.

4.1. Distribution of papers and their sources

To start with, we analyzed the evolution of scientific productions. The number of publications and their distribution over time-related to the deep learning application in agriculture is shown in Fig. 3. We observe that the number of publications started to increase significantly from the year 2018 (with 74 publications). Specifically, the number of publications keeps up. It went from 74 in 2018 to 337 in 2020 and a peak of 495 in 2021.

The significant development of technologies in the last decades contributed to this increase in publications. The use of computers, computer vision, IoT manufacturing, and funding of agricultural projects have prompted the scientific and agro-industrial communities.

In addition, our selection contained a wide variety of journals. As shown in Table 1, we present the journals that published the most studies in precision agriculture indexed in the Web of Sciences from 2015 to 2022. The specialized journals in agronomic studies or remote sensing are the most active in terms of publications of scientific articles. For example, Elsevier's "Computers and Electronics in Agriculture", covering the development and application of computer science, software, electronics, and monitoring systems to solve agricultural

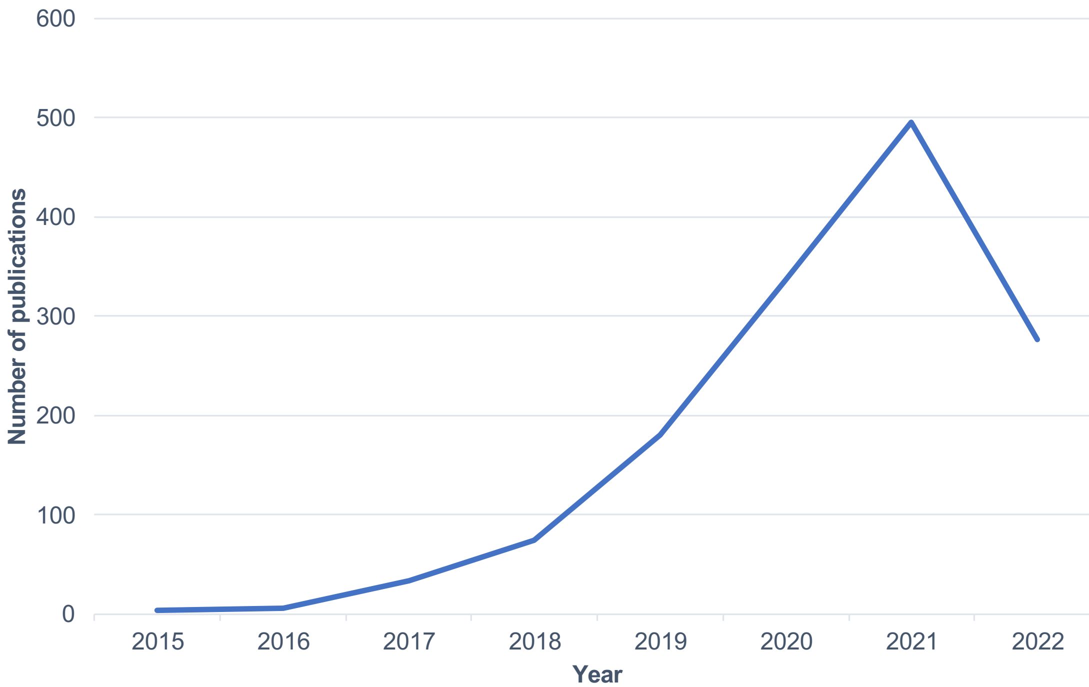

Fig. 3. Annual scientific publications.

Table 1
Top-10 relevant sources.

Rank	Sources	Count
1	Computers and Electronics in Agriculture	142
2	Remote Sensing	95
3	Sensors	58
4	IEEE Access	53
5	Applied Sciences-Basel	33
6	Agronomy-Basel	26
7	Frontiers In Plant Science	26
8	Agriculture-Basel	22
9	CMC—Computers Materials & Continua	21
10	International Journal of Advanced Computer Science and Applications	14

Table 2
Most Relevant Affiliations.

Rank	Affiliations
1	China Agricultural University
2	University of Sydney
3	Zhejiang University
4	Wageningen University Research
5	Northwest A&F University China
6	University of Florida
7	IOWA State University
8	Beijing Technology Business University
9	King Saud University
10	Jeonbuk National University

problems, is the most widely used source or journal for publications with 142 publications. It is succeeded by remote sensing journals such as "Remote Sensing" with 95 publications in total that also focus on applications with IoT. Among the most cited sources, we have "IEEE Access" from the Institute of Electrical and Electronics Engineers with 34 publications in total.

The top 10 sources contributed to the literature with 490 documents, or about 33.61% of the total publications.

4.2. Corresponding author's country and academic publications

This stage of our study focuses on the country and academic affiliations of the authors. This analysis allows us, to better understand the geographic distribution of researchers contributing to agriculture. From an academic perspective (as showed in Table 2), the China Agricultural University tops list followed by the University of Sydney in terms of publication. From the USA, universities like "IOWA State University" and "University of Florida" are reported.

Additionally, the Fig. 4 gives a graphical representation of the countries and publications of the corresponding authors. Along with Table 3, they list their number of publications and the analysis of the number of publications in a single country (SCP), multiple countries (MCP), and the ratio of publications in multiple countries. China, India, and the United States are the most important country with a total of 320; 219 and 53 publications.

China at the top of the list has 242 single-country publications (SCP) and 78 multi-country publications (MCP), with an MCP ratio of 0.29. It is followed by India with 148 for MS and 35 for PCM. The United States has 109 (SCP) and 39 MCP.

4.3. Top manuscripts by citations

Document citation analysis studies the influence of articles in the literature. In doing so, we performed a citation analysis to identify the most influential studies on the application of deep learning in agriculture and recapitulated the content. The Table 4 list the top ten most influential documents in terms of the total number of citations (TC) or average citations per year (ACY). The publications by Kamilaris and Prenafeta-Boldú, (2018); Kussul, Lavreniuk, Skakun and Shelestov, (2017) lead the list with 1016 and 657 total citations respectively, followed by Fuentes, Yoon, Kim and Park, (2017); Weiss, Jacob and Duveiller, (2020) with 657 and 342 total citations.

The authors (Kamilaris & Prenafeta-Boldú, 2018; Weiss et al., 2020) present summaries of deep learning in agriculture in general and the use of remote sensing in agriculture in particular. Kamilaris et al. (Kamilaris & Prenafeta-Boldú, 2018) conducted a survey on research based on deep learning applied to the agricultural domain. A total of 40 relevant papers

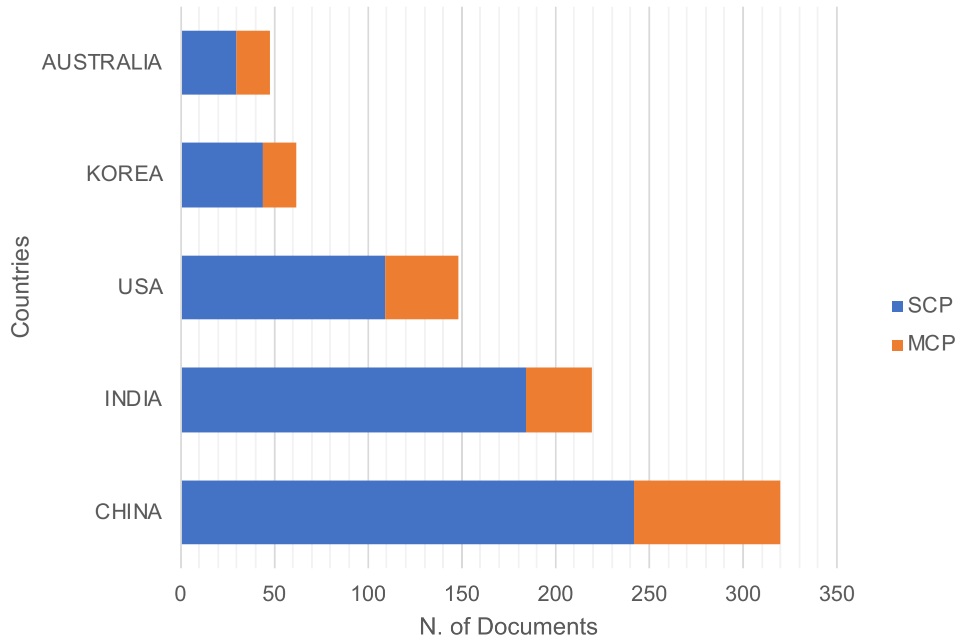

Fig. 4. Corresponding author's country and publications.

Table 3
Corresponding author's country and publications.

Country	Articles	SCP	MCP
CHINA	320	242	78
INDIA	219	184	35
USA	148	109	39
KOREA	62	44	18
AUSTRALIA	48	30	18

were identified, including the domain and problem they address, the models used, the data sources, etc. Additionally, they compared the performance of deep learning with other existing methods. Several emerging opportunities exist for strengthening the role of remote sensing in agricultural applications, according to Weiss et al., (2020). As a complement to these previous efforts, this current work aims to help agriculture users interested in deep learning applications. We will provide an overview of what deep learning has to offer agriculture based on literature review tools. It represents the most cited journals, articles, or keywords.

In the agriculture sector, accurate and earlier detection of fungal attacks in crops could help to develop an effective treatment technique while substantially reducing economic losses. Developments in deep neural networks have allowed researchers to improve the accuracy of object detection and recognition models by iterating over a training dataset. The authors (Fuentes et al., 2017) present a solution to this problem. They proposed a deep learning-based approach to detect plant diseases and pests in tomato crops (Fuentes et al., 2017). They combined meta-architectures such as Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD) with other architectures based on feature extractors, such as VGGNet from the Visual Geometry Group (VGG) at Oxford University or Residual Neural Network (ResNet) from Microsoft Research. To increase the performance of their approach, the authors used the data augmentation technique during the training. The comparative results proved the performance of their approach on standard architectures with a mean Average Precision of 83% for Faster R-CNN with VGG-16 or 82.53% for SSD with ResNet-50. The authors (Maryam Rahnemoonfar & Clay Sheppard, 2017) have built a methodology based on convolutional neural networks for crop yield estimation. Their objective is to reduce the cost of labeling (tagging) training data for the object-counting problem by creating a set of secondary datasets for training. Using a modified version of the GoogleNet or Inception and ResNet model coupling architecture, their algorithm counts the exact number of fruits or flowers. Experimental results trained on simulated data returned an average accuracy of 91% on a set of real images.

To support agriculture, (Khan, Khan, Yousaf, Khurshid & Abbas, 2018; Kussul et al., 2017; Zhong, Hu & Zhou, 2019) illustrate the development of techniques based on remote sensing. The authors (Kussul et al., 2017; Zhong et al., 2019) compare machine learning models to CNN for crop classification, used to delimit crop areas. Kussul et al. compare the models as Multi-Layer Perceptron (MLP) or Random Forest with CNN for crops (wheat, corn, soybeans, etc.) classification (Kussul et al., 2017). Landsat-8 and Sentinel-1A satellites for this classification acquire multi-temporal data. Experiments have shown that CNNs achieve better performance with an average accuracy of 88%. Zhong et al. proposed the crop classification based on deep learning from remote sensing time series (Zhong et al., 2019). In this study, deep learning models based on LSTM and one-dimensional convolutional layers (Conv1D) are compared with models such as XGBoost, Random Forest, and Support Vector Machine (SVM). The experimental results showed that Conv1D is effective and efficient for representing the time series in multi-temporal classification tasks with an accuracy of 85.54%. In summary, thirteen (13) categories (such as rice, corn, tomatoes, vineyards, etc.) of summer crops in Yolo County, California, USA, were selected for the classification task.

