Unmanned Aerial Vehicle-based Applications in Smart Farming: A Systematic Review

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***Abstract*—On one hand, the emergence of cutting-edge technologies like AI, Cloud Computing, and IoT holds immense potential in Smart Farming and Precision Agriculture. These technologies enable real-time data collection, including high-resolution crop imagery, using Unmanned Aerial Vehicles (UAVs). Leveraging these advancements can revolutionize agriculture by facilitating faster decision-making, cost reduction, and increased yields. Such progress aligns with precision agriculture principles, optimizing practices for the right locations, times, and quantities. On the other hand, integrating UAVs in Smart Farming faces obstacles related to technology selection and deployment, particularly in data acquisition and image processing. The relative novelty of UAV utilization in Precision Agriculture contributes to the lack of standardized workflows. Consequently, the widespread adoption and implementation of UAV technologies in farming practices are hindered. This paper addresses these challenges by conducting a comprehensive review of recent UAV applications in Precision Agriculture. It explores common applications, UAV types, data acquisition techniques, and image processing methods to provide a clear understanding of each technology's advantages and limitations. By gaining insights into the advantages and challenges associated with UAV-based applications in Precision Agriculture, this study aims to contribute to the development of standardized workflows and improve the adoption of UAV technologies.**

Keywords*—Artificial intelligence; internet of things; sensor; big data; cloud; unmanned aerial vehicle; smart farming

I. Introduction

The agriculture industry is currently undergoing a significant transformation fueled by cutting-edge technologies, offering promising prospects for enhanced farm productivity and profitability. Precision Agriculture, which focuses on the precise application of inputs where and when they are needed, represents the third stage of the modern agricultural revolution. Advanced farm knowledge systems, empowered by the abundance of data, have further propelled the evolution of Precision Agriculture [1]. Numerous studies have demonstrated the positive impacts of adopting Precision Agriculture technologies, such as increased net returns and operating profits, as reported by the U.S. Department of Agriculture (USDA) [2]. Moreover, there is a growing emphasis on implementing these technologies in environmentally conscious ways to ensure sustainable farm production. However, effectively harnessing the vast amount of data generated by crops remains a persistent challenge [3].

To address these challenges, it is crucial to explore and integrate cutting-edge technologies in the realm of Smart Farming and Precision Agriculture. Unmanned Aerial Vehicles (UAVs), Cloud Computing, Internet of Things (IoT), Big Data analytics, and Artificial Intelligence (AI) have emerged as key enablers of innovation in this domain [4]. UAVs equipped with advanced sensors and imaging capabilities allow for real-time data collection, including high-resolution imagery of crops. Cloud Computing provides the infrastructure for data storage, processing, and analysis, while IoT facilitates the seamless integration of various agricultural devices and sensors. Big Data analytics and AI techniques enable intelligent insights and decision-making based on the collected data [5], [6].

This paper aims to delve into the theoretical background and related work of UAV, Cloud, IoT, Big Data, and AI approaches in Smart Farming and Precision Agriculture. Additionally, authors propose a comprehensive systematic review study that investigates the current state of research and development in this area. By analyzing existing literature, in order to identify the gaps, challenges, and opportunities for utilizing these technologies in the context of Smart Farming and Precision Agriculture, Fig. 1, depicted below, offers valuable insights into the evolution characteristics and challenges of agricultural development, spanning from Farming 1.0 to Farming 5.0. This figure serves as a valuable tool to showcase the effective utilization and evolution of technologies within the realms of Smart Farming and Precision Agriculture. The problem statement of this study revolves around the lack of a standardized framework for leveraging UAVs, Cloud Computing, IoT, Big Data, and AI in Smart Farming and Precision Agriculture. This lack of standardization hinders the widespread adoption and implementation of these technologies, limiting their potential benefits for farmers, agricultural productivity, and sustainable practices. To address this problem, our proposed solution is to conduct a systematic review that synthesizes existing research, identifies key insights, and provides recommendations for the development of standardized frameworks and practices in this field.

The motivation behind this work stems from the immense potential of integrating UAVs, Cloud Computing, IoT, Big Data analytics, and AI in Smart Farming and Precision Agriculture. By leveraging these technologies effectively, farmers can make faster and more informed decisions, reduce costs, optimize resource utilization, and increase yields. Moreover, this integration aligns with the growing demand for sustainable farming practices and the need to meet the rising global food demands. The contribution of this paper lies in the comprehensive review of existing literature, which consolidates knowledge, identifies research gaps, and proposes recommendations for the future development of Smart Farming and Precision Agriculture. By providing insights into the theoretical foundations, related work, problem statement, proposed solution, and motivation,

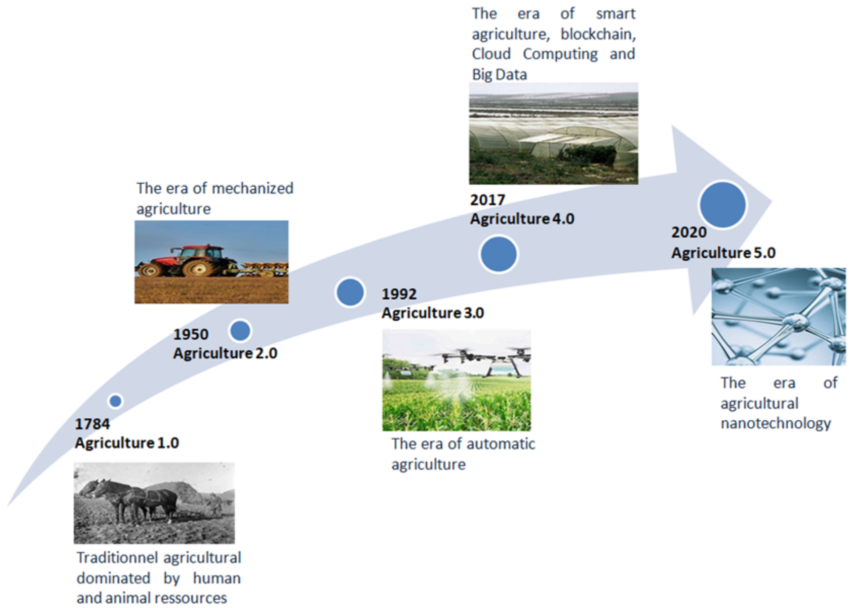

Fig. 1. Characteristics and challenges of agricultural development (from Farming 1.0 to Farming 5.0.

in order to advance the understanding and adoption of UAVs, Cloud Computing, IoT, Big Data analytics, and AI in the agricultural domain.

This paper is structured as follows. Firstly, Section 1 presents the theorical background of UAV, Cloud, IoT, Big Data and AI approaches. Afterwards, current technical components of Smart farning and precision agriculture in the research area are specified. Within this section, a more in-depth reflection is carried out on the rising of AI and IoT in smart farming. Secondly, Section 2 describes the detailed process steps of the systematic review and the defined research methodology of this study. Then, Section 3 summarizes the research results. Section 4 describes the discussion with challenges and future directions of this research study. Finally, a conclusion is presented in the last section of this paper.

II. Background

A. Unnamed Aerial Vehicles for Agriculture

Unmanned Aerial Systems (UAS), also known as drones, have become increasingly popular in agriculture due to their ability to provide a quick, cost-effective and efficient way to gather data and perform tasks on large fields and crops [7]. UAS (Unmanned Aerial Systems) indeed come in different types and can be equipped with a variety of sensors and cameras presented in Fig. 2 that can capture high-resolution images, aerial maps and thermal imagery, which can be used for a range of agriculture applications, including:

- Crop monitoring: UAS can be used to gather real-time data on crop health, growth, and yield potential.
- Irrigation management: Drones can be equipped with infrared cameras to identify areas that are in need of irrigation and to help optimize water use.
- Pest and disease management: Drones can be used to detect and map the spread of pests and diseases in crops, helping farmers to take timely action to prevent or treat these issues.
- Field mapping: UAS can produce high-resolution maps of fields, providing data on soil structure, topography, and plant populations, which can be used to make informed decisions about planting, fertilization and other aspects of crop management.
- Livestock management: Drones can be used to monitor the health and behavior of livestock, as well as to keep track of the location of animals.

