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Review article

Smart Farming in Europe

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ABSTRACT

Smart Farming is the new term in the agriculture sector, aiming to transform the traditional techniques to innovative solutions based on Information Communication Technologies (ICT). Concretely, technologies like Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), Image Processing, Machine Learning, Big Data, Cloud Computing, and Wireless Sensor Networks (WSNs), are expected to bring significant changes in this area. Expected benefits are the increase in production, the decrease in cost by reducing the inputs needed such as fuel, fertilizer and pesticides, the reduction in labor efforts, and finally improvement in the quality of the final products. Such innovative methods are crucial in recent days, due to the exponential increase of the global population, the importance of producing healthier products grown with as much fewer pesticides, where public opinion of European citizens is sensitized. Moreover, due to the globalization of the world economy, European countries face the low cost of production of other low-income countries. In this vein, Europe tries to evolve its agriculture domain using technology, aiming at the sustainability of its agricultural sector. Although many surveys exist, most of them tackle in a specific scientific area of Smart Farming. An overview of Smart Farming covering all the involved technologies and providing an extensive reference of good practices around Europe is essential. Our expectation from our work is to become a good reference for researchers and help them with their future work. This paper aims to provide a comprehensive reference for European research efforts in Smart Farming and is two-fold. First, we present the research efforts from researchers in Smart Farming, who apply innovative technology trends in various crops around Europe. Second, we provide and analyze the most significant projects in Europe in the area of Smart Farming.

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1. Introduction

Agriculture plays a vital role throughout human history from ancient years since now, as it is essential for the survival of humans species. During this period, it has seen many evolutions, from the domestication of animals and plants a few thousands of years ago, to the systematic use of crop rotations and other advancements in farming practices a few hundred years ago. Human-made fertilizers and pesticides were the last innovation a few decades ago. Nowadays, we are experiencing a new evolution in the agriculture sector, called Smart Farming [1], which is based on Information and Communications Technologies (ICT). Smart Farming is aiming to increase productivity and improving the quality of the final product while reducing cost production. To achieve that, a range of recent technologies are used, including Unmanned Aerial Vehicles (UAVs) [2], Unmanned Ground Vehicles (UGVs) [3,4], Image Processing, Machine Learning, Big Data, Cloud Computing, and Wireless Sensor Networks (WSNs).

Smart Farming is the new term in the agriculture domain which promises to bring revolution in food management and production. It can be considered that Smart Farming is the evolution of the term Precision Agriculture [5]. Moreover, an equivalent term in literature to Smart Farming is Smart Agriculture. In this manuscript, we will use the term Smart Farming.

The authors Samir KC, and Wolfgang Lutz discussed the worst scenario [6] that predicts that the world population will reach the amount of 12.6 billion in 2100, which will result in a growing demand for food production. The global history has shown that humanity was able to overcome such increases in food demand [7], mainly based on the adoption of new technologies enabling significant increases in food production per given arable land [8]. Thus, the future in agriculture sustainability comes probably through recent technologies in ICT.

In addition, fertilizer and pesticides have been used widely during the last decades, which yields significant worries for the final quality of the products and their impact on the health of the public, as well as for the environmental impact [9,10]. Precision agriculture was intending to reduce chemical inputs by precisely using them in specific areas where and when there were needed [11,12]. Smart Farming, the evolution of Precision Agriculture with recent technologies, aiming to reduce them even more.

Furthermore, water management in agriculture sector is of paramount importance and should be used wisely in the future [13] in order to protect remaining resources from disappearing. Thus, water management has been presented in recent years as one of the main applications in Smart Farming, and many research papers propose smart irrigation systems [14,15] to reduce water consumption and the amount of wastewater.

Moreover, agriculture is the primary income of a high percentage of people around the world, as well as in many developing countries is contributing a vast amount in their Gross Domain Product (GDP) [16]. Furthermore, globalization of economy demands low-cost production, which has a negative impact on farmers in the developed countries. Thus, they have to find innovative solutions to decrease cost production. The aforementioned innovative ICT technologies can give the opportunity to farmers and agronomists to take decisions at farm level depending on the collected data from UAVs, satellites or wireless sensors, or operate precisely at the plant level. Precision will also reduce the chemical inputs like fertilizers and pesticides, and as a consequence, it will reduce cost production and improve the quality of the products. Moreover, UGVs will lessen the labor effort since they can work without or with limited man intervention with accuracy and efficiency.