According to Khan et al., (2018) hyperspectral imagery has a great potential in the analysis of plant diseases or crop yield estimation. Indeed, advances in the ground or airborne IoT based on hyperspectral imagery have refined the evaluation of crop stresses or vegetation characterization by traditional techniques. Today, existing connected object technologies (Internet of Things or IoT) need to add intelligent elements and pass from "perception" to "cognition" by combining IoT and cognitive methods (Foukalas, 2020). In the cognitive IoT (CIoT), the self-organizing networking technology can use group collaboration among the nodes to accomplish the common mission, which reflects the reasoning, distribution, and robustness of the IoT. Cognitive IoT enables organizations to learn from data from connected devices, sensors, machines, and other sources and infuses intelligence into industrial operations and the experiences of products and machines stakeholders.

Table 4
The most global cited documents in the WoS database.

TC Rank	Documents	DOI	Total Citations
1	KAMILARIS A, 2018, COMPUT ELECTRON AGRIC	10.1016/j.compag.2018.02.016	1016
2	KUSSUL N, 2017, IEEE GEOSCI REMOTE SENS LETT	10.1109/LGRS.2017.2681128	657
3	FUENTES A, 2017, SENSORS	10.3390/s17092022	342
4	WEISS M, 2020, REMOTE SENS ENVIRON	10.1016/j.rse.2019.111402	304
5	ZHONG L, 2019, REMOTE SENS ENVIRON	10.1016/j.rse.2018.11.032	263
6	KHAN MJ, 2018, IEEE ACCESS	10.1109/ACCESS.2018.2812999	226
7	RAHNEMOONFAR M, 2017, SENSORS	10.3390/s17040905	208
8	GHOSAL S, 2018, PROC NATL ACAD SCI U S A	10.1073/pnas.1716999115	170
9	LATEEF F, 2019, NEUROCOMPUTING	10.1016/j.neucom.2019.02.003	161
10	ZHU J, 2018, IEEE INTERNET THINGS J	10.1109/JIOT.2017.2759728	157

TC per Year Rank	Publication (Authors, Year, Source, Ref)	DOI	TC per Year
1	KAMILARIS A, 2018, COMPUT ELECTRON AGRIC	10.1016/j.compag.2018.02.016	203,2
2	KUSSUL N, 2017, IEEE GEOSCI REMOTE SENS LETT	10.1109/LGRS.2017.2681128	109,5
3	WEISS M, 2020, REMOTE SENS ENVIRON	10.1016/j.rse.2019.111402	101,333
4	ZHONG L, 2019, REMOTE SENS ENVIRON	10.1016/j.rse.2018.11.032	65,75
5	FUENTES A, 2017, SENSORS	10.3390/s17092022	57
6	KHAN MJ, 2018, IEEE ACCESS	10.1109/ACCESS.2018.2812999	45,2
7	LATEEF F, 2019, NEUROCOMPUTING	10.1016/j.neucom.2019.02.003	40,25
8	RAHNEMOONFAR M, 2017, SENSORS	10.3390/s17040905	34,667
9	GHOSAL S, 2018, PROC NATL ACAD SCI U S A	10.1073/pnas.1716999115	34
10	ZHU J, 2018, IEEE INTERNET THINGS J	10.1109/JIOT.2017.2759728	31

Indeed, they constitute a development lever for future agriculture by increasing the capacity to learn, think, and understand problems in complex situations. In this digitalization of the agricultural system, the users have a high need to automate the collection and analysis of data on the production sites and improve the failures of the productive system (weeding, harvesting, treatment, etc.). Zhu et al. implement a novel mechanism for scheduling information transmission between connected objects using a deep reinforcement learning (Deep Q-Learning) technique (J. Zhu et al., 2018). The Q-Learning method learns a policy, which indicates which action to perform in each state of the system. This facilitates the comparison of the probable recompense for taking the available actions to be optimized without having the initial knowledge of the states of the environment. The learning of the Q-Learning algorithm is a gradual optimization process until convergence is achieved by selecting the optimal actions. Therefore, Deep Q-Learning plays an important role in the transmission and reception of data packets in wireless networks to maximize the system traffic flow between the nodes of the system.

4.4. Keyword analysis

4.4.1. Most relevant keywords

The keywords chosen by the authors were words that describe the limits and impact of their article in the scientific community. The keyword analysis is the compilation of keywords from related works in a field. It identifies the keywords and reveals their trends and the directions taken by the research (Dixit & Jakhar, 2021; Uddin, Singh, Pinto & Olmos, 2015). By doing, the top-22 keywords are presented in Table 5. We eliminated some inconsistencies by merging semantically identical or similar keywords "CNN" and "convolutional neural network".

Fig. 5 shows a chart of the most popular author keywords in the data collected using a word cloud visualization in this work. The size of a chart element is proportional to the number of documents where the keyword appears. These keywords correspond to the main topics of research interest in agriculture for which researchers have provided resolutions based on deep learning.

On the one hand, the Table 5 shows the keywords refer to specific agricultural challenges: crop “segmentation, “image recognition” with backend image processing and feature extraction, "plant diseases”, “weed identification” or “insect pest” recognition. On the other hand, they present research covering more technical topics on deep learning, like “image processing”, “transfer learning”, “convolutional neural networks”, “computer vision”, “feature extraction”, and “image classification”.

An interesting element of this analysis is the exploitation of Internet of Things (IoT) technologies and remote sensing. The IoT (C.-J. Chen, Huang, Li, Chang & Huang, 2020; Y.-S. Chen et al., 2020) can simultaneously collect hyperspectral images in different wavelengths and RGB images in large quantities, or drones for surveillance, estimation, and detection purposes, but also precision irrigation (Bah, Hafiane & Canals, 2018; Panday, Pratihast, Aryal & Kayastha, 2020).

In doing so, the presence of machine learning in the top-10 of keywords is not surprising. Indeed, several works have performed comparative tests between deep learning and machine learning models. Others use machine learning models as classifiers in neural networks during supervised and unsupervised learning.

Through these keywords, we can see that agriculture is faced with many difficulties such as fungal attacks caused by diseases, insect pests, and weeds that can affect crop productivity. A traditional resolution of these difficulties can lead to farmers abusing agricultural intrants and degrading the quality of production with adverse effects and impacts on human health and the environment. To overcome these difficulties, one promising solution is the digitalization of agriculture, which offers opportunities for the automatization of collected data processing. They

Table 5
Most relevant Keywords.

Rank	Terms	Occurrences	Rank	Terms	Occurrences
1	deep learning	895	12	weed identification	60
2	precision agriculture	493	13	image processing	58
3	CNN (convolutional neural network)	345	14	artificial intelligence	56
4	plant disease	167	15	transfer learning	56
5	machine learning	158	16	feature extraction	53
6	internet of things	130	17	long short-term memory	44
7	object detection	124	18	insect pest	39
8	image classification	119	19	segmentation	34
9	computer vision	104	20	hyperspectral data	23
10	remote sensing	84	21	data augmentation	22
11	image segmentation	72	22	recurrent neural network	21

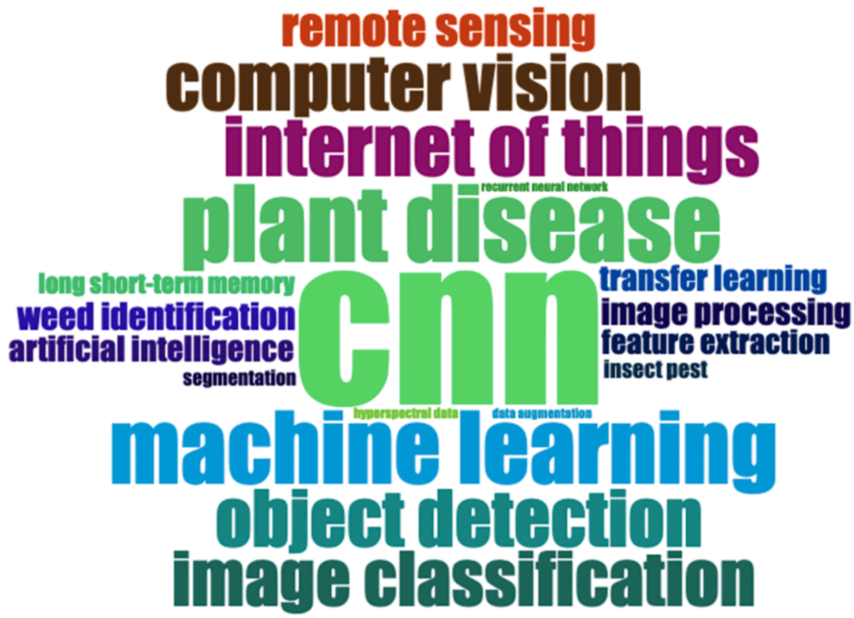

Fig. 5. Most relevant Keywords.

consist in combining the potentialities of a set of technologies including IoT, and deep neural networks, which have shown encouraging results, particularly in the field of computer vision. In addition, the working principle of deep learning facilitates feature extraction, transfer learning, or remote sensing in farm monitoring and management. This encourages the early identification of problems in crops with levers for limiting the use of intrants (pesticides, chemical treatments, etc.), and for improving agricultural yields.

4.4.2. Keyword, country, and source relationships

The countries such as China, the United States, India, and Brazil have an active research community on these topics related to precision agriculture. As shown in Fig. 6, we have a visualization of three fields' main elements (e.g., journals, keywords, countries), and their links using a