Overall, the use of UAS in agriculture provides a new tool for farmers to gather data, monitor their crops and make more informed decisions, ultimately leading to improved yields, increased efficiency and reduced costs.

B. Cloud, Internet of Things, Big data and IA

1) Cloud: computing plays a crucial role in smart farming, which is an application of the Internet of Things (IoT) in agriculture. The cloud enables farmers to store, process, and analyze large amounts of data generated from various IoT devices and sensors on their farms [9]. This data can include information on weather patterns, soil moisture levels, crop growth, and even the health of livestock. By analyzing this data in real-time, farmers can make more informed decisions about crop management and animal husbandry, leading to increased productivity and efficiency.

Additionally, cloud-based solutions can provide farmers with access to advanced algorithms and predictive analytics tools that can help them optimize their farming operations. For example, cloud-based machine learning models can predict

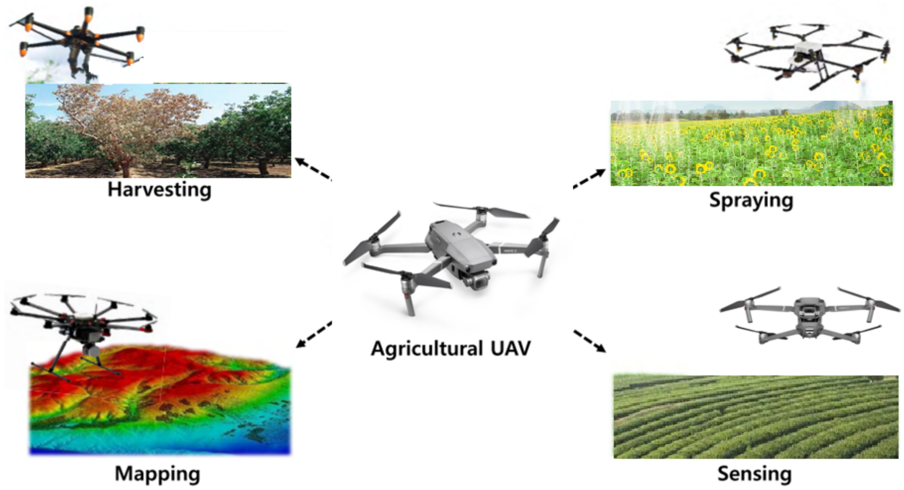

Fig. 2. Different types of agricultural UAVs (Harvesting UAV, Spraying UAV, Mapping UAV, Sensing UAV) [8].

crop yields, identify pest infestations, and suggest the most appropriate treatments. Furthermore, the cloud allows farmers to monitor their farms remotely and receive real-time updates on conditions and activities.

2) Internet of Things: The concept of the Internet of Things (IoT) pertains to a network comprising physical devices, vehicles, appliances, and various objects. These entities are equipped with sensors, software, and connectivity features that empower them to gather and exchange data via the internet. These connected devices can communicate and interact with each other, as well as with humans, creating a vast ecosystem of interconnected systems [10]. The IoT has the potential to revolutionize various sectors, including agriculture, healthcare, transportation, smart homes, and many others, by enabling increased automation, efficiency, and data-driven decision-making. In smart farming, IoT is used to gather real-time data from various sources such as weather stations, soil moisture sensors, and crop and animal monitoring systems.

IoT devices and sensors in smart farming can range from simple weather sensors to more complex systems such as precision agriculture systems that use Global Positioning System (GPS) to monitor the growth and health of crops. These devices can also be connected to irrigation systems, allowing farmers to control the amount of water they use based on real-time soil moisture levels. One of the key benefits of IoT in smart farming is that it enables farmers to make data-driven decisions in real-time. This leads to more efficient use of resources and improved crop yields. IoT also enables farmers to monitor their farms remotely, reducing the need for on-site visits and freeing up more time for other tasks.

In addition to its direct benefits, IoT in smart farming can also help address important global challenges such as food security and sustainability [11]. By using technology to optimize their operations, farmers can produce more food using fewer resources, reducing their carbon footprint and helping to ensure that future generations have access to safe and healthy food. Overall, the Internet of Things is revolutionizing the way farming is done and is poised to play a crucial role in the future of agriculture.

Wireless Sensor Networks (WSNs) are networks of small, low-cost, and low-power devices that can be used to monitor and collect data from the environment [12]. These devices, called “nodes”, are equipped with sensors, microcontrollers, and wireless communication capabilities, allowing them to transmit data wirelessly to a central location for analysis.

WSNs are widely used in a variety of applications, including smart farming, where they are used to monitor soil moisture, temperature, light, and other environmental parameters that affect crop growth [13]. The data collected by the sensor nodes can be used to make informed decisions about irrigation, fertilization, and other agricultural practices, leading to increased efficiency and higher crop yields.

One of the key benefits of WSNs is that they are low-cost and easy to deploy, making them accessible to farmers of all sizes and resources. They are also scalable, allowing farmers to add more nodes as their needs grow [14]. Finally, a review of 77 research papers published between 2012 and 2022 on the implementation of IoT in various agricultural applications showed that roughly 16% focused on precision agriculture and the same percentage on irrigation monitoring. 13% of the papers delved into soil monitoring, while temperature and animal monitoring were each covered in 11% of the research. Air and disease monitoring each received 5% of attention, with water monitoring accounting for 7%. Fertilization monitoring was the least studied, with only 4% of the research papers devoted to it in [15].

C. Big Data

Big Data plays a significant role in the context of smart farming. Smart farming involves the application of advanced technologies, such as sensors, Internet of Things (IoT) devices, and data analytics, to enhance agricultural practices and decision-making processes [16]. These technologies generate vast amounts of data from various sources, including weather conditions, soil moisture levels, crop health indicators, and machinery performance.

Big Data analytics allows for the collection, storage, processing, and analysis of large volumes of agricultural data in real-time or near-real-time. By applying advanced analytics techniques, such as machine learning and predictive modeling, valuable insights can be extracted from this data. These insights can help optimize farming practices, improve resource allocation, enhance crop yield, and enable more informed decision-making for farmers and agricultural stakeholders [17]. Furthermore, Big Data analytics can enable predictive capabilities in smart farming. By leveraging historical data and machine learning algorithms, models can be developed to forecast disease outbreaks, pests infestation, crop yield, and market demand. These predictive insights empower farmers to make proactive decisions, mitigate risks, and optimize resource allocation. In summary, the integration of Big Data analytics in smart farming allows for data-driven decision-making, optimization of agricultural practices, and the potential for increased productivity, sustainability, and profitability in the agriculture industry [18], [19].

D. Artificial Intelligence

Artificial Intelligence (AI) encompasses the creation of computer systems capable of executing tasks typically requiring human intelligence, including pattern recognition, prediction, and learning from experience. In smart farming, AI is used to automate various processes and make more informed decisions [16]. One of the key applications of AI in smart farming is precision agriculture, where AI algorithms are used to analyze data from various sources, such as weather stations and sensors, to determine the best practices for growing crops. For example, AI can be used to optimize irrigation and fertilization practices, leading to increased efficiency and higher yields. AI can also be used in animal husbandry to monitor the health and behavior of livestock. Also, AI algorithms can be used to detect signs of illness in animals, such as changes in their heart rate or behavior, and alert farmers to take action. Another application of AI in smart farming is in the detection and control of pests and diseases. AI algorithms can be used to analyze images of crops and detect signs of pests or diseases, allowing farmers to take proactive measures to address them. In conclusion, AI is a valuable tool in the development of smart farming, enabling farmers to make more informed decisions and automate various processes [20]. By using AI, farmers can improve efficiency, increase yields, and reduce waste, making a valuable contribution to the future of agriculture. However, it's important to note that while AI has the potential to greatly benefit the agriculture industry; it also presents challenges, such as the need for large amounts of data and the potential for bias in algorithms. Thus, it's important to approach the integration of AI in smart farming with caution and a focus on ethical and sustainable practices.

III. METHODOLOGY

In recent years, the academic community has extensively analyzed numerous works related to smart farming development from various perspectives. For instance, [21] introduced a systematic review focusing on precision farming. Then, authors in [22] provided a review on technologies in precision agriculture, highlighting innovations, technologies, and applications. Also, authors in [23] explored the use of big data on smart farming, emphasizing the primary opportunities and challenges associated with this technology. Additionally, [24] conducted a quantitative literature review, offering an overview of academic production in smart farming.