Our work is motivated by the growing importance of Smart Farming in European Union (EU), driven by the evolution of recent technologies of computer science such as Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), Image Processing, Machine Learning, Big Data, Cloud Computing, and Wireless Sensor Networks (WSNs). The adoption of Smart Farming will allow EU to boost its agricultural output whilst ensuring the sustainability of the European agriculture sector. Under this perspective, EU is supporting cutting-edge research and innovation with many researchers around Europe working on innovative projects with the technologies mentioned above, aiming to drive agriculture to a new era. We are going through a period where good practices are essential to be promoted, in order to set the pillars for Smart Farming of the future.

Although there exist various surveys on Smart Farming technologies, most of them are focusing on specific areas of Smart Farming. In [17] the authors P. Radoglou-Grammatikis et al. provides a detailed overview of Precision Agriculture and investigate in detail 20 UAV applications for crop monitoring processes or spraying tasks. G. Kakamoukas et al. [18] presenting an extensive review of Flying Ad-hoc Networks (FANETs) routing protocols, suitable for UAV deployment for six different applications in Smart Farming, namely Crop Scouting, Crop Surveying and Mapping, Crop Insurance, Cultivation Planning and Management, Application of Chemicals, and Geofencing. In [19] E. Hamuda et al. provides a survey of image processing techniques for plant extraction and segmentation in the field. The authors S. Wolfert et al. discuss the state-of-the-art of Big Data applications in Smart Farming and identify the related socio-economic challenges [20]. The authors K. Liakos et al. present a comprehensive review of research dedicated to applications of machine learning in agricultural production systems [21]. Moreover, in [22] A. Kalimaris et al. provides a survey of Deep Learning research efforts applied in the agricultural domain. In [23], the authors A. Lytos et al. presents the state-of-the-art agriculture systems and big data architectures both in research and commercial status, aiming to bridge the knowledge gap between agriculture systems and exploitation of big data.

Concentrated work in surveys on the state-of-the-art research work will help future researchers on their efforts. Our approach is aiming to present Smart Farming from a spherical view and show various aspects of its concept. In this paper, we are trying to provide an extensive reference on related work of research in Smart Farming around Europe. Besides, none of the existing surveys are providing such a large number of relevant research work in European countries. The expectation for our work is to become a good reference for future researchers involved with Smart Farming.

More specifically, the contribution of this paper is summarized as follows:

- First, we are presenting the most valuable research efforts in Smart Farming in Europe. We categorize all the related research papers depending on the involved technologies. In addition, we are indicating their efforts in field operations on the applied types of crops.
- Furthermore, we provide a statistical analysis among the referred papers based on the involved technologies, the evaluated crop types, the field operations, and the countries where evaluation take place.
- We are presenting and analyzing the European Projects, that are relevant to Smart Farming. We are providing a categorization depending on the involved technologies and their operations in the field, as well as the crops species on which they have been tested and evaluated.
- Moreover, we discuss, in brief, the projects mentioned above, and provide a statistical analysis of the technology trends in Smart Farming, based on the described projects.

The remaining of this paper is organized as follows: In Section 2 we discuss the related technologies involved with Smart Farming such as Unmanned Aerial Vehicles (UAV), Unmanned Ground Vehicles (UGV), and Wireless Sensor Networks. In Section 3, we are analyzing the involved technologies from ICT such as Image Processing, Machine Learning, Big Data, and Cloud Computing. In Section 4, we provide in brief the research efforts in Smart Farming, which have been tested and evaluated in crops around Europe. Section 5 is focused on the projects in Smart Farming funded in European countries. In Section 6, we are presenting a summary of future research trends, and finally, Section 7 concludes this survey paper.