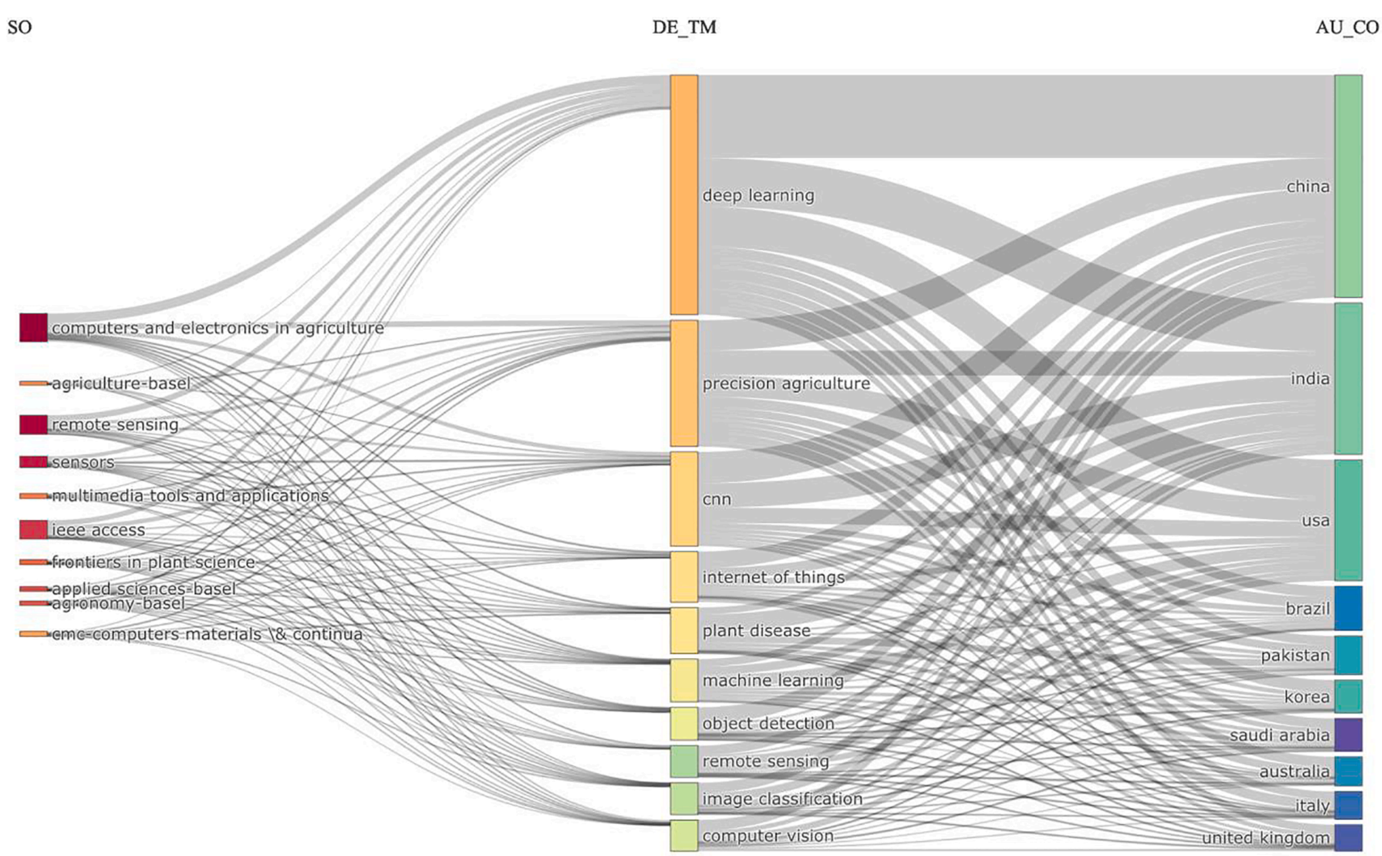

Fig. 6. Citation flow by Sankey diagram. SO: publication sources, DE_TM: author keywords, AU_CO: Countries.

Sankey diagram (e.g., type of flow diagram). In this Sankey diagram flow representation, the size of an element indicates its importance, which is proportional to the number of nodes it has. The analysis shows the sources (journals most often) in which authors have published the most and the most discussed research topics identified through keywords in the relevant countries.

5. Discussion

We will discuss the key result of the bibliometrics process research in this section. Among the agricultural challenges, crop health under the threat of fungal attacks will be addressed. Increasing the production of cultures requires research in this domain.

5.1. Research distribution in precision agriculture

The section summarizes the potential of deep learning in agriculture to prevent fungal attacks that reduce crop productivity. In other words, it highlights some works in the literature related to the identification of diseases, weeds, or insect pests in crops.

In agriculture, the traditional recognition and identification (visual inspection by experts or biological examination) of problems and their risks on farms is time-consuming and becomes almost impossible when farms are large. Neural networks use computer vision whose main purpose is to allow a machine to analyze, process, and understand one or several images captured from a data acquisition system. Computer vision facilitates the automatic counting, localization, or recognition of objects and considerably improves the quality of agricultural activities. Table 6 to Table 8 provide a classification of some research works in deep learning applied to the agricultural sector according to their approach, the type of problems, experimental dataset, and the results obtained. It is common for studies to propose specific parameters and several models for the accuracy of the learning technique. The best parameters and the best result are selected from several experimental designs and presented in the tables.

We observed from Table 6 to Table 8 that CNN is the most widely used deep learning algorithm for agricultural tasks. However, the CNNs do not consider the spatial relationships between features in an image. They are sensitive to variations in the images of a class to be predicted, hence the need for a large quantity of training dataset. In some studies, this problem is solved by data augmentation with the Generative Adversarial Networks organs technique, by a series of image transformations through rotation, zooming, or other image processing methods.

The architecture of a deep neural network is known to be useful for making learning more efficient. Most of the work uses standard architectures that have already proven to be the backbone for experimental evaluations. The architectures LeNet (Lecun, Bottou, Bengio & Haffner, 1998) and AlexNet (Krizhevsky, Sutskever & Hinton, 2012) were introduced more than a decade ago. Both networks were relatively shallow and are composed of two (2) and five (5) convolution layers respectively. They employed large receptive field cores in the layers close to the input and smaller cores in the layers that are closer to the output.

Since 2012, thanks to the ImageNet Large Scale Visual Recognition Competition (ILSRV), we have seen an explosion of new, deeper architectures with small kernels. More and more, these architectures can be deployed on embedded devices such as smartphones or drones. The first ones to explore deep layers to address this challenge took up work by (Russakovsky et al., 2014) by building the so-called VGGNet architectures (Simonyan & Zisserman, 2014). Afterward, various other architectures emerged. They consist of multiple convolution blocks: GoogleNet (Szegedy et al., 2014), Inception (Szegedy, Ioffe, Vanhoucke & Alemi, 2016), ResNet (He, Zhang, Ren & Sun, 2015), DenseNet (Huang, Liu, van der Maaten & Weinberger, 2018), MobileNet (Howard et al., 2017). There are also other types of algorithms applied with CNN for identification that is more accurate or detection of crops. The Yolo or CNN models based on Region Proposal Network (RPN) allow for example a localization of diseases or insect pests by listing the coordinates of rectangular regions containing the object.

Today, smartphones, cameras, robots, or autonomous vehicles are discovering the accuracy and efficiency of deep learning algorithms under real-ground conditions (Bah et al., 2018; Kerkech, Hafiane & Canals, 2020; Y. Li, Wang, Dang, Sadeghi-Niaraki & Moon, 2020; Ruigrok, van Henten, Booij, van Boheemen & Kootstra, 2020; Tufail et al., 2021). The development of automated and multitasking machinery saves labor and can help farmers to boost production. For example, drones can spray pesticides against weeds, pests, or diseases with accuracy. To this end, it is necessary to find a trade-off between the research of precision of deep models and the reduction of training parameters, which is correlated to the computing time. This implies that it is possible to reduce the parameters of the initial model without degrading its performance by examining the contribution of layers when inferring the model (Chattopadhyay, Sarkar, Howlader & Balasubramanian, 2017; Nagasubramanian et al., 2019; Zeiler & Fergus, 2013). When the model is used in real situations such as plant diagnosis, the reduction of classifier parameters is important for memory and computational efficiency.

It is therefore essential to select features and evaluate influence factors when developing these classifiers (Hariri, Bagheri & Davoodi, 2022). Layer visualization during feature extraction or input prediction is a first step to building architectures with fewer learning parameters and weakly supervised object localization (Choe et al., 2020; Zhang, Cao & Wu, 2020). Furthermore, it was demonstrated that Visions Transformers (ViT) achieve very competitive performances for vision applications like image classification, object detection, and semantic image segmentation (Steiner et al., 2022). Compared to convolutional neural networks, which can present inductive biases when trained on small datasets, the contributions of ViTs are interesting for researchers who wish to optimize the performance of their final model according to their computational resources. Recently, (Reedha, Dericquebourg, Canals & Hafiane, 2022) investigate visual transformers (ViT) and apply them to weed and crop classification in Unmanned Aerial Vehicles images.

5.2. Dataset for agricultural field

Many public image datasets like ImageNet (Krizhevsky et al., 2012), MS COCO (Lin et al., 2015), Pascal VOC (Everingham, Van Gool, Williams, Winn & Zisserman, 2007, 2012) are available to evaluate deep learning models. Using these datasets, it has been possible to evaluate the performance of the algorithms for classification, detection, localization, or object segmentation problems. Despite the sufficient size of these datasets, they are mainly composed of generic objects that cannot be directly applied to farms. To address the agricultural dataset limitation, some investigators have proposed large-scale image datasets: projects like NBAIR (NBAIR, 2022), AgriPest (R. Wang et al., 2021), DeepWeeds (Olsen et al., 2019), PlantVillage (Arun & Gopal, 2019) IP102 (Wu, Zhan, Lai, Cheng & Yang, 2019), and web repositories as plant leaf disease (Munnangi, 2019/2022; Rai, 2021), cotton diseases (Naik, 2020/2022), Insect pests (Xie et al., 2018; Yue, 2018). They usually consist of color images in Red, Green, and Blue (RGB) format, taken under different environmental conditions but also files annotated for object detection. Table 9 lists several common datasets and their characteristics related to the agricultural field. The annotations are present in some of these datasets on some images.

5.3. Evaluation metrics

Deep learning requires a large quantity of training dataset to train neural networks. They are exploited by networks with complex architectures having a significant training parameter. Moreover, it is a very expensive task to train these networks from scratch for hardware re-

Table 6
Related work on weed identification.

Paper	Approach	Problem definition	Challenges	Dataset	Result
(Razfar, True, Bassiouny, Venkatesh & Kashef, 2022)	MobileNetV2, ResNet50, and three custom CNN Models. *With* epochs: 10, learning rate: 10−5 (reduced to 10−6 on the plateau), batch size: 64, optimizer: Adam	Weed detection system within a soybean plantation using deep learning models	The Raspberry PI controller was used to deploy network architectures for edge computing.	400 images for 4 classes include crop weeds. *Acquisition*: Use (dos Santos Ferreira, Matte Freitas, Gonçalves da Silva, Pistori & Theophilo Folhes, 2017) which images are captured by the UAV	Accuracy: 97.70% for custom CNN with 4 layers.
(Reedha et al., 2022)	ViT-B32 and ViT-B16 models based EfficientNet and ResNet models. *With* The initial learning rate was set to 0.0001 with a reducing factor of 0.2. The batch size was set to 8 and the models trained for 100 epochs. Training use early stopping	Self-attention paradigm via the ViT to address the weeds and crops classification	While weeds and crops share many attributes similarity as color, texture, and shape, the attention-based deep network proposed to learn features faster, decreases the training cost	4000 samples for each of 3 classes of crop and weed classes, only off-type beet class up to 3265 samples. *Acquisition*: Data were collected using a high-resolution camera mounted on a UAV, which was deployed in beet, parsley, and spinach fields.	F1-score with 5-folds cross validation: ViT B-16: 99.40% ViT B-32: 99.20%
(Partel, Kakarla & Ampatzidis, 2019)	CNN-based tiny-YOLOV3(Redmon, 2014/2022) for object detector.	Development and evaluation of a smart sprayer to differentiate between weeds and tomato plants on real and artificial data.	A prototype for a smart sprayer using deep learning to detect specific target weeds was developed and evaluated.	1000 weed images of targets and non-targets label *Acquisition*: Three cameras acquired images simultaneously on a resolution of 640 × 480 pixels	One of the experiments provided a precision of 90% and a recall of 89% with artificial plants, and 59% and 44% respectively with real plants.
(Ruigrok et al., 2020)	CNN Darknet-53 based on YOLOv3 for object detectors + data augmentation (translation, rotation, etc.).	Plant weed detection system integrated into a spraying robot.	Development of an automated spraying system for potatoes	2260 images of the training dataset split into 6383 sugar beet and 1709 potato annotations *Acquisition:* The images acquired by the camera system with a resolution of 2048 1538 pixels.	Recall: 57%, Precision: 84%
(Bah et al., 2018)	CNN based ResNet18) + feature extraction and fine-tuning. *With* learning rate of 0.01 epochs: 200	Deep learning of unsupervised data labeling for crop weed detection in drone images from bean and spinach fields.	Combine supervised and unsupervised training datasets. The developed method could be a key technique for online weed detection with UAV.	Supervised data labeling: - 28,886 bean training dataset −14,188 spinach training dataset Unsupervised data labeling: - 9616 bean training dataset - 8606 spinach training dataset *Acquisition:* A DJI Phantom 3 Pro-drone that embeds a 36-megapixel (MP) RGB camera acquired images.	Spinach fields: Areas Under the Curve (AUC): 94.34% (unsupervised data labeling) and 95.70% (supervised data labeling). Beanfield: AUC: 88.73% (unsupervised data labeling) and 94.84% (supervised data labeling)
(Lottes, Behley, Milioto & Stachniss, 2018)	A combination of CNN (Fully Convolutional DenseNet) + Autoencoder *With* Optimizer: rmsprop Batch size: 10 initial learning rate: 0.01 The training stops after 200 epochs.	Crop and weed classification system on sugar beets.	An approach for agriculture robots providing semantic segmentation per pixel between crops and weeds. The spatial organization of plants in a row using 3D convolutions on a sequence of images.	Subset training dataset image: - 10,036 for Bonn2016 dataset - 864 for Bonn2017 dataset - 2584 for Stuttgart dataset *Acquisition*: An agricultural field robot is sued to record the dataset on a sugar beet farm near Bonn in Germany for three months in the spring of	F1-score: 92.4% for test n°1 (training on Bonn2016 and testing on Stuttgart) and 86.6% on test n°2 (training on Bonn2016 and testing on Bonn2017).