In order to enhance the existing analyses, the present study seeks to conduct a comprehensive review of UAV based applications in the field of smart farming. To accomplish this objective, we employed the Preferred Reporting Items for Systematic Reviews (PRISMA) methodology [25], a framework specifically designed to facilitate literature reports and systematic reviews. In October 2022, authors conducted a search using the available search tool on the Scopus database website. Additionally, another search was performed in april 2023 within the same database to include papers published in the year 2023. Scopus was selected due to its extensive coverage and relevance in similar bibliographic reviews mentioned in [24] and [26]. Our search strategy focused on terms related to technological applications in agriculture, such as "Precision Agriculture," "Precision Farming," "Smart Farming," and "Smart Agriculture," in conjunction with "UAV" and related terms. The publication date of articles was not a basis for exclusion. However, we restricted our research scope to journal and conference articles published in English. To ensure methodological rigor, this systematic review adhered to the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), with the most recent version being 2020. In Table I, you will find a compilation of the research questions (RQ) that the Systematic Literature Review (SLR) aims to address.

In this paper, a systematic literature review (SLR) was conducted to assess recent research papers on the use of IoT, Big data, Cloud & AI techniques in the field of Smart farming. However, advancements in technology and the increasing availability of digital resources have led to the development of new systematic review process, but the traditional systematic literature review methodology remains the standard approach for conducting systematic reviews, new tools and techniques are emerging that can enhance the process and provide additional benefits to researchers and decision-makers. However, it is important to consider the limitations of these new approaches and to ensure that the results of the systematic review remain reliable and trustworthy. The following are the steps involved in the systematic literature review methodology: In this context, lookup has produced a plethora of SLR standards that should be observed to reap tremendous empirical research. In this paper, we concentrate on the SLR guidelines proposed by authors in [19], which can be classified into the following categories. There are four steps:

- Step 1: Identifying the research goal(s).
- Step 2: Research subject framing (conceptual boundaries).
- Step 3: Using inclusion/exclusion criteria to collect data.
- Step 4: Validation of the research findings is the fourth step.

TABLE I. RESEARCH QUESTIONS OF THE STUDY

Number	Research Question (RQ)
RQ1	What are the various applications of UAVs in Precision Agriculture?
RQ2	Which crops are monitored by UAV systems?
RQ3	How can UAV-based technologies be adapted for use in different types of crops or farming environments?
RQ4	What types of data can be obtained through the use of UAVs?
RQ5	Which methods of data processing can be employed to analyze the agricultural data collected by UAVs?
RQ6	What are the challenges associated with using drones for disease detection in agriculture?
RQ7	What are the potential ethical and legal implications associated with the use of drones in agriculture, and how can these issues be addressed?

A. Research Objectives

This study attempts to systematically analyze possible future possibilities for IoT, Cloud, Big Data and AI in Smart Farming by analyzing current knowledge and the state of the research, with a focus on recent research advancements. This paper is interested in learning how this study topic has changed throughout time. Furthermore, the outcomes of the evaluation will be utilized to identify critical activities for future study as well as practical applications.

B. Framing of the Research Subject

The goal of this study is to evaluate Big Data, Cloud, internet of things, artificial intelligence technologies for Smart Farming in a systematic way. As a result, the research subject, i.e. the conceptual boundaries, were defined in the agriculture environment using the terms "Unnamed Aerial Vehicle", "Big Data", "Cloud", "internet of things", "artificial intelligence" and related concepts "machine learning" and "deep learning." The following Table II displays the Inclusion and exclusion criteria identified to refine the search request.

C. Data Collection by Using Criteria

A definition of search parameters, databases, search keywords, and publication time is also required by the SLR. The selection of search resources and the choice of search phrases are both part of the search strategy. To find the papers, automated search engine from the most relevant sources were chosen: Scopus. A further examination of similar databases (ACM Digital Library and Emerald) revealed significant variations in the research studies that resulted. As a result, Scopus was used as the primary database for secondary data evaluation in this research study. The systematic research approach [24] and the inclusion and exclusion criterias, which are based on the process query depicted in Fig. 3.

Screening the article title, abstract, and keywords for relevant literature for Blockchain, IoT and AI in the subject areas of management was the first step. We included a variety of document formats in this stage and limited them to the English language. This first method was mostly utilized to obtain a sense of where research was at the time. As a result, the study was not limited intialy to a specific period. In total, 536 studies were found as a result of this method. We concentrated on studies in the areas of Smart Farming and Precision Agriculture in the second step. As a consequence, we narrowed down the previously identified 536 publications to 186 papers that contained the terms Smart Farming or Precision Agriculture.

TABLE II. INCLUSION CRITERIA (IC) AND EXCLUSION CRITERIA (EC).

Number	Question
IC1	Paper published in a peer reviewed scientific journal
IC2	Works published in English
IC3	Articles on Computer Science Subject Area
IC4	Keywords on Agriculture, Unmanned Aerial Vehicles, Machine Learning
EC1	Reviews, conference papers, conference reviews, letters, books, book chapters and editorials are excluded from this study
EC2	Works that do not provide enough information on the methodology adopted and that do not report their results in a clear way are excluded.
EC3	Articles whose full text is not available are excluded

TABLE III. QUALITY ASSESSMENT QUESTIONS

Number	Question
Q1	Have the study's objectives been effectively communicated and defined?
Q2	Is the scope and context of the study clearly outlined and appropriately described?
Q3	Has the proposed solution been thoroughly explained and supported by empirical evidence?
Q4	Do the variables utilized in the study demonstrate both validity and reliability?
Q5	Is the research process adequately documented and transparent?
Q6	Have all the research questions been adequately addressed?
Q7	Are any negative findings presented or discussed within the study?
Q8	Are the main findings clearly stated, emphasizing credibility, validity, and reliability?

Furthermore, we created a ranking of all detected keywords, which was utilized to verify the meta-search query for the current database investigation. In our research strategy, no important terms were left out. To evaluate only high-quality studies, the study was limited to conference papers, conference reviews, articles, or reviews in the third step. In conclusion, the final meta-search query was as follows:

Research Query : ("UAV" OR "Unnamed Aerial Vehicle") AND ("Machine Learning" OR "Deep Learning") AND ("IoT technology" OR "IoT" OR "Internet of Things" OR "internet-of-things") AND ("Smart Farming" OR "Smart Agriculture" OR "Precision Farming" OR "Precision Agriculture") AND ("Cloud Computing").

The chosen papers were evaluated using eight quality assessment questions listed in Table III [27]. Scores of 1 (high quality), 0.5 (moderate quality), or 0 (poor quality) were given to each paper. Papers that received a total score below four were removed from the study.

IV. RESULTS

This section present the results obtained and content analysis on the complete texts of the identified papers. The initial stage of the selection process involved screening the title, abstract, and introduction of each paper to ascertain its relevance. The subsequent step was to eliminate papers that did not meet the exclusion criteria outlined in Table II. As a result, 80 papers were identified as the basis for the further research process. It is important to note that quotation marks are used to ensure that multi-word terms are searched together, preventing individual words from being considered separately. After conducting the search, the resulting articles were manually reviewed by analyzing their titles, keywords, abstracts, and texts. Duplicate articles were eliminated, and the remaining articles were assessed to determine whether