2. Related technologies

In this section, we are introducing the main technological evolutions involved with Smart Farming such as Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), and Wireless Sensor Networks (WSN). We are analyzing and discussing their characteristics while providing the main potential benefits from their usage in the agriculture section as well as the recent research trends in their area.

2.1. Unmanned Aerial Vehicles (UAVs)

The last years, there is a growing interest in inspecting the health and monitoring the growth of large fields of crops with autonomous techniques. The new technology trend in this domain is Unmanned Aerial Vehicles (UAVs) aiming to offer multiple applications in Smart Farming such as remote sensing, crop estimation, weed detection, water management, and spraying. In more detail, UAVs' main contribution in Smart Farming is remote sensing [24] by providing the appropriate information through captured images from visible, near-infrared, thermal spectrum cameras or even from laser scanners. UAVs can also be used in crop estimation where images acquired are used to evaluate crop growth through a 3D reconstruction of the cultivation. More specifically, programming techniques allow to create a 3D model of the vegetation structure for precision study [25]. Moreover, by applying several flights with a UAV within a seasonal period, we can have a historical overview to inspect the growth of vegetation [26]. Also, weed mapping [27] is another beneficial operation in the field, which can reduce chemical inputs as well as labor efforts from farmers. Furthermore, multispectral cameras, as one of the primary equipment of UAVs, can be used in water management techniques [28] where captured images can provide information about the humidity of the cultivation. Finally, spraying [29] is another operation where UAVs are tested on the field, aiming to reduce inputs of pesticides by acting precisely where and when it is needed.

UAVs seems to be the best solution since they are effective in giving the farmer a bird's eye view of his fields in a short time, with low operational cost. In particular, UAVs allow him to inspect with one flight many acres of crops in less than one hour. Thus, he can get an overall estimation of potential problems without wasting time by walking around the field. This fact allows interfering precisely when and where there is a need for fertilizer or pesticides, thus reducing operational cost and producing healthier products for consumers.

Alternative techniques for inspection of large fields of crops are, manned airborne and satellite inspection, but the cost of both of them are high, and they have not the flexibility of UAVs. For example, different kind of sensors, imaging, or no-imaging can be easily applied to a low-cost UAV, providing in a few minutes various types of data. Following a predefined path to cover an area, several hundred pictures can be captured to create an overall image for the coverage of a field.

Numerous kinds of UAVs exist today, suitable for various applications, from surveillance systems to disaster response missions. A comprehensive review of the classification of UAVs and their potential applications are discussed by M. Hassanalian and A. Abdelkefi [30]. Nowadays, in the agriculture domain, they are mainly used only two types of UAVs, fixed wing and rotary wing. Both of them have the advantages and disadvantages which are presented in summary in Table 1. In particular, fixed wing UAVs can cover large areas in a few minutes, but they lack in image resolution comparing with rotary wing UAVs since they fly in higher altitudes. In addition, they can operate with winds up to 45 km/h, and their flights can last more time since they consume less power as they are taking advantage of their aerodynamic shape. On the other hand, rotary wing UAVs can fly in low altitudes and operate with accuracy, so they are suitable even for operations like spraying.

Despite the freedom that a UAV can give to a farmer in their work, there are many regulations in the countries worldwide [31] which sets significant barriers to their development in the field. They are aiming to reduce the possibilities of congestion with other airspace users and the possible damage to people or property on the ground. In addition, privacy concerns is another issue on which regulations should be conformed to protect the private life of people as well as to protect restricted areas like jails, military areas, or industrial buildings.

Table 1
Comparison between fixed wing and rotary wing UAVs.

	Fixed Wing 	Rotary Wing 
Speed	High	Low
Coverage	Large	Small
Resolution	cm/inch per pixel	mm per pixel
Take-off and landing area	Large	Small
Flight time	High	Low
Wind resistance	High	Low

2.2. Unmanned Ground Vehicles (UGV)

Recent evolution in robotics is aiming to participate in every part of human activities in the next decades. In the agriculture section, Unmanned Ground Vehicles (UGVs) are making their first steps [3,4], and they are promising to lessen the labor effort as well as to boost the accuracy of the operations in the field. Quite a few solutions already exist in the experimental stage, showing that UGVs can play a fundamental role in Smart Farming in the next decades. In order to become practical for use in everyday activities in the field, researchers still have to resolve many issues. Future UGVs should be cost-effective, operate precisely in an unstructured agriculture farm while being inherently safe for humans. In addition, they should increase the performance and reliability of their operations while reducing their size.