(*continued on next page*)

Table 6 (*continued*)

Paper	Approach	Problem definition	Challenges	Dataset	Result
				2016 (Chebrolu et al., 2017).	
(Espejo-Garcia, Mylonas, Athanasakos, Fountas & Vasilakoglou, 2020)	Combining convolutional neural networks such as Xception, Inception-ResNet, VGGNet, MobileNet, and DenseNet for feature extraction with other machine learning classifiers like SVM, Gradient Boosting *With* Optimizer: Adam Batch size: 16, 32 Epoch: 40, 80 Data augmentation: rotation, zooming; Gaussian	Transfer learning for crops and weed identification.	Combines deep and machine learning models extract the features with a deep model and perform the weed classification with a machine learning model like SVM.	504 image for training dataset(AUAgroup, 2019/2021a). *Acquisition*: The pictures had been taken with a Nikon D700 camera that delivers 12-megapixel images.	F1-score: 99.29% (Fine-tuned DenseNet + Support Vector Machine). F1-score: 98% (Feature extraction + DenseNet + Support Vector Machine)
(Tufail et al., 2021)	Modification of ResNet18 and MobileNet-v2 pre-trained on ImageNet by replacing their last layers with an SVM classifier. *With* Optimizer: SGD with momentum.	Tobacco weed and crop detection for a tractor-mounted boom sprayer	The algorithms are deployed on a tractor-mounted boom sprayer in tobacco fields and autonomously perform spot spraying of the site.	Tabacco: 412 images Weed: 403 images *Acquisition*: Images of weeds and tobacco plants are captured in Pakistan in the tobacco fields in Swabi, Khyber Pakhtunkhwa.	Accuracy of: ResNet18:100% MobileNetV2: 81%

sources (computational speed and storage). To address this challenge, some works consider transfer learning techniques, the combination of several training techniques to validate their approach (Arsenovic, Karanovic, Sladojevic, Anderla & Stefanovic, 2019; C.-J. Chen et al., 2020; Kerkech et al., 2020). The experimental results obtained are measured using the common metrics such as Accuracy, F-score, Precision, Recall, and mean Average Precision (mAP) given by Eqs. (2)–8 respectively. They each indicate the percentage of misclassified instances compared to correctly classified instances. However, the F1-score or mAP measures seem to be good compromises when comparing multiple classifiers on different datasets.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$Accuracy(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n} 1(\hat{y}_i = y_i) \tag{5}$$

where $\hat{y}_i$ is the predicted value of the i th observation (sample), y_i its true value and n the number of observations (samples), and TP, TN, FP, FN are true positive, true negative, false positive, and false negative.

The $F - score$ is a harmonic mean of precision and recall. With the best score of 1 and the worst score of 0, it is calculated as follows:

$$F_\beta = \left(1 + \beta^2\right)\frac{Precison * Rappel}{\beta^2 Precison + Rappel} \tag{6}$$

When $\beta = 1$, the formula becomes:

$$F_1 = 2\frac{Precison * Rappel}{Precison + Rappel} \tag{7}$$

The AP is obtained by calculating the average precision (Pedregosa et al., 2011). We then simulated experiments based on average precision (AP). This metric will help us to compare the performance of different architectures by providing the prediction value for each label. AP is a summary of a precision-recall curve by varying a decision threshold and it is computed by the following formula:

$$AP = \sum_n (R_n - R_{n-1})P_n \tag{8}$$

where P_n and R_n are the precision and recall at the n-th threshold. We add a micro average precision that measures the score of all classes together.

5.4. Future of deep learning in agriculture

Agriculture has undergone a remarkable development over the last decades thanks to new technologies. The resulting new practices offer farmers operational efficiency in their activities and better profitability. The computing power of machines, the use of computer vision in IoT, and deep neural networks have attracted both scientific and agribusiness communities' attention. To discover the limitations of different works, we analyzed their experiments, the structure of their networks, or their results. Some studies are based on very few datasets, while others lack information about the experimental setup (hardware, time, memory). However, the analysis results present some limitations in terms of the visualization of the influential factors in the prediction and the use of multiple classifiers.

Firstly, if multiple classifiers are included in the experiments, then it is necessary to conduct statistical tests to analyze the significance of the achieved results (Benavoli, Corani, Demšar & Zaffalon, 2017; Demšar, 2006). Demšar et al. examined several statistical non-parametric tests, safety, and robustness and studied their suitability in machine learning to analyze significant differences in classification performance. The tests that have been recommended are the Wilcoxon signed ranks test for the comparison of two classifiers and the Friedman test with posthoc tests for the comparison of multiple classifiers on multiple datasets. The results of this test can be presented using Critical Difference (CD) plots for clarity.

Secondly, when we want to estimate the robustness of a model centered on random sampling, the cross-validation technique on the training data is useful. In most research, the sampling of training data is random. We find generally the following splits: 80/20 (respectively 70/30, 60/40) which represents 80% of the data set for training and validation (respectively 70%, 60%) and 20% is for the test set (respectively 30%, 40%). Otherwise, the results of the learning process will depend on a particular random choice for the training and test sets. This cross-validation technique, which is very costly in terms of computation,

Table 7
Related work on crop disease identification.

Paper	Approach	Problem definition	Challenges	Dataset	Result
(Mostafa et al., 2022)	AlexNet, SqueezeNet, GoogLeNet, ResNet-50, and ResNet-101 are + data augmentation.	Guava Disease Detection.	With the limited data available, they are pre-processed and enhanced using a color histogram and an unsharp masking technique. The enhanced data was then augmented using the affine transformation method.	321 images for five classes (canker, dot, rust, mummification, healthy). *Acquisition*: A high display-quality camera collected guava disease-based RGB image dataset.	Accuracy of ResNet-101: 97.74% Accuracy of ReseNet-50: 99.54%
(Yang, Yang, He, Zhang & He, 2022)	Proposed LFC—Net, a Location network, a Feedback network, and a Classification network of strawberry diseases in real planting environments *With* Optimizer: SGD, Epoch: 5 000, Batch size: 32, and the initial learning: 1e-4		Real-time strawberry disease classification and analysis systems in the cloud service. A self-supervision mechanism allows the model to identify diseased regions in strawberry images without annotations such as bounding boxes.	2 400 of 14 classes of strawberry disease images. *Acquisition*: Images are collected by web scraping	Accuracy:92.48% Precision: 90.68% Recall: 86.32% F1 score: 88.45%
(Kerkech et al., 2020)	SegNet (Badrinarayanan, Kendall & Cipolla, 2017) for Segmentation Network-based LeNet5	Mildew disease detection in the vine field using a deep learning segmentation approach	Combination/fusion of the visible and infrared UAV images to improve disease detection.	4 classes (shadow, ground, healthy and symptoms) for 70,560 patches images of size (17, 640 samples for each class *Acquisition:* The UAV Quadcopter drone was used in the data acquisition.	Leaf-level eval average result Accuracy: 82.20% for fusion Visible range intersect infrared range 90.23% for fusion Visible range union infrared. Grapevine-level average result Accuracy: 88.14% for fusion Visible range intersect infrared range 95.02% for fusion Visible range union infrared.
(Y. Guo et al., 2020)	VGG16 and RPN algorithms are used *With* Optimizer: SGD Batch size 256 Learning rate 0.001 Epoch: 400	Plant disease detection and recognition.	CNN and RPN algorithms are used to recognize and locate disease leaves in real or complex environments.	Training data includes Plant Photo Bank of China (PPBC) acquired by Crawler technology and plantVillage sub-dataset: 537 black rot, 1032 bacterial plaque disease, 293 rust, and 2852 healthy leaves.	Accuracy: 83.75%
(Verma, Chug & Singh, 2020)	Proposed CNN named Capsule Networks[1] (X. Guo, 2017/2022; Sabour, Frosst & Hinton, 2017) (CapsNet) *With* Epochs: 100 Batch size: 32	Classification of potato diseases.		3 classes (healthy, early blight, late blight) for 3000 leaf images of diseases in potato plants. *Acquisition*: The images are from the plantVillage project.	Accuracy: 91.83%
(Arsenovic et al., 2019)	CNN (AlexNet, VGG19, InceptionV3, DenseNet201, ResNet152) + data augmentation with Generative Adversarial Networks (GANs) *With* Batch sizes: 32, 64 Optimizer: SGD, Adam momentum: 0.9 learning rate: 0.001	Addressing the limitations of deep learning-based plant disease detection approaches.	Several experiments were conducted to test the impact of their proposal in real environmental conditions.	79,265 images for 42 different classes (both healthy and diseased)(Mohanty, 2021).	Mean Average Precision: 93.67%
(Coulibaly, Kamsu-Foguem, Kamissoko & Traore, 2019)	CNN (VGG16) + transfer learning + data augmentation Optimize: SGD Learning rate: 10−4 momentum of 0.9 epoch:60	Detection of mildew disease in millet-based on transfer learning	Several experiments have highlighted the need for transfer learning and data augmentation on small amounts of data.	126 images of diseased and healthy millet to identify mildew. *Acquisition*: The images are captured on the internet and in the field.	Accuracy: 95% F1-score: 91.75% Precision: 90.50%, Recall: 94.50%
(Picon et al., 2019)	CNN (ResNet50)	Plant disease classification incorporating contextual information (such as plant species and weather conditions)	The application is encapsulated in a docker container with a REST service to allow the connection with the mobile application.	121,955 images for eight diseases *Acquisition:* RGB images are taken by a smartphone.	Accuracy: 98%
(Nagasubramanian et al., 2019)	CNN models join the spatial and spectral dimension. *With*	Soybean plant disease identification in the hyperspectral image	Deep learning with a saliency map based model	1823 images include 940 healthy images and 150 infected (diseased) images.	Accuracy: 95.7 3%. Recall: 92%;

(*continued on next page*)

Table 7 (*continued*)

Paper	Approach	Problem definition	Challenges	Dataset	Result
	Optimizer: Adam Batch size: 32 learning rate: 10−6 β1 = 0.9, β2 = 0.999, epsilon = 10−8. Epochs: 126	using deep learning with a saliency map based model explainability and visualization approach	explainability and visualization approach.	*Acquisition*: Hyperspectral camera	Precision: 82%; F1-Score: 87%
(Singh, Chouhan, Jain & Jain, 2019)	CNN Optimizer: SGD learning rate: 0.01 Momentum: 0.9, Epoch: 100	Classification of mango leaves infected.	The work is validated on a real-time captured dataset consisting of 1070 images of mango leaves.	Four classes of 1130 mango images from plantVillage dataset.	Accuracy: 97.13%
(Fuentes et al., 2017)	Faster RCNN, R-FCN, combined SSD + VGGNet, ResNet *With*: Optimize: SGD Learning rate: 0.01 Momentum: 0.09 Weight decay:1e-6 Batch size: 15	Identification and recognition of diseases and pests that affect tomato plants.	Validation of the model is performed on images acquired in the real world.	Ten classes of 5000 classification images and 43,398 annotated after data augmentation. *Acquisition*: With camera devices, the images were collected under several conditions depending on the time.	mean Average Precision: 83.06%

[1] https://github.com/XifengGuo/CapsNet-Keras.

also avoids over-learning. It consists in splitting the dataset into k parts (folds) and each of the k parts is used in turn as a test set. The rest (of the k-1 other parts) is used for training and validation. The performance measure is the average of the calculated values obtained in each round.