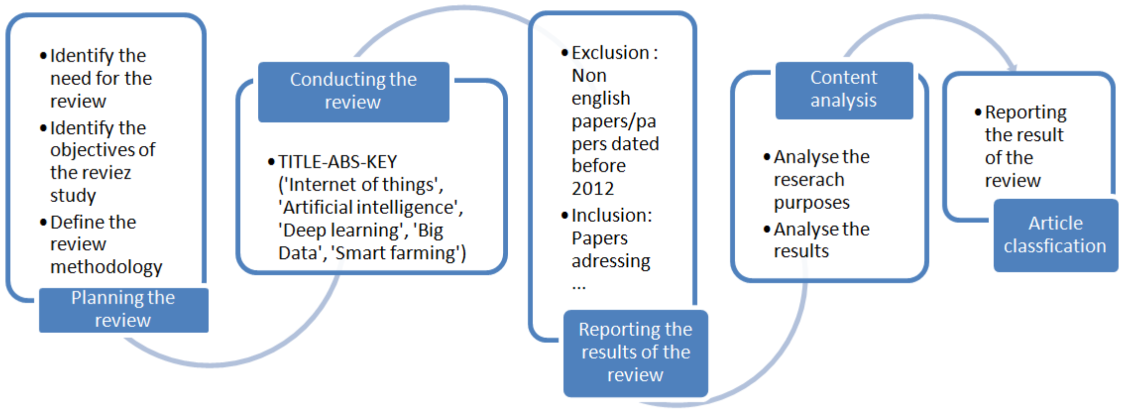

Fig. 3. Process steps of the systematic literature review.

they were relevant to the study's objectives. Valid articles were those that focused on IoT-based solutions for agricultural problems, were not literature reviews, were written in English, Portuguese, or Spanish, and pertained to agriculture rather than livestock activities. The study's search and selection process is summarized in Fig. 4. The initial search yielded 536 articles, which were then analyzed and narrowed down to 186 articles that met the study's eligibility criteria. During the screening phase, 350 articles were deemed invalid and discarded based on their lack of relevance to the study's objectives. Of these, 65% did not focus on smart farming. Additionally, almost 35% of the discarded papers were literature reviews or studies related to smart farming that did not involve IoT. A small number of papers pertained to smart farming but did not address IoT (about 5% were related to sensors), and some papers had abstracts or texts that were not available (about 2%).

In the eligibility phase, the content of the 80 remaining articles was reviewed using the same criteria as in the screening phase. Of these, 23 articles were discarded, with 27% not related to IoT and 32% not to smart farming. The remaining 41% were literature reviews or papers without available content. This research analysis conducted in 57 articles that were eligible for inclusion in the study's sample.

A. Description Analysis

57 papers were ultimately assigned to the topic and rated as relevant for deep analysis, out of a total of 536 papers that had been previously identified regarding the application of Cloud, Big Data, IoT, AI, within UAV Application in Smart Farming. The distribution of the selected studies' suitability, which was assessed by reading their titles and abstracts, the distribution of articles published per year is shown in Fig. 5, then the distribution of documents per year per source is provided in Fig. 6 and finally the Fig. 7 describe the distribution of documents by appropriateness.

The decrease in research on the application of drones in precision agriculture may be multiple and dependent on various factors such as funding, research priorities, technological advancements, etc. However, some possible hypotheses can be suggested: Recent technological advancements may have solved a significant portion of the issues related to drone application in precision agriculture, thereby reducing the need for further research in this field. Funding for research in this field may have been reduced or directed towards other research areas. The scientific community may be transitioning to other agricultural monitoring technologies or methods, such as the use of remote sensors or satellites. It is also possible that the number of scientific publications on the subject has decreased, but research is still ongoing in other contexts as provided in the distribution of document by subject area provided in Fig. 8, such as in the private industry. Ultimately, it is important to realize that the decrease in research in a given field does not necessarily imply that research should be abandoned or that previous results are no longer relevant. Existing research can still be used to improve existing applications and guide future research.

Out of the 166 full texts in the field of smart farming that were found, 96 papers (58%) were rated as having high appropriateness, 53 papers (32%) as having medium appropriateness, and 17 papers (10%) as having low appropriateness in relation to the goal of this research project. Book chapters are of total of 21%, while research articles are 44%, and reviews are 23%.

Based on the 166 complete articles that were found, Fig. 8 displays the distribution of document types in the field of smart farming by subject area.

B. Content Analysis

The complete texts of the papers were reviewed and identified in this section. Table IV summarizes the most important clusters, primary references, to group the chosen literature into related clusters, we engaged in a thorough content analysis. In addition Table V complete this set of research documents by UAV articles analyzed by characteristics and limitations identified in the survey.

IoT (Internet of Things) technology is transforming the agricultural industry by enabling farmers to collect and analyze data from various sources to make informed decisions. However, like any technology, IoT also presents challenges and issues, particularly in the context of smart farming. Table VI provides a comparison of IoT issues and challenges in smart farming:

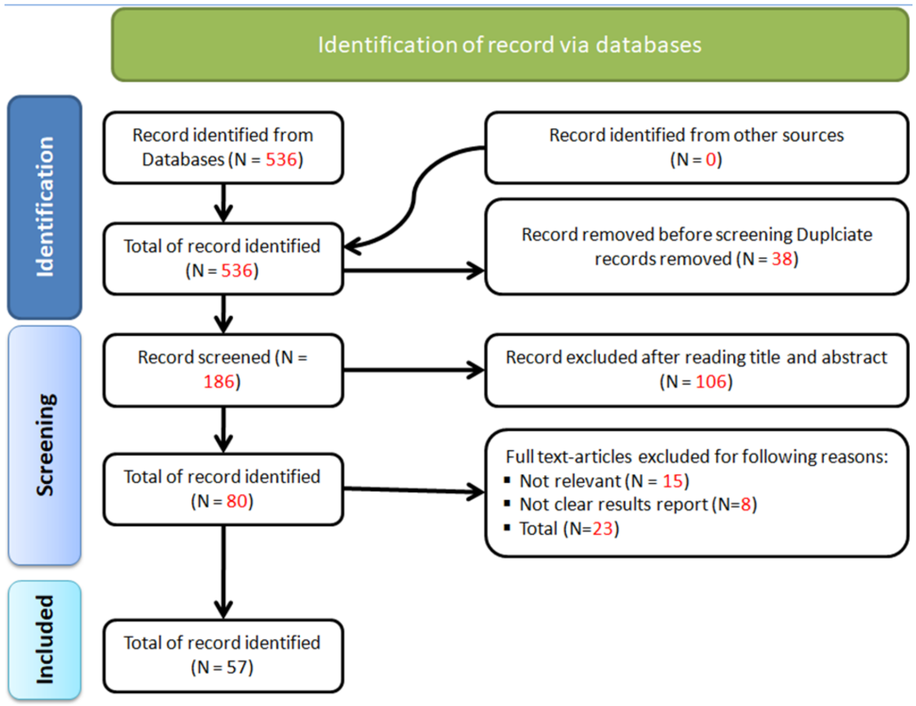

Fig. 4. Flow chart of databases search criteria and identification process of records.

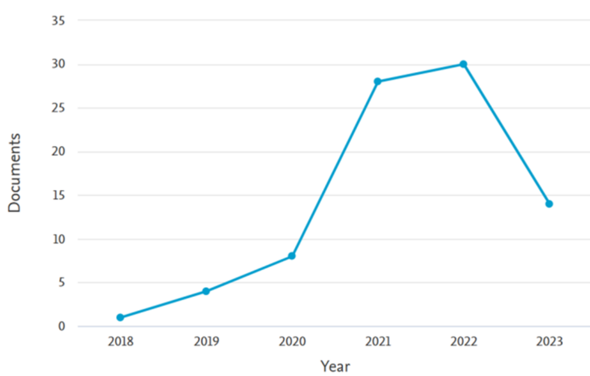

Fig. 5. Distribution of articles published per year.

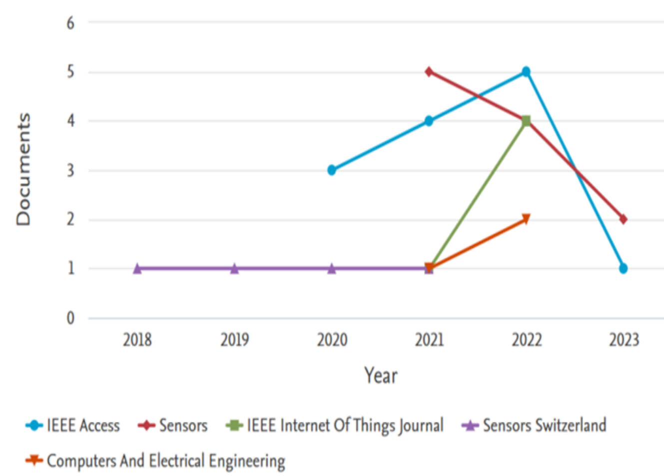

Fig. 6. Distribution of documents per year per source.

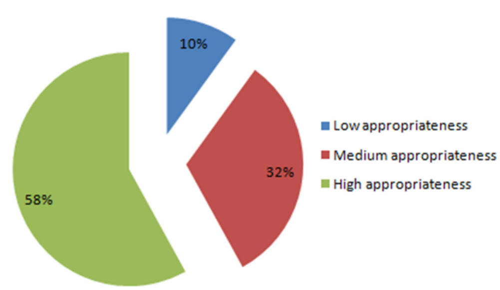

Fig. 7. Distribution of document by appropriateness.

RQ1. What are the Various Applications of UAVs in Precision Agriculture?

The use of Artificial Intelligence (AI) and cloud technology in Unmanned Aerial Vehicles (UAVs) has brought about significant improvements in smart farming. Here are some of the impacts:

- Soil Analysis: UAVs can be used to collect soil samples, analyze soil moisture levels, and assess soil quality, which can help farmers optimize fertilization and irrigation practices.
- Planting: UAVs can be used to plant seeds precisely and efficiently, reducing labor costs and increasing planting accuracy. Crop spraying: UAVs equipped with spraying systems can be used to apply pesticides, herbicides, and fertilizers accurately, reducing the en-

TABLE IV. SELECTED PRIMARY STUDIES IN SCOPUS

Ref	Authors	Year	Technology and Subject Area
[28]	I. Buja et al.	2021	Plant diseases
[29]	K.A. Awan et al.	2020	Cloud based IoT
[30]	M.E. Pérez-Pons et al.	2021	Sustainable agricultural market
[20]	P. Placidi et al.	2021	Crop health monitoring
[22]	T. Kawai	2021	Agricultural systems
[12]	A.Z. Bayih et al.	2022	Sustainable Smallholder Agriculture
[[13]	T. Qayyum et al.	2022	Clustering model in smart farming
[14]	J. Bravo-Arrabal et al.	2021	The internet of cooperative agents
[9]	D. Loukatos et al.	2023	Malfunction Detection of Water Pump Equipment
[11]	N.N. Thilakarathne et al.	2022	Crop Recommendation Platform
[10]	A. Saleh et al.	2022	Edge Node for IoT-Enabled Sensor Networks
[3]	A. Cravero et al.	2022	Agricultural Big Data
[6]	G. Giray et C. Catal	2021	Sustainable agriculture
[1]	S. Pal et al.	2023	IoT-Based Smart Farming
[31]	Z. Nurlan et al.	2022	Wireless Sensor Network
[32]	F.S. Alrayes et al.	2023	Fuzzy Logic-IoT-Cloud Environment
[33]	S.S. Sarnin et al.	2019	Smart insects repeller
[15]	Y. Liu et al.	2022	Intelligent Data Management System
[34]	P. Deepika et B. Arthi	2022	Plant pest detection
[35]	K. Sharma et al.	2022	Predictive Analysis and Smart agriculture
[36]	W. Zhao et al.	2023	Smart Irrigation and Crop Monitoring
[37]	T. Sutikno et D. Thalmann	2022	Internet of things
[38]	A. Zervopoulos et al.	2020	Wireless sensor network synchronization
[39]	C.G.V.N. Prasad et al.	2022	Edge Computing and Blockchain
[40]	M.L. Rathod et al.	2022	Cloud Computing and Networking
[41]	C.H. Wu et al.	2020	Long Short-Term Memory
[42]	S. Yadav et al.	2022	Disruptive Technologies - Sentiment Analysis.
[43]	C. Bersani et al.	2022	Monitoring and Control of Smart Greenhouses
[44]	M. Junaid et al.	2021	Smart agriculture cloud
[45]	J. Almutairi et al.	2022	UAV-Enabled Edge-Cloud Computing Systems
[46]	B. Almadani et S.M. Mostafa	2021	IoT based multimodal communication model
[47]	A.S.P. Pamula et al.	2022	Real-Time Monitoring
[48]	E. Petkov et al.	2023	Smart Egg Incubation
[49]	S. Chaterji et al.	2021	Digital Agriculture
[50]	S. Katiyar et A. Farhana	2021	Artificial Intelligence and IoT
[51]	M.Z. Islam et al.	2022	QoS Provisioning
[52]	Y. Gong et al.	2022	Grid-Based coverage path planning
[53]	R. Winkler	2021	Environmental monitoring

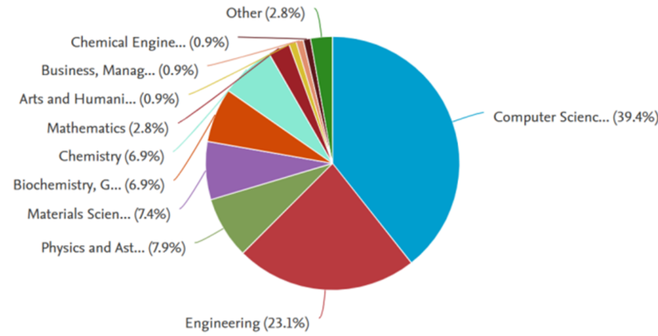

Fig. 8. Distribution of document by subject area.

vironmental impact and saving time and money.

- Irrigation Management: UAVs equipped with thermal sensors can be used to identify areas of the field that need irrigation, allowing farmers to optimize water usage and reduce waste.
- Yield Mapping: UAVs can be used to generate yield maps, which can help farmers optimize crop management practices and increase overall yield.
- Livestock Monitoring: UAVs equipped with cameras can be used to monitor livestock, detect health problems, and track animal behavior.
- Crop Monitoring: UAVs equipped with sensors and cameras can be used to monitor crop health and growth, detect diseases, pests, and stress factors affecting the crop and generate crop health maps.

The integration of AI and cloud technology in UAVs has brought about significant improvements in smart farming. It has enabled precision agriculture, increased efficiency, reduced environmental impact, and enabled real-time monitoring of farm operations. Also, drones have revolutionized many industries, including precision agriculture. So the Fig. 9 provide significant UAV applications in precision agriculture using AI and Cloud Technologies. Overall, UAVs can significantly improve efficiency, accuracy, and sustainability in precision agriculture, making it a valuable tool for modern farmers.

RQ2. WHICH CROPS ARE MONITORED BY UAV SYSTEMS?

Unmanned Aerial Vehicle (UAV) systems are increasingly being used for crop monitoring and management in agriculture. Various types of crops can be monitored using UAV systems, including different Cereals. These crops are often monitored for growth stages, yield prediction, and disease detection [63]. Fruits and vegetables: Such as grapes, citrus, apples, tomatoes, and potatoes. UAV systems can monitor the growth and health of these crops, detect pests and diseases, and assess yield. Oilseeds: Such as soybeans, sunflowers, and canola. UAV systems can be used to monitor crop growth, assess the health of plants, and predict yields. Specialty crops: Such as coffee, tea, cocoa, and tobacco. UAV systems can help monitor the health of these crops, detect early signs of disease or pest

TABLE V. CHARACTERISTICS AND LIMITATIONS OF THE RESEARCH: SET OF UAV ANALYZED ARTICLES BY PUBLICATION YEAR, SHORT DESCRIPTION, AUTHOR AND AREA OF APPLICATION