Thirdly, the accuracy of a model's prediction is inversely proportional to its explicability, i.e., deep learning models are opaque to humans. This concept of explainability or eXplainable AI (XAI) has been supported by the United States Department of Defense Agency (DARPA) generating a reorientation of the problems related to machine learning (Gunning, 2016). We note the missing items related to this new preoccupation with an explainable artificial intelligence in most of the studied works. The objective of explainability is to provide users a warranty, a justification, confidence in the use of learning models and to propose recommendations for the improvement of their performance. For example, we can visualize the set of features (such as pixels in an image) that contributed to the model's decision or provide insights into its working(Rauber, Fadel, Falcao & Telea, 2017; Simonyan, Vedaldi & Zisserman, 2014; Zeiler & Fergus, 2013).

In addition, because deep neural networks have so many parameters, training them requires a lot of computation times, a large quantity of data, and significant energy consumption.

To reduce the computational cost (Khodaverdian, Sadr & Edalatpanah, 2021) and energy (Khodaverdian et al., 2021) and increase the accuracy of classification, propose a combination of convolutional layers with Gated Recurrent Unit or GRU layers. Researchers (Reedha et al., 2022) use visual transformers (ViT) and attention maps to learn features faster, reducing training costs.

There is a strong need to clarify the use of deep learning algorithms in sensitive areas of human health or nutrition. This is the perspective behind the potential contribution of explainability (Bach et al., 2015; Chattopadhyay et al., 2017; Ribeiro, Singh & Guestrin, 2016; Simonyan et al., 2014) in the agricultural field. This provides some opportunities to enroll farmers as actors in the training process from ground data for a smarter, more humane, and environmentally friendly agricultural practice. The participation of these actors can be realized on three levels:

1 Acquisition and preparation of training data to be processed later
2 Assistance in the analysis of partial results to guide the further learning process in a progressive manner
3 Evaluation of the learning process by expressing the level of satisfaction with interactions.

Hence, the deployment of data analysis or processing solutions forces scientists to formulate new ways of perceiving and interpreting the world. This is particularly evident in the field of deep learning and computer vision, which rely on mathematical, electronic, and computer tools to enable progress in the extraction of knowledge from data sets. We, therefore, present an interactive optimization of the development of an intelligent agricultural system in Fig. 7. It allows the concatenation of all the information and results obtained during the training process with end-user (agricultural actors) participation. The deployment of a precision agriculture system incorporating explainable artificial intelligence is possible in real-life situations. Indeed, there are currently some practical examples of agricultural applications trying to address this explicability requirement. For example, visualization maps have been used to identify stress levels and infection types at the plant level (Ghosal et al., 2018; Nagasubramanian et al., 2019).

6. Conclusion

Precision agriculture is a recent science that is certainly still in its young phase. Deep learning can make a decisive contribution to the analysis of agricultural data, in this case by using computer vision to enable a machine to automatically analyze and understand the visual world. This offers the opportunity to develop intelligent systems, which appear to be one of the many possible ways to tackle the economic, environmental, and social challenges in agriculture. This literature review shows a richness of work in recent years that describe the development of various systems using deep learning to solve various problems in precision agriculture. The problems addressed are mainly yielded losses caused by factors affecting crop growth. In bibliometric methodology, we explored only documents from the Web of Science database. We analyzed the thematic structures and new directions of agricultural research based on deep neural networks were proposed.

Bibliometric analyses show that the most active countries are China, the United States, India, and Brazil. The hot topics covered include plant disease, feature extraction, transfer learning, disease detection, weed detection, insect pests, convolutional neural networks, image processing, remote sensing, and IoT. Convolutional neural networks (CNNs) are one of the most used architectures thanks to their successful application in deep learning. However, the use of deep learning algorithms in precision agriculture raises many challenges whose resolution is useful to enhance this field and facilitate its appropriation by the stakeholders:

- The limited quantity and quality of training data are an important barrier to more accurate decisions suggested by intelligent systems (decision support systems or spatial analysis tools) in the agricultural

Table 8
Related work on pest identification.

Paper	Approach	Problem definition	Challenges	Dataset	Result
(Bereciartua-Pérez et al., 2022)	Unet, FCRN (Fully Convolutional Regression Network) DenseNet model *With* Optimizer: RMSE Learning rate:0.01 σ=9, l_2=10–5 Iteration: 2000	Insect counting in leaves using density map estimation approach based on deep learning and image processing (segmentation and counting).	The resulting application is accessible on a smartphone through the REST API for a real application.	The available dataset is 731 images. *Acquisition*: Images were acquired under different lighting conditions and at different seasons with 3 different cameras: 24 M pixel Olympus camera, 20 Mpixel Nikon camera, and Samsung Galaxy A8 smartphone.	The results on real field tests obtained MAE of 3.36, RMSE of 7.84, and R2 of 0.97 values.
(Wei, Chen, Luo, Long & Wang, 2022)	Proposed MFFNet based on encoder-decoder structure is compared ResNet-50 and VGG-16 *With* Optimize: SGD learning scheduler is set to Poly, momentum: 0.9 Weight decay: 1e-4 learning rate: 1e-3 Number iteration: 80, 000		As compared to standard models like ResNet or VGGNet, MFFNet "multi-scale feature fusion" provides a performance gain with fewer training parameters.	12 common crop pests at the adult and larval stages for 67, 200 images *Acquisition*: the experiment is downloaded from Baidu, Google, and Yahoo through a web crawler	Accuracy of MFFNet: 98. 2%
(Y.-S. Chen et al., 2020)	Pest detection-based YOLO model combined classification with SVM classifier and apply entire and partial transfer learning.	Pest detection as counting	Propose a framework that combines deep learning, edge computing, and cloud service for pest detection and localization in the image.	1600 cotton images for fifteen pest classes and one no pest class. *Acquisition:* An insect is trapped on a sticky object and then photographed by a camera in real conditions.	mean Average Precision: 90%, Accuracy: 90.2%, Recall: 85%
(Alves, Souza & Borges, 2020)	CNN (fine-tuning the ResNet34 model) + transfer learning + data augmentation (rotation, zooming, intensity variation). *With* Learning rate: 0.1 for 1000 iterations	Classification of pests in cotton crops using deep residual neural networks.	A classification system is proposed for the major cotton pests (primary and secondary). Changing the learning rate or batch normalizing ResNet improves its overall accuracy.	Eleven pest insects *Acquisition*: Different researchers around the world acquire images, the authors themselves in the field acquire others, and others are available on the internet.	Accuracy: 98.1%
(F. Wang, Wang, Xie, Yang & Liu, 2020)	Deeppest: CNN (ResNet-50) + fusion contextual information were employed in pest detection and recognition. *With* Optimizer: rmsprop Learning rate: 0.001 Momentum: 0.9 Batch size: 2	Detection of pests from images of rice or wheat crops	An effective pest detection model considers contextual information (such as geographical location or ambient temperature).	Wheat mite, Sticky worm, Rice planthopper 17,192 pest images with 76,595 pest annotations. *Acquisition:* Using a Sony CX-10 CCD camera, all images are captured by a research device.	mean Average Precision: 74.3%
(R. Li et al., 2019)	CNN (ResNet-50) + Region Proposal Network (RPN) *With* Optimizer: SGD mini-batch size of 2. Momentum: 0.9 learning rate: 0.02	Pest localization and recognition in the wheat-field environment.	Building a trained multi-scale model that separates the input image into different resolutions to improve test performance	4400 images for four classes *Acquisition*: Cameras are used to capture the images	mean Average Precision: 83.23%
(Dawei et al., 2019)	CNN (AlexNet) *With* Epoch: 10	Detection and recognition of pests using transfer learning	Human experts check the classifier's performance.	484 images of ten types of pests *Data acquisition*: A digital camera is used for some samples, while an online resource is used for others.	Accuracy: 93.84%
(Thenmozhi & Reddy, 2019)	Proposed CNN (VGGNet) and transfer learning. *With* Optimizer: SGD Learning rate: 5e-5, 1e-4, 5e-4 and 1e-3 Batch size: 10–130.	The classification and identification of crop (rice, wheat, maize, soybean, and sugarcane) insect pests.	Uses multiple datasets to validate their methodology.	Three datasets: 40 classes of insects with NBAIR (NBAIR, 2022), 24 classes of Xie1 (Xie et al., 2015), and 40 classes of Xie2 (Xie et al., 2018).	Accuracy: 96.75%, 97.47%, and 95.97% for insect datasets of NBAIR, Xie1, and Xie2.
(C.-J. Chen et al., 2020)	CNN (YOLOv3) and Long Short-Term Memory (LSTM) to pests predict. *With* Optimizer: SGD Learning rate: 1e-4	An agricultural system that uses environmental information from weather stations and IoT sensors to detect pests.	Sensors are used to analyze the life cycle of pests so that farmers can be notified quickly of pest appearances and damage.	687 images of Tessaratoma papillosa. *Acquisition:* Mobile apps and drones are used to collect Tessaratoma papillosa images.	Accuracy: 90%; mAP: 92%

Table 9
Public datasets related to agriculture.