Reference	Author	Publication year	Description	Characteristics	Limitations
[54]	N. A. Sehree and A. M. Khidhir	2022	Classification of olive tree cases based on deep convolutional neural network using unmanned aerial vehicle (UAV) imagery	This paper proposes a framework that integrates UAVs with IoT and cloud computing for smart agriculture. The authors demonstrate the feasibility of the proposed framework through a case study. They conclude that the proposed framework can improve crop yield and reduce costs for farmers.	The authors primarily focus on the challenges associated with implementing UAV-based systems, rather than discussing potential solutions or strategies for overcoming these challenges. While this is an important aspect to consider, a more detailed analysis of potential solutions or strategies could be useful for practitioners and researchers in the field.
[55]	J. M. Jurado et al.	2020	Individual characterization of olive trees through multi-temporal monitoring and multispectral mapping on 3D models.	This study proposes an intelligent UAV-based system that uses deep learning and IoT for crop growth monitoring. The authors demonstrate the effectiveness of the proposed system through experiments. They conclude that the proposed system can accurately monitor crop growth and help farmers make informed decisions.	The authors used a greenhouse to conduct their experiments, which may not accurately reflect the challenges and limitations of implementing a UAV-based crop monitoring system in an outdoor agricultural environment.
[56]	P. Rallo et al.	2020	Investigating the use of UAV imagery to enhance genotype selection in olive breeding programs.	This paper proposes a novel approach to weed detection in smart agriculture using UAVs and deep learning. The authors demonstrate the effectiveness of the proposed approach through experiments. They conclude that the proposed approach can accurately detect weeds and help farmers reduce the use of herbicides.	The authors used only one type of UAV (a DJI Phantom 4 Pro drone) for their experiments. Different types of UAVs have different capabilities, such as flight time, payload capacity, and camera quality, which could impact the effectiveness and accuracy of a UAV-based weed detection system.
[57]	A. Safonova et al.	2021	Estimating the biovolume of olive trees using multi-resolution image segmentation with Mask Region-based Convolutional Neural Network (R-CNN) on UAV imagery.	The authors demonstrate the feasibility of the proposed system through experiments. They conclude that the proposed system can improve crop yield and reduce costs for farmers.	The authors do not address any potential security or privacy concerns related to the use of IoT and UAV-based systems in smart farming.
[58]	A. Di Nisio et al.	2020	Rapid detection of olive trees affected by Xylella fastidiosa using multispectral imaging from UAVs.	This study proposes a UAV-based smart farming system that uses machine learning and cloud computing. The authors demonstrate the effectiveness of the proposed system through experiments. They conclude that the proposed system can improve crop yield and reduce costs for farmers	The system's ability to handle varying weather conditions, crop types, and growth stages. Additionally, the authors do not discuss any potential environmental impacts of using UAVs for crop monitoring and the potential disruption to local wildlife.
[59]	A. Castrignanò et al.	2021	Development of a semi-automatic approach to detect Xylella fastidiosa in olive trees at an early stage. This method utilizes UAV multispectral imagery.	This study proposes a UAV-based crop monitoring system that uses IoT	The study may have only tested the UAV-based crop monitoring system in a limited range of environmental conditions, which may limit the generalizability of the findings.
[60]	Šiljeg et al.	2023	Utilizing Geospatial Object-Based Image Analysis (GEOBIA) and Vegetation Indices for extracting olive tree canopies from highly detailed UAV multispectral imagery.	This study proposes a UAV-based crop monitoring system that uses IoT	The study may have only tested the UAV-based crop monitoring system in a limited range of environmental conditions, which may limit the generalizability of the findings.

TABLE VI. CHARACTERISTICS OF THE RESEARCH: COMPARISON OF IOT ISSUES AND CHALLENGES IN UAV APPLICATIONS ON SMART FARMING (Y-YES, N-NON AND N/A-NON APPLICABLE)

Properties	**[61]**	**[36]**	**[45]**	**[54]**	**[55]**	**[56]**	**[62]**	**[57]**	**[58]**	**[59]**	**[13]**
Security	Y	N	N	N	N	N	Y	N	N	N	N
Control actuators Network lifetime	Y	Y	N	N	N	Y	N	N	N	N	N
Network latency Transmission reliability Quality of experience (QoE)	Y	Y	N	N	N	Y	N	N	N	N	N
Reduce risk of pesticides harming Animals or Human Semantic interoperability	Y	Y	N	N	N	Y	N	N	N	N	N
Detection of weather conditions Yes	Y	Y	N	N	N	Y	N	N	N	N	N
Preventive measures using IoT Semantic interoperability	Y	Y	N	N	N	Y	N	N	N	N	N
Architecture	Y	Y	N	N	N	Y	N	N	N	N	N
Reduce communication cost Quality of Service (QoS)	Y	Y	N/A	N	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Sensing and actuators as a service (SaaS) Handle multi-keyword search.	N/A	N/A	N/A	N/A	Y	N/A	Y	N/A	N/A	N	N
Failure detection Prediction for IoT	N/A	N/A	N/A	N	Y	N	N	N	N/A	N/A	N/A
Increased computational time Faster detection rate for crop disease	Y	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Y	Y	N/A
Reduced the time of diagnosis of animal illness.	Y	Y	N/A	N	N	Y	N/A	N	N	N	N/A
Enhanced data transmission	N	N	N	N	N	N	N	N	N	N	N
Interactive voice response with farmers Determination of soil condition	N	N	N	N	N	N/A	N/A	N/A	N	N	N
Soil conductivity Protection of crop disease using IoT	N	N	N	N	N	N	N/A	N/A	N/A	N/A	N/A
Color-based segmentation for early detection and utilization of three-dimensional point cloud	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

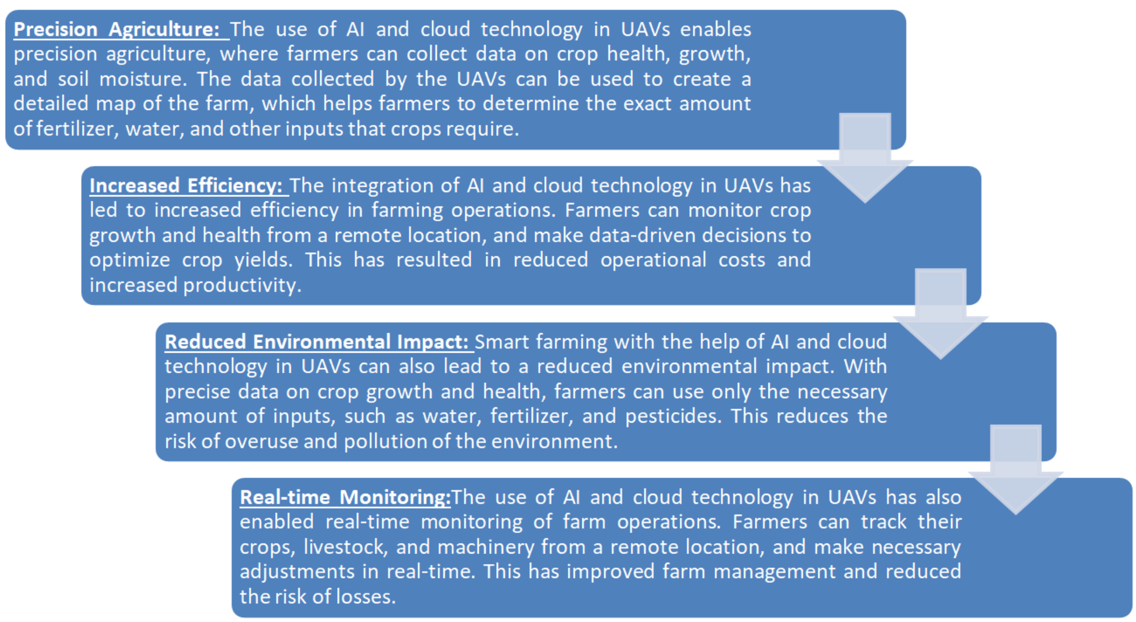

Fig. 9. Significant UAV applications in smart farming using AI and cloud.

infestations, and optimize harvest. While the use of UAV systems for crop monitoring has several advantages, there are also some limitations to the types of crops that can be effectively monitored. Here are some of the limitations collected by analyzing the following articles [64], [65], [66]. So, there are several limitations to using UAVs for crop monitoring. Firstly, UAVs can only cover a limited area in a single flight, which makes it difficult to monitor large farms efficiently. Secondly, UAVs are affected by weather conditions and may not be able to fly in adverse weather, which can impact data collection. Thirdly, UAVs require skilled operators and specialized equipment, which can be costly and time-consuming to maintain. Then, regulations around the use of UAVs can be complex and vary between countries, which can add another layer of complexity to their use in crop monitoring. These limitations must be carefully considered when deciding whether to use UAVs for crop monitoring and when planning a UAV-based monitoring program.