Reference	Purpose	Classes	Plant	Features *input image size, classes, samples*
DeepWeeds (Olsen et al., 2019)	Classification of multiple weed species based on deep learning	17,509 images for eight (8) different weed species	The acquisition instrument consists of Raspberry Pi3, Arduino Uno, and custom electronics shield	Each class contains between 1009 and 1125 images of the corresponding species
AgriPest (R. Wang et al., 2021)	A benchmark dataset pest detection	49,707 images and 264,728 objects for 14 categories of pests	The acquisition instrument consists of three components: mobile client, CCD camera, and temperature-humidity sensor	AgriPest focuses on small pest detection to meet the requirements of practical applications
PlantVillage (Hughes & Salathe, 2015)	An open access repository of images on plant health and unhealthy leaf images.	54,303 healthy and unhealthy leaf images were divided into 38 categories by species and disease.	Digital cameras (Sony DSC - Rx100/13 20.2 megapixels).	More than 50,000 leaf images of 14 crops and 26 diseases, labeled and categorized into 38 plant-disease pairs, are available in three versions: colored, grayscale and segmented
IP102 (Wu et al., 2019)	A large-scale benchmark Dataset for insect pests	75, 222 images for 102 classes	Internet as the primary source to collect images (Google, Flickr, Bing, etc.) and insect science websites	Pests are often difficult to differentiate because the object colors and background are similar. The images contain throughout the life cycle of the pests, and they are difficult to classify, especially during the larval period. Pests are often similar to each other.
Early crop dataset[1] (AUAgroup, 2019/2021b)	Crop and weed identification	> 200 images for four classes		This repository contains field images of early-stage tomatoes, cotton, velvetleaf, and black nightshade
Plant Seedlings Dataset[2] (Giselsson, Dyrmann, Jørgensen, Jensen & Midtiby, 2017)	Weeds and Crops classification	5539 plant images (RGB, segmented) for 12 species	Dataset is collected by the Aarhus University Signal Processing group	Each class contains colorful images that show plants in different stages of growth.
IP41(K. Wang et al., 2022)	IP41, for crop pest recognition	46,567 original images of crop pests from 41 classes	The image data consist of pictures from search engines (Google, Baidu, 360, Yahoo, and Bing), and pictures were taken by farmers in natural settings.	Dataset has a low imbalance rate
Sugarbeets2016(Chebrolu et al., 2017)	Agricultural dataset for the plant classification, localization, and mapping on sugar beet fields	> 10,000 images include RGB and NIR images for sugar beet plants and more than nine different types of weed species	Robot of four-channel multi-spectral	Collected data on a sugar beet field during a crop season, covering the various growth stages of the plants
Insect pest Xie 2018	Insect pest classification	4500 insect images with 40 types collected from a crop field.	Images were captured by the use of digital cameras	Most of these pest images were captured in real-life conditions
Insect pest Xie 2015	Insect pest classification	613 insects images with 24 insect species	Images were captured by the use of digital cameras	
NBAIR(NBAIR, 2022)	approximately 4500 pest images for 40 classes		National Bureau of Agricultural Insect Resources	Provides images of important insects in agriculture, mainly for identification purposes.
Cassava disease (Mwebaze, Gebru, Frome, Nsumba & Tusubira, 2019)	Cassava Disease Classification	9436 labeled and 12,595 unlabeled image for 4 diseases and healthy plant leaves	Images are collected by farmers through a smartphone application	The number of images per class is unbalanced. The two disease classes CMD and CBSD have 72% of the images.

[1] https://github.com/AUAgroup/early-crop-weed.
[2] https://vision.eng.au.dk/plant-seedlings-dataset/.

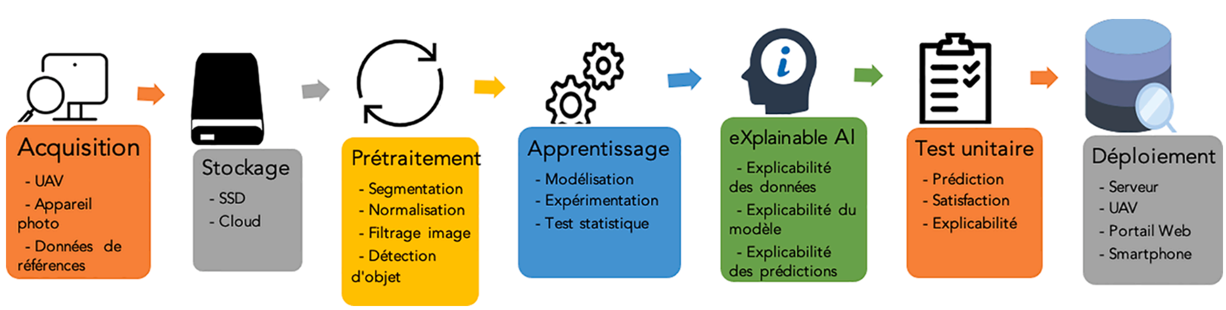

Fig. 7. Intelligent agricultural system pipeline (SSD: Solid-State Drive; UAV: Unmanned Aerial Vehicle).

domain, which is undergoing a digital evolution with new constraints to respect environmental standards.

- The depth of neural network architectures, the large number of parameters, and the complexity of the algorithms do not simplify computation times and energy consumption. This may lead to additional procedures (e.g., additional constraints for embedded systems) for their appropriate deployment on connected objects in agriculture.
- The understanding of the reasoning mechanisms underlying deep machine learning systems needs to be improved. It is therefore

useful to provide some explanations for a better comprehension of the predictions provided.

In addition, collaborations between agricultural researchers and companies can further assist farmers with the development of vision-based vehicle guidance systems and autonomous mobile agricultural robots. Drones can fly agricultural areas that are hardly accessible to humans in a few minutes and the treatments can be applied with precision, near the plant, without the farmer having any contact or exposure to the product.

We consider the paper will open the way for further research on agricultural development. In our future work, we would like to build on the results of this study and focus on developing a predictive model based on the Vision Transformer (ViT) (Dosovitskiy et al., 2021) an alternative to the Convolutional Neural Network (CNN) which applied to sequences of image patches can perform very well in image classification tasks. The Vision Transformer (ViT) achieves excellent results compared to convolutional networks with less computational resources for training. Future work will explore agricultural paradigms related to ecological collapse and climate change.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Affouard, A., Lombardo, J.-.C., Goëau, H., Bonnet, P., & Joly, A. (2019). Pl@ntNet. https://hal.archives-ouvertes.fr/hal-02096020.

Alves, A. N., Souza, W. S. R., & Borges, D. L. (2020). Cotton pests classification in field-based images using deep residual networks. *Computers and Electronics in Agriculture, 174*, Article 105488. https://doi.org/10.1016/j.compag.2020.105488

Aria, M., & Cuccurullo, C. (2017). bibliometrix : An R-tool for comprehensive science mapping analysis. *Journal of Informetrics, 11*(4), 959-975. https://doi.org/10.1016/j.joi.2017.08.007

Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., & Stefanovic, D. (2019). Solving current limitations of deep learning based approaches for plant disease detection. *Symmetry*. MDPI. https://doi.org/10.3390/sym11070939 (Vol. 11, Numéro 7).

Arun, P.J., .& Gopal, G. (2019). Data for : Identification of plant leaf diseases using a 9-layer deep convolutional neural network. 1. https://doi.org/10.17632/tywbtsjrjv.1.

AUAgroup. (2021a). Early-crop-weed. https://github.com/AUAgroup/early-crop-weed (Original work published 2019).

AUAgroup. (2021b). Early-crop-weed. https://github.com/AUAgroup/early-crop-weed (Original work published 2019).

Bach, S., Binder, A., Montavon, G., Klauschen, F., Müller, K.-. R., & Samek, W. (2015). On Pixel-Wise Explanations for Non-Linear Classifier Decisions by Layer-Wise Relevance Propagation. *PloS one, 10*(7), Article e0130140. https://doi.org/10.1371/journal.pone.0130140

Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). SegNet : A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 39*(12), 2481-2495. https://doi.org/10.1109/TPAMI.2016.2644615

Bah, M. D., Hafiane, A., & Canals, R. (2018). Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. *Remote sensing*. MDPI. https://doi.org/10.3390/rs10111690 (Vol. 10, Numéro 11).

Benavoli, A., Corani, G., Demšar, J., & Zaffalon, M. (2017). Time for a Change : A Tutorial for Comparing Multiple Classifiers Through Bayesian Analysis. *Journal of Machine Learning Research, 18*(77), 1-36.

Bereciartua-Pérez, A., Gómez, L., Picón, A., Navarra-Mestre, R., Klukas, C., & Eggers, T. (2022). Insect counting through deep learning-based density maps estimation. *Computers and Electronics in Agriculture, 197*, Article 106933. https://doi.org/10.1016/j.compag.2022.106933

Chattopadhyay, A., Sarkar, A., Howlader, P., & Balasubramanian, V.N. (.2017). Grad-CAM++ : Improved visual explanations for deep convolutional networks. https://doi.org/10.1109/WACV.2018.00097.

Chebrolu, N., Lottes, P., Schaefer, A., Winterhalter, W., Burgard, W., & Stachniss, C. (2017). Agricultural robot dataset for plant classification, localization and mapping on sugar beet fields. *The International Journal of Robotics Research, 36*(10), 1045-1052. https://doi.org/10.1177/0278364917720510

Chen, C., Paul, R. J., & O'Keefe, B. (2001). Fitting the jigsaw of citation : Information visualization in domain analysis. *Journal of the American Society for Information Science and Technology, 52*(4), 315-330. https://doi.org/10.1002/1532-2890(2000)9999:9999<::AID-ASI1074>3.0.CO;2-2

Chen, C.-. J., Huang, Y.-. Y., Li, Y.-. S., Chang, C.-. Y., & Huang, Y.-. M. (2020a). An AIoT based smart agricultural system for pests detection. *IEEE access*. IEEE-INST ELECTRICAL ELECTRONICS ENGINEERS INC. https://doi.org/10.1109/ACCESS.2020.3024891 (Vol. 8, p. 180750-180761).

Chen, G., & Xiao, L. (2016). Selecting publication keywords for domain analysis in bibliometrics : A comparison of three methods. *Journal of Informetrics, 10*(1), 212-223. https://doi.org/10.1016/j.joi.2016.01.006

Chen, Y.-. S., Hsu, C.-. S., & Lo, C.-. L. (2020b). An entire-and-partial feature transfer learning approach for detecting the frequency of pest occurrence. *IEEE access*. IEEE-INST ELECTRICAL ELECTRONICS ENGINEERS INC. https://doi.org/10.1109/ACCESS.2020.2992520 (Vol. 8, p. 92490-92502).

Choe, J., Oh, S.J., .Lee, S., Chun, S., Akata, Z., & Shim, H. (2020). Evaluating Weakly Supervised Object Localization Methods Right. arXiv:2001.07437 [cs]. http://arxiv.org/abs/2001.07437.

Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., & Traore, D. (2019). Deep neural networks with transfer learning in millet crop images. *Computers in Industry, 108*, 115-120. https://doi.org/10.1016/j.compind.2019.02.003

Dawei, W., Limiao, D., Jiangong, N., Jiyue, G., Hongfei, Z., & Zhongzhi, H. (2019). Recognition pest by image-based transfer learning. *Journal of the Science of Food and Agriculture, 99*(10), 4524-4531. https://doi.org/10.1002/jsfa.9689

De Bellis, N. (2009). *Bibliometrics and citation analysis : From the science citation index to cybermetrics*. Scarecrow Press.

Demšar, J. (2006). Statistical Comparisons of Classifiers over Multiple Data Sets. *Journal of Machine Learning Research*, 1-30.

Dixit, A., & Jakhar, S. K. (2021). Airport capacity management : A review and bibliometric analysis. *Journal of Air Transport Management, 91*, Article 102010. https://doi.org/10.1016/j.jairtraman.2020.102010

dos Santos Ferreira, A., Matte Freitas, D., Gonçalves da Silva, G., Pistori, H., & Theophilo Folhes, M. (2017). Weed detection in soybean crops using ConvNets. *Computers and Electronics in Agriculture, 143*, 314-324. https://doi.org/10.1016/j.compag.2017.10.027

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., et al. (2021). An image is worth 16 × 16 words : Transformers for image recognition at scale. *ICLR*.

Espejo-Garcia, B., Mylonas, N., Athanasakos, L., Fountas, S., & Vasilakoglou, I. (2020). Towards weeds identification assistance through transfer learning. *COMPUTERS and electronics in agriculture*. ELSEVIER SCI LTD. https://doi.org/10.1016/j.compag.2020.105306 (Vol. 171).

Everingham, M., Van Gool, L., Williams, C.K.I., Winn, J., & Zisserman, A. (2007). The pascal visual object classes challenge 2007 (VOC2007) results. http://www.pascal-network.org/challenges/VOC/voc2007/workshop/index.html.

Everingham, M., Van Gool, L., Williams, C.K.I., Winn, J., & Zisserman, A. (2012). The pascal visual object classes challenge 2012 (VOC2012) results. http://www.pascal-network.org/challenges/VOC/voc2012/workshop/index.html.

Foukalas, F. (2020). Cognitive IoT platform for fog computing industrial applications. *Computers & Electrical Engineering, 87*, Article 106770. https://doi.org/10.1016/j.compeleceng.2020.106770

Fuentes, A., Yoon, S., Kim, S., & Park, D. (2017). A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition. *Sensors, 17*(9), 2022. https://doi.org/10.3390/s17092022

Gandonou, J.-M.A. (2005). ESSAYS on precision agriculture technology adoption and risk management. 227. https://uknowledge.uky.edu/gradschool_diss/227.

Garfield, E. (1972). Citation Analysis as a Tool in Journal Evaluation : Journals can be ranked by frequency and impact of citations for science policy studies. *Science (New York, N.Y.), 178*(4060), 471-479. https://doi.org/10.1126/science.178.4060.471

Ghosal, S., Blystone, D., Singh, A. K., Ganapathysubramanian, B., Singh, A., & Sarkar, S. (2018). An explainable deep machine vision framework for plant stress phenotyping. *Proceedings of the National Academy of Sciences, 115*(18), 4613-4618. https://doi.org/10.1073/pnas.1716999115

Giselsson, T.M., .Dyrmann, M., Jørgensen, R.N., .Jensen, P.K., .& Midtiby, H.S. (.2017). A public image database for benchmark of plant seedling classification algorithms. arXiv preprint.

Gundolf, K., & Filser, M. (2013). Management Research and Religion : A Citation Analysis. *Journal of Business Ethics, 112*(1), 177-185. https://doi.org/10.1007/s10551-012-1240-7

Gunning, D. (2016). Explainable artificial intelligence (XAI). https://www.darpa.mil/attachments/XAIIndustryDay_Final.pptx.

Guo, X. (2022). CapsNet-Keras [Python]. https://github.com/XifengGuo/CapsNet-Keras (Original work published 2017).

Guo, Y., Zhang, J., Yin, C., Hu, X., Zou, Y., Xue, Z., et al. (2020). Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming. *Discrete Dynamics in Nature and Society, 2020*, 1-11. https://doi.org/10.1155/2020/2479172

Gupta, J. (2019,. octobre 11). The role of artificial intelligence in agriculture sector. https://customerthink.com/the-role-of-artificial-intelligence-in-agriculture-sector/.

Hariri, A. H., Bagheri, E., & Davoodi, S. M. R. (2022). Presenting a model for the diagnosis of heart failure using cumulative and deep learning algorithms : A case study of tehran heart center. *Big Data and Computing Visions, 2*(1), 18-30. https://doi.org/10.22105/bdcv.2022.325710.1043

He, K., Zhang, X., Ren, S., & Sun, J. (2015). Deep Residual Learning for Image Recognition. arXiv:1512.03385 [cs]. http://arxiv.org/abs/1512.03385.

Howard, A.G., .Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T. et al. (2017). MobileNets : Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv:1704.04861 [cs]. http://arxiv.org/abs/1704.04861.

Huang, G., Liu, Z., van der Maaten, L., & Weinberger, K.Q. (.2018). Densely Connected Convolutional Networks. arXiv:1608.06993 [cs]. http://arxiv.org/abs/1608.06993.

Hughes, D.P., .& Salathe, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics. https://arxiv.org/abs/1511.08060v2.

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture : A survey. *Computers and Electronics in Agriculture, 147*, 70-90. https://doi.org/10.1016/j.compag.2018.02.016

Kerkech, M., Hafiane, A., & Canals, R. (2020). Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach. *Computers and electronics in agriculture*. ELSEVIER SCI LTD. https://doi.org/10.1016/j.compag.2020.105446 (Vol. 174).

Khan, M. J., Khan, H. S., Yousaf, A., Khurshid, K., & Abbas, A. (2018). Modern Trends in Hyperspectral Image Analysis : A Review. *IEEE access : practical innovations, open solutions, 6*, 14118–14129. https://doi.org/10.1109/ACCESS.2018.2812999

Khodaverdian, Z., Sadr, H., & Edalatpanah, S. A. (2021a). A Shallow Deep Neural Network for Selection of Migration Candidate Virtual Machines to Reduce Energy Consumption. In *2021 7th International Conference on Web Research (ICWR)* (p. 191-196). https://doi.org/10.1109/ICWR51868.2021.9443133

Khodaverdian, Z., Sadr, H., Edalatpanah, S.A., .& Solimandarabi, M.N. (.2021). Combination of convolutional neural network and gated recurrent unit for energy aware resource allocation (arXiv:2106.12178). arXiv. http://arxiv.org/abs/2106.12178.

Koskinen, J., Isohanni, M., Paajala, H., Jääskeläinen, E., Nieminen, P., Koponen, H., et al. (2008). How to use bibliometric methods in evaluation of scientific research? An example from Finnish schizophrenia research. *Nordic Journal of Psychiatry, 62*(2), 136-143. https://doi.org/10.1080/08039480801961667

Krell, F.-. T. (2009). The Poverty of Citation Databases : Data Mining Is Crucial for Fair Metrical Evaluation of Research Performance. *Bioscience, 59*(1), 6-7. https://doi.org/10.1525/bio.2009.59.1.2

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. Éds.. In F. Pereira, C. J. C. Burges, L. Bottou, & K. Q. Weinberger (Eds.), *Advances in neural information processing systems*. Curran Associates, Inc (Vol. 25) https://proceedings.neurips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data. *IEEE Geoscience and Remote Sensing Letters, 14*(5), 778-782. https://doi.org/10.1109/LGRS.2017.2681128

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436-444. https://doi.org/10.1038/nature14539

Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE, 86*(11), 2278-2324. https://doi.org/10.1109/5.726791

LeCun, Y., Kavukcuoglu, K., & Farabet, C. (2010). Convolutional networks and applications in vision. In *Proceedings of 2010 IEEE International Symposium on Circuits and Systems* (p. 253-256). https://doi.org/10.1109/ISCAS.2010.5537907

Li, R., Wang, R., Zhang, J., Xie, C., Liu, L., Wang, F., et al. (2019). An effective data augmentation strategy for CNN-Based pest localization and recognition in the field. *IEEE access*. IEEE-INST ELECTRICAL ELECTRONICS ENGINEERS INC. https://doi.org/10.1109/ACCESS.2019.2949852 (Vol. 7, p. 160274-160283).

Li, Y., Wang, H., Dang, L. M., Sadeghi-Niaraki, A., & Moon, H. (2020). Crop pest recognition in natural scenes using convolutional neural networks. *Computers and Electronics in Agriculture, 169*, Article 105174. https://doi.org/10.1016/j.compag.2019.105174

Liakos, K., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine Learning in Agriculture : A Review. *Sensors, 18*(8), 2674. https://doi.org/10.3390/s18082674

Lin, T.-.Y., Maire, M., Belongie, S., Bourdev, L., Girshick, R., Hays, J. et al. (2015). Microsoft COCO : Common Objects in Context. arXiv:1405.0312 [cs]. http://arxiv.org/abs/1405.0312.

Lottes, P., Behley, J., Milioto, A., & Stachniss, C. (2018). Fully convolutional networks with sequential information for robust crop and weed detection in precision farming. *IEEE robotics and automation letters*. IEEE-INST ELECTRICAL ELECTRONICS ENGINEERS INC. https://doi.org/10.1109/LRA.2018.2846289 (Vol. 3, Numéro 4, p. 2870-2877).

MacRoberts, M.h., & MacRoberts, B.r. (2010). Problems of citation analysis : A study of uncited and seldom-cited influences. *Journal of the American Society for Information Science and Technology, 61*(1), 1-12. https://doi.org/10.1002/asi.21228

MacRoberts, M. H., & MacRoberts, B. R. (2018). The mismeasure of science : Citation analysis: JOURNAL OF THE ASSOCIATION FOR INFORMATION SCIENCE AND TECHNOLOGY. *Journal of the Association for Information Science and Technology, 69*(3), 474-482. https://doi.org/10.1002/asi.23970

Mas-Tur, A., Roig-Tierno, N., Sarin, S., Haon, C., Sego, T., Belkhouja, M., et al. (2021). Co-citation, bibliographic coupling and leading authors, institutions and countries in the 50 years of Technological Forecasting and Social Change. *Technological Forecasting and Social Change, 165*, Article 120487. https://doi.org/10.1016/j.techfore.2020.120487

Mohanty, S. (2021). PlantVillage dataset. https://github.com/spMohanty/PlantVillage-Dataset.

Mostafa, A. M., Kumar, S. A., Meraj, T., Rauf, H. T., Alnuaim, A. A., & Alkhayyal, M. A. (2022). Guava Disease Detection Using Deep Convolutional Neural Networks : A Case Study of Guava Plants. *Applied Sciences, 12*(1), 239. https://doi.org/10.3390/app12010239

Munnangi, M. (2022). Crop : Plant disease identification using app. https://github.com/Manikanta-Munnangi/CROP-Plant-Disease-Identification-Using-App (Original work published 2019).

Mwebaze, E., Gebru, T., Frome, A., Nsumba, S., & Tusubira, J. (2019). ICassava 2019Fine-Grained visual categorization challenge.

Nagasubramanian, K., Jones, S., Singh, A. K., Sarkar, S., Singh, A., & Ganapathysubramanian, B. (2019). Plant disease identification using explainable 3D deep learning on hyperspectral images. *Plant methods*. BMC. https://doi.org/10.1186/s13007-019-0479-8 (Vol. 15, Numéro 1).

Naik, K.C. (.2022). Cotton-Disease-Prediction-Deep-Learning. https://github.com/krishnaik06/Cotton-Disease-Prediction-Deep-Learning (Original work published 2020).

NBAIR. (2022). Insect pests in indian agroecosystems. https://databases.nbair.res.in/insectpests/index.php.

Olsen, A., Konovalov, D. A., Philippa, B., Ridd, P., Wood, J. C., Johns, J., et al. (2019). DeepWeeds : A Multiclass Weed Species Image Dataset for Deep Learning. *Scientific Reports, 9*(1), 1-12. https://doi.org/10.1038/s41598-018-38343-3

Ou, S., & Kim, H. (2019). Identification of citation and cited texts for fine-grained citation content analysis. *Proceedings of the Association for Information Science and Technology, 56*(1), 740-741. https://doi.org/10.1002/pra2.156

Panday, U. S., Pratihast, A. K., Aryal, J., & Kayastha, R. B. (2020). A Review on Drone-Based Data Solutions for Cereal Crops. *Drones, 4*(3), 41. https://doi.org/10.3390/drones4030041

Partel, V., Kakarla, C., & Ampatzidis, Y. (2019). Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *COMPUTERS and electronics in agriculture*. ELSEVIER SCI LTD. https://doi.org/10.1016/j.compag.2018.12.048 (Vol. 157, p. 339-350).