In conclusion, while UAV systems can be an effective tool for crop monitoring, there are limitations to the types of crops that can be effectively monitored. Crop height, density, size, weather conditions, and sensor limitations are all factors that

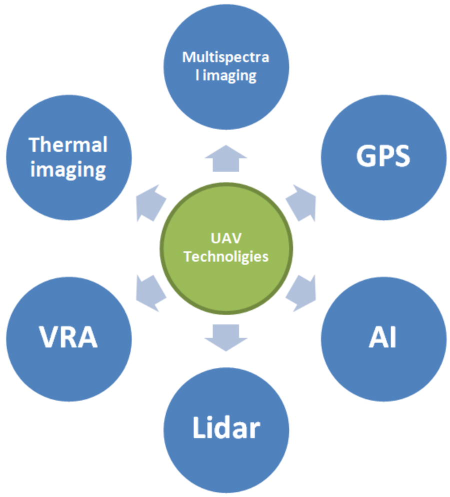

Fig. 10. UAV system technologies.

can affect the effectiveness of UAV monitoring. Generally, UAV systems can provide farmers with valuable insights and data to optimize crop management, increase productivity, and reduce the use of pesticides and fertilizers.

RQ3. How can UAV-based Technologies be Adapted for use in Different Types of Crops or Farming Environments?

Precision agriculture involves the use of various technologies to optimize crop management and increase yields. Unmanned Aerial Vehicle (UAV) systems are becoming increasingly popular in precision agriculture due to their ability to collect high-resolution data quickly and efficiently. Here are some UAV system technologies in Fig. 10 that are commonly adopted in precision agriculture:

- Multispectral imaging: UAVs equipped with multispectral cameras can capture images of crops at different wavelengths, providing valuable information on plant health, stress levels, and nutrient deficiencies.
- Thermal imaging: Thermal cameras mounted on UAVs can detect differences in temperature across a field, helping to identify areas of stress or water deficiency in crops.
- Lidar (Light Detection and Ranging): UAVs equipped with Lidar technology can create high-resolution 3D maps of crops and terrain, which can be used for crop modeling and yield prediction.
- Global Positioning System (GPS): UAVs equipped with GPS can precisely navigate and collect data on a field, helping farmers to monitor crop growth and identify problem areas.
- Machine learning and artificial intelligence: UAV systems can collect vast amounts of data that can be analyzed and processed using machine learning and artificial intelligence algorithms.
- Variable rate application (VRA): UAV systems can be used for VRA, where the data collected can be used to tailor crop management practices to specific areas of a field, optimizing inputs like fertilizers and pesticides, reducing costs and environmental impact.

Overall, these UAV system technologies can provide farmers with detailed information on crop health, growth, and yield potential, helping them to make more informed decisions on crop management and increase productivity.

RQ4. What Types of Data Can be Obtained Through the use of UAVs?

Unmanned Aerial Vehicles are deployed in various applications, including agriculture, environmental monitoring, and infrastructure inspection. UAVs are equipped with sensors that can capture different types of data. Here are some examples of data that can be acquired by UAVs:

- Visual imagery: UAVs can capture high-resolution visual imagery using cameras that range from standard RGB cameras to more specialized cameras like multispectral, hyperspectral, and thermal cameras. These images can be used to monitor vegetation health, detect anomalies, and map land cover.
- LiDAR: LiDAR sensors can be mounted on UAVs to generate high-resolution 3D maps of the terrain, vegetation, and structures. This data can be used for precise measurements of features such as height, volume, and biomass.
- GPS data: UAVs can collect GPS data, which can be used to generate maps, track the drone's position, and measure distances. Environmental data: UAVs can be equipped with sensors that measure environmental variables such as temperature, humidity, and air quality. This data can be used for environmental monitoring and disaster response.
- Magnetic and acoustic data: UAVs can be equipped with magnetometers to measure the magnetic field of the Earth's surface. This data can be used for geological surveys and mineral exploration. UAVs can also be equipped with microphones to capture acoustic data.

Overall, UAVs can capture a wide range of data types, which can be used for various applications in fields such as agriculture, environmental monitoring, infrastructure inspection, and disaster response.

RQ5. Which Methods of Data Processing can be Employed to Analyze the Agricultural Data Collected by UAVs?

The data acquired by UAVs in precision agriculture can be processed and analyzed using various techniques to extract useful information. Here are some examples of data processing methods that can be used to exploit agricultural data acquired by UAVs described in Fig. 11.

- Image processing: UAVs capture high-resolution images of crops, which can be processed using image processing techniques to extract information such as crop health, leaf area index, and crop growth stage.

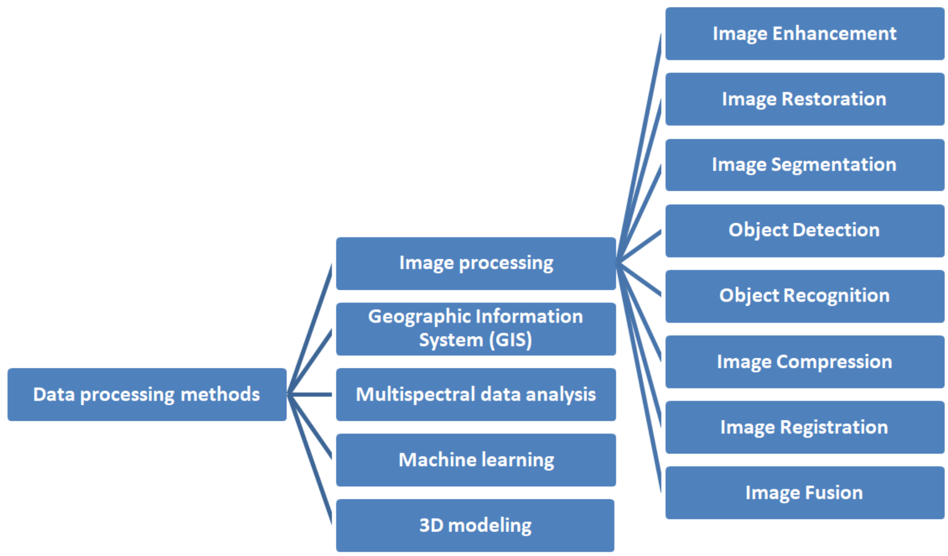

Fig. 11. Data processing methods used to exploit data collected by UAV.

- Geographic Information System (GIS): UAV data can be integrated with GIS to create maps that provide valuable information about crop health, yield, and soil properties.
- 3D modeling: UAVs can capture data in the form of point clouds using LIDAR sensors, which can be used to create 3D models of the field. These models can be used to estimate crop height, biomass, and plant spacing.

In summary, the data acquired by UAVs in precision agriculture can be processed and analyzed using various techniques to extract valuable information about crop health, yield, and soil properties. These techniques include image processing, GIS, multispectral data analysis, machine learning, and 3D modeling.

RQ6. What are the Challenges Associated with using Drones for Disease Detection in Agriculture?

The challenges can be categorized into two primary groups: dataset-related challenges and model-building challenges. Dataset-related challenges encompass deformations in the image dataset, insufficient availability of expert-labeled data, significant randomness in the data, and inadequate representation of classes in the dataset. Challenges associated with model building are the scarcity of training samples, extended training and processing times. Out of the papers analyzed, only two proposed potential solutions for these difficulties. The use of UAV in smart farming has become increasingly popular due to their ability to collect vast amounts of data quickly and accurately. However, the integration of Internet of Things (IoT) technologies into UAV applications also brings unique challenges and issues. The Table VI provides a comparison of the key challenges and issues related to IoT in UAV applications for smart farming.

RQ7. What are the Potential Ethical and Legal Implications Associated with the use of Drones in Agriculture, and how can these Issues be Addressed?

The use of drones in agriculture presents various ethical and legal implications that need to be considered and addressed. From an ethical standpoint, privacy concerns arise as drones can capture sensitive information about individuals or their properties. There is also the potential for drones to infringe on airspace regulations, endangering other aircraft or public safety. Furthermore, the automation and autonomy of drones raise questions about accountability and liability in case of accidents or damage caused by these devices. To address these issues, several measures can be implemented. Firstly, clear regulations and guidelines should be established regarding the operation of drones in agricultural settings. These regulations should address aspects such as flight restrictions, licensing requirements, and privacy protection. Adequate enforcement mechanisms should be in place to ensure compliance.