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., et al. (2011). Scikit-learn : Machine learning in Python. *Journal of Machine Learning Research, 12*, 2825-2830.

Picon, A., Seitz, M., Alvarez-Gila, A., Mohnke, P., Ortiz-Barredo, A., & Echazarra, J. (2019). Crop conditional Convolutional Neural Networks for massive multi-crop plant disease classification over cell phone acquired images taken on real field conditions. *Computers and electronics in agriculture*. ELSEVIER SCI LTD. https://doi.org/10.1016/j.compag.2019.105093 (Vol. 167).

Rahnemoonfa, Maryar, m, & Sheppard, Clay (2017). Deep Count : Fruit Counting Based on Deep Simulated Learning. *Sensors, 17*(4), 905. https://doi.org/10.3390/s17040905

Rai, S. (2021). Tomato plant leaf Disease detection using CNN. *Nerd For Tech.* https://medium.com/nerd-for-tech/tomato-plant-leaf-disease-detection-using-cnn-2ee2dd8ab77a.

Rauber, P. E., Fadel, S. G., Falcao, A. X., & Telea, A. C. (2017). Visualizing the Hidden Activity of Artificial Neural Networks. *IEEE Transactions on Visualization and Computer Graphics, 23*(1), 101-110. https://doi.org/10.1109/TVCG.2016.2598838

Razfar, N., True, J., Bassiouny, R., Venkatesh, V., & Kashef, R. (2022). Weed detection in soybean crops using custom lightweight deep learning models. *Journal of Agriculture and Food Research, 8*, Article 100308. https://doi.org/10.1016/j.jafr.2022.100308

Redmon, J. (2022,. juillet 1). Yolov3-tiny. https://github.com/pjreddie/darknet/blob/b1ab3da442574364f82c09313a58f7fc93cea2bd/cfg/yolov3-tiny.cfg (Original work published 2014).

Reedha, R., Dericquebourg, E., Canals, R., & Hafiane, A. (2022). Transformer Neural Network for Weed and Crop Classification of High Resolution UAV Images. *Remote Sensing, 14*(3), 592. https://doi.org/10.3390/rs14030592

Rejeb, A., Rejeb, K., Abdollahi, A., Zailani, S., Iranmanesh, M., & Ghobakhloo, M. (2021). Digitalization in Food Supply Chains : A Bibliometric Review and Key-Route Main Path Analysis. *Sustainability, 14*(1), 83. https://doi.org/10.3390/su14010083

Research and Markets. (2017,. décembre 21). AI in agriculture market 2017-2025—Focus on precision farming, drone analytics, agriculture robots & livestock monitoring—Research and markets. https://www.businesswire.com/news/home/20171221005505/en/AI-in-Agriculture-Market-2017-2025-Focus-on-Precision-Farming-Drone-Analytics-Agriculture-Robots-Livestock-Monitoring-Research-and-Markets.

Ribeiro, M.T., .Singh, S., & Guestrin, C. (2016). «Why Should I Trust You? » : Explaining the Predictions of Any Classifier. arXiv:1602.04938 [cs, stat]. http://arxiv.org/abs/1602.04938.

Ruigrok, T., van Henten, E., Booij, J., van Boheemen, K., & Kootstra, G. (2020). Application-specific evaluation of a weed-detection algorithm for plant-specific spraying. *Sensors*. MDPI. https://doi.org/10.3390/s20247262 (Vol. 20, Numéro 24).

Sabour, S., Frosst, N., & Hinton, G.E. (.2017). Dynamic routing between capsules. https://doi.org/10.48550/arXiv.1710.09829.

Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management : Mapping the territory. *International Journal of Production Research*, 1-24. https://doi.org/10.1080/00207543.2022.2029611

Simonyan, K., Vedaldi, A., & Zisserman, A. (2014). Deep Inside Convolutional Networks : Visualising Image Classification Models and Saliency Maps. arXiv:1312.6034 [cs]. http://arxiv.org/abs/1312.6034.

Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. https://arxiv.org/abs/1409.1556v6.

Singh, U. P., Chouhan, S. S., Jain, S., & Jain, S. (2019). Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease. *IEEE access*. IEEE-INST ELECTRICAL ELECTRONICS ENGINEERS INC. https://doi.org/10.1109/ACCESS.2019.2907383 (Vol. 7, p. 43721-43729).

Small, H. (1973). Co-citation in the scientific literature : A new measure of the relationship between two documents. *Journal of the American Society for Information Science, 24*(4), 265-269. https://doi.org/10.1002/asi.4630240406

Steiner, A., Kolesnikov, A., Zhai, X., Wightman, R., Uszkoreit, J., & Beyer, L. (2022). How to train your vit? data, augmentation, and regularization in vision transformers (arXiv:2106.10270). arXiv. https://doi.org/10.48550/arXiv.2106.10270.

Szegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. (2016). Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning. arXiv:1602.07261 [cs]. http://arxiv.org/abs/1602.07261.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D. et al. (2014). Going Deeper with Convolutions. arXiv:1409.4842 [cs]. http://arxiv.org/abs/1409.4842.

Thenmozhi, K., & Reddy, U. S. (2019). Crop pest classification based on deep convolutional neural network and transfer learning. *Computers and electronics in agriculture*. ELSEVIER SCI LTD. https://doi.org/10.1016/j.compag.2019.104906 (Vol. 164).

Tran, D.V., .& Nguyen, N. (2007). The concept and implementation of precision farming and rice integrated crop management systems for sustainable production in the twenty-first century.

Tufail, M., Iqbal, J., Tiwana, M. I., Alam, M. S., Khan, Z. A., & Khan, M. T. (2021). Identification of tobacco crop based on machine learning for a precision agricultural sprayer. *IEEE access*. IEEE-INST ELECTRICAL ELECTRONICS ENGINEERS INC. https://doi.org/10.1109/ACCESS.2021.3056577 (Vol. 9, p. 23814-23825).

Uddin, A., Singh, V. K., Pinto, D., & Olmos, I. (2015). Scientometric mapping of computer science research in Mexico. *Scientometrics, 105*(1), 97-114. https://doi.org/10.1007/s11192-015-1654-y

Verma, S., Chug, A., & Singh, A. P. (2020). Exploring capsule networks for disease classification in plants. In *Journal of Statistics and Management Systems, 23*(2, SI), 307-315. https://doi.org/10.1080/09720510.2020.1724628. NumérosTARU PUBLICATIONS.

Vokurka, R. J. (1996). The relative importance of journals used in operations management research A citation analysis. *Journal of Operations Management, 14*(4), 345-355. https://doi.org/10.1016/S0272-6963(96)00092-7

Wang, F., Wang, R., Xie, C., Yang, P., & Liu, L. (2020). Fusing multi-scale context-aware information representation for automatic in-field pest detection and recognition. *Computers and electronics in agriculture*. ELSEVIER SCI LTD. https://doi.org/10.1016/j.compag.2020.105222 (Vol. 169).

Wang, K., Chen, K., Du, H., Liu, S., Xu, J., Zhao, J., et al. (2022). New image dataset and new negative sample judgment method for crop pest recognition based on deep learning models. *Ecological Informatics, 69*, Article 101620. https://doi.org/10.1016/j.ecoinf.2022.101620

Wang, R., Liu, L., Xie, C., Yang, P., Li, R., & Zhou, M. (2021). AgriPest : A Large-Scale Domain-Specific Benchmark Dataset for Practical Agricultural Pest Detection in the Wild. *Sensors, 21*(5), 1601. https://doi.org/10.3390/s21051601

Web of Science Group. (2022). *Trusted publisher-independent citation database*. Web of Science Group. https://clarivate.com/webofsciencegroup/solutions/web-of-science/.

Wei, D., Chen, J., Luo, T., Long, T., & Wang, H. (2022). Classification of crop pests based on multi-scale feature fusion. *Computers and Electronics in Agriculture, 194*, Article 106736. https://doi.org/10.1016/j.compag.2022.106736

Weiss, M., Jacob, F., & Duveiller, G. (2020). Remote sensing for agricultural applications : A meta-review. *Remote Sensing of Environment, 236*, Article 111402. https://doi.org/10.1016/j.rse.2019.111402

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-. J. (2017). Big Data in Smart Farming – A review. *Agricultural Systems, 153*, 69-80. https://doi.org/10.1016/j.agsy.2017.01.023

Wu, X., Zhan, C., Lai, Y., Cheng, M.-. M., & Yang, J. (2019). IP102 : A Large-Scale Benchmark Dataset for Insect Pest Recognition. *IEEE CVPR*, 8787-8796.

Xie, C., Wang, R., Zhang, J., Chen, P., Dong, W., Li, R., et al. (2018). Multi-level learning features for automatic classification of field crop pests. *Computers and Electronics in Agriculture, 152*, 233-241. https://doi.org/10.1016/j.compag.2018.07.014

Xie, C., Zhang, J., Li, R., Li, J., Hong, P., Xia, J., et al. (2015). Automatic classification for field crop insects via multiple-task sparse representation and multiple-kernel learning. *Computers and Electronics in Agriculture, 119*, 123-132. https://doi.org/10.1016/j.compag.2015.10.015

Yang, G., Yang, Y., He, Z., Zhang, X., & He, Y. (2022). A rapid, low-cost deep learning system to classify strawberry disease based on cloud service. *Journal of Integrative Agriculture, 21*(2), 460-473. https://doi.org/10.1016/S2095-3119(21)63604-3

Yue, Y. (2018). Data for : Pest identification via deep residual learning in complex background [Data set]. Mendeley. https://doi.org/10.17632/XHDM7TW356.2.

Zeiler, M.D., .& Fergus, R. (2013). Visualizing and Understanding Convolutional Networks. arXiv:1311.2901 [cs]. http://arxiv.org/abs/1311.2901.

Zhang, C.-.L., Cao, Y.-.H., & Wu, J. (2020). Rethinking the Route Towards Weakly Supervised Object Localization. arXiv:2002.11359 [cs]. http://arxiv.org/abs/2002.11359.

Zhong, L., Hu, L., & Zhou, H. (2019). Deep learning based multi-temporal crop classification. *Remote Sensing of Environment, 221*, 430-443. https://doi.org/10.1016/j.rse.2018.11.032

Zhu, J., Song, Y., Jiang, D., & Song, H. (2018a). A New Deep-Q-Learning-Based Transmission Scheduling Mechanism for the Cognitive Internet of Things. *IEEE Internet of Things Journal, 5*(4), 2375-2385. https://doi.org/10.1109/JIOT.2017.2759728

Zhu, N., Liu, X., Liu, Z., Hu, K., Wang, Y., Tan, J., et al. (2018b). Deep learning for smart agriculture : Concepts, tools, applications, and opportunities. *International Journal of Agricultural and Biological Engineering, 11*(4), 21–28. https://doi.org/10.25165/j.ijabe.20181104.4475

Zimmerman, C. (2008,. novembre 1). The five "R's" of precision. https://precision.agwired.com/2008/11/11/the-five-rs-of-precision/.

Zwaenepoel, P., & Le Bars, J. M. (1997). L'agriculture de précision. *Ingénieries eau-agriculture-territoires, 12*, 67-79.