Secondly, public awareness campaigns and education initiatives can inform both farmers and the general public about the responsible and legal use of drones in agriculture. This can help foster understanding and mitigate privacy concerns. Additionally, technological solutions can be developed to enhance privacy protection, such as implementing geofencing mechanisms that restrict drone access to certain areas or utilizing data anonymization techniques. Collaboration between stakeholders, including farmers, drone operators, regulatory bodies, and legal experts, is crucial for developing comprehensive guidelines and frameworks that address the ethical and legal implications of drone use in agriculture. Regular review and updates of regulations can also ensure they remain relevant as technology evolves. Ultimately, a balanced approach is needed that considers the benefits of drone technology in agriculture while safeguarding privacy, public safety, and legal compliance.

TABLE VII. SIGNIFICANT REVIEW STUDIES ON UAV BASED APPLICATIONS ON SMART FARMING COMPARED TO THIS SYSTEMATIC REVIEW

References	Objectives of the review	Method/Guidelines	Analysis Criteria	Results
[67]	Help potential researchers detect relevant IoT problems and, based on the application requirements, adopt suitable technologies.	SLR	Recent advancements and challenges of Internet of Things in smart farming	The upcoming studies, inventions, and initiatives mostly in field of IoT-based smart agriculture would improve the quality of living for farmers and result in significant improvements in the agricultural sector.
[68]	Pinpoints the challenges in implementing the solutions in the farmer's field in real-time.	SLR	Recent trends in computer vision such as generative adversarial networks (GAN), vision transformers (ViT) and other popular deep learning architectures.	Integration of the deep learning computer vision approaches with the UAV, and spectral data can help in building advanced-intelligent solutions.
[69]	Presents an analysis of drone technologies and their modifications with time in the agriculture sector in the last decade.	SLR	Artificial Intelligent (AI) and deep learning for the remote monitoring of crops has	There is a ramp in drone application for precision agriculture after 2017. This is due to the reduction of weight, cost of UAVs, and increment in payload capability
[26]	Suggest further research to improve the current food production globally	SLR	The application of smart farming to crop and animal production and post-harvesting	An effective Intelligent IoT system for smart farming can start the beginning of the journey toward by providing more information within the farming system for non-academics and researchers.
Proposed Systematic Review	Propose future research directions and highlight areas of improvement for the effective implementation of these technologies in agriculture.	SLR & PRISMA	Data collection and sensing technologies, AI and data analysis techniques, IoT and connectivity, Cloud computing and data management, Performance and effectiveness, Challenges and limitations	Exploration of the integration of unmanned aerial systems (UAS), AI, IoT, and cloud technologies specifically in the context of smart farming, providing an up-to-date and in-depth analysis of the benefits, challenges, and future research directions in this rapidly evolving field.

V. DISCUSSIONS

The reason to conduct this systematic review on UAV-based applications in smart farming using AI, IoT, and cloud technologies is to provide a comprehensive overview of the current state-of-the-art in this field. This review aims to gather and analyze existing research studies, to identify gaps in the literature, and to provide insights into the potential of these technologies for smart farming.

The systematic review will contribute to the research field in several ways. Firstly, it will provide a clear understanding of the current state-of-the-art in UAV-based applications in smart farming, including the various applications, benefits, and challenges associated with the use of these technologies. Secondly, it will identify gaps in the literature and areas where further research is needed. This will help researchers to focus their efforts on areas that are most promising and where further advancements are needed. Thirdly, it will provide insights into the potential of these technologies to transform the agriculture industry, promote sustainable farming practices, and address global food security challenges.

UAV-based applications in smart farming using AI, IoT, and cloud technologies face several data challenges that must be addressed for successful implementation. These challenges include acquiring and efficiently storing the large amounts of data generated by UAVs, ensuring the quality and reliability of the data, processing and analyzing the data in real-time using AI and cloud technologies, seamlessly integrating the UAV-based applications with other systems, and ensuring data privacy and security. Overcoming these challenges will require the development of robust data management strategies, advanced algorithms for data analysis, secure and interoperable systems, and effective policies and regulations for data privacy and security. Addressing these challenges will be crucial for the successful implementation of UAV-based applications in smart farming and the realization of their potential benefits for the agricultural industry. Meteorological conditions can have a significant impact on UAV-based applications in smart farming that use AI, IoT, and cloud technologies. For example, wind speed and direction can affect the stability and maneuverability of the UAV, which can impact the quality of the data collected. Similarly, rain, fog, and low-light conditions can affect the quality of the images and sensor readings collected by the UAV, which can impact the accuracy of the data analysis.

Extreme weather conditions such as hurricanes, thunderstorms, and blizzards can also pose safety risks for the UAV and the personnel operating it. High winds, lightning, and heavy precipitation can damage the UAV or cause it to crash, while snow and ice can affect its mobility and stability. To mitigate the impact of meteorological conditions on UAV-based applications in smart farming, it is important to have reliable weather forecasting systems in place. This can help farmers and operators plan UAV flights around weather patterns, avoiding unsafe conditions and optimizing data collection.

Additionally, it is important to use UAVs equipped with weather-resistant sensors and cameras that can operate in a range of environmental conditions. This can help ensure the accuracy and reliability of the data collected, even in adverse weather conditions. In summary, meteorological conditions can have a significant impact on UAV-based applications in smart farming, and it is important to have reliable weather forecasting systems and weather-resistant equipment to mitigate these effects.

Overall, this systematic review will be a valuable resource for researchers, policymakers, and practitioners interested in UAV-based applications in smart farming using AI, IoT, and cloud technologies. It will help to identify areas where further research is needed, and provide insights into the potential of these technologies to address some of the most pressing challenges facing the agriculture industry today.

By validating and comparing the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) results with the presented objectives, scenarios, and analysis criteria in Table VII, this systematic review aims to enhance the existing survey methodology. It strives to provide an updated research review based on established guidelines, which can have several advantages. So, by employing a validated methodology and adhering to established guidelines like PRISMA, this work aims to provide a reliable, transparent, and up-to-date resource that can contribute to the existing body of knowledge in UAV-based applications in smart farming using AI, IoT, and cloud technologies. Despite the numerous benefits associated with the use of UAVs, AI, IoT, and cloud technologies in smart farming, there are still some limitations and challenges that need to be addressed in the future. One of the main limitations is the high cost of acquiring and maintaining these technologies, which may limit their adoption by smallholder farmers. Another limitation is the lack of regulatory frameworks and policies to guide their use, particularly in developing countries. Overall, this systematic review will be a valuable resource for researchers, policymakers, and practitioners interested in UAV-based applications in smart farming using AI, IoT, and cloud technologies. It will help to identify areas where further research is needed, and provide insights into the potential of these technologies to address some of the most pressing challenges facing the agriculture industry today. Despite the numerous benefits associated with the use of UAVs, AI, IoT, and cloud technologies in smart farming, there are still some limitations and challenges that need to be addressed in the future.

VI. Conclusion

In conclusion, this paper provides a comprehensive overview of the utilization of unmanned aerial vehicules (UAS), or drones, in agriculture and the integration of AI, IoT, and cloud technologies for precision farming. The systematic review conducted following the PRISMA method highlights the potential of UAV-based applications in smart farming using these advanced technologies. The major takeaways from this work include the significant potential of UAVs in enhancing agricultural productivity and sustainability. The findings demonstrate that UAVs offer valuable capabilities for data collection, precision monitoring, and decision-making in large-scale farming operations. The integration of AI, IoT, and cloud technologies further enhances these capabilities by enabling real-time data analysis, remote accessibility, and efficient resource management. The justification for this research lies in the growing importance of technology-driven solutions in modern agriculture. By leveraging UAVs and advanced technologies, farmers can make informed decisions, optimize resource usage, and improve crop yields. The presented work serves as a valuable resource for researchers, policymakers, and practitioners interested in understanding the potential and challenges of UAV-based applications in smart farming.

Moving forward, future research should focus on developing more advanced machine learning models to enhance accuracy in crop yield predictions and pest infestation identification. Additionally, exploring the feasibility of drones for other agricultural tasks such as irrigation management and soil analysis can provide valuable insights. Conducting empirical studies will further validate the benefits and limitations of these technologies in agriculture.

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