An UGV can perform various tasks [32] in the field like seeding [33,34], harvesting [35], weeding [36,37], spraying [38], pruning [39], and crop monitoring [40]. Existing UGVs have been tested on numerous crops including grapes, peppers, cucumbers, tomatoes, asparagus, sunflowers, sugar beet, and hazelnuts.

To provide operational abilities to a robotic system, we have to equip it with various instruments, but the most important equipment is a camera. Even an ordinary camera can be the eyes of the UGV, as Computer Vision techniques give it the capability to move autonomously around the field and perform the desired tasks, like seeding, harvesting, and distinguish the crops from the weeds. Moreover, cameras in infrared light can be used to detect the moisture of the leaves or potential diseases.

Furthermore, modern technologies in sensors are used to equip UGVs with capabilities like soil moisture or pH measurements. UGVs are also able to communicate with weather stations and be informed about the forecast or download data from Knowledge Management Systems and apply the corresponding actions in the fields. Finally, researchers aim to develop UGVs which can work in swarms or cooperate with UAVs [32,41] to perform complex tasks.

Expected benefits from UGVs when they reach their potential are numerous. For example, they will bring a reduction of labor effort, which will also result in a decrease in operational cost. In addition, they will offer precise appliance of fertilizers and pesticides, which will also help in cost reduction, lessen the environmental impact, and produce better products. Finally, the small size of the UGVs comparing with the existing heavy machinery will avoid the massive soil compaction and reduce energy consumption.

2.3. Wireless Sensor Networks (WSNs)

Wireless connectivity is of paramount importance in Smart Farming since almost all connected devices need to receive or send data wirelessly. Depending on the bandwidth required, the transmission distance, and the energy consumption available, we have to choose between different available technologies for Smart Farming applications. Various wireless technologies have been used during the last decades, like Bluetooth Low Energy (BLE), WiFi, 3G/4G, SigFox, Narrowband IoT (NB-IoT), and LoRa [14]. More specifically, if we require high bandwidth but not very long distance of transmission, WiFi is mandatory, whereas when we need to transmit in long distance a small amount of data, NB-IoT and LoRa wireless technologies are more appropriate.

In addition, most of the sensors used for measurements work on batteries and need to transmit on long distance. The appropriate networks suitable for them are those who consume low energy. These networks are called Low Power Wide Area Networks (LPWANs), and SigFox, NB-IoT, and LoRa, belong in this category.

In Table 2 we present a comparison of the most frequently used WSNs in the agriculture domain.

Bluetooth Low Energy (BLE) is an evolution of Bluetooth technology, which extends distance coverage and lowers power consumption. It can operate theoretically in a distance up to 100 m with transmission speed up to 2 Mbps. Although it is not used very often in the agriculture sector, it can be part of indoor implementation like greenhouse monitoring.

ZigBee is also a WSN protocol for small distance achieving lower data rates than BLE protocol. In addition, it has low power consumption so it can be used mainly at indoor activities like greenhouse monitoring [42], for pesticide and fertilizer control, and at smart irrigation systems.

WiFi is a wireless local area network (WLAN) protocol commonly used in home and office networking, but it can also offer its advantages in the agriculture sector. The new standard 802.11.ac of WiFi can theoretically reach data rates up to 1.3 Gpbs to distance up to 100 m. It is suitable for applications where high bandwidth is required, such as implementations with UAVs and UGVs.

The cellular networks 3G/4G and soon 5G, have been used widely in Smart Farming for data aggregation from sensors deployed in the field. The upcoming 5G will offer low latency, reliability, and high bandwidth that are important in tasks with machinery usage where human safety is of paramount importance. Thus, it will support Device to Device (D2D) communication in real-time and support a huge number of devices [43]. Finally, cellular networks are already offering wide coverage in rural areas, and 5G is expected to extend it even more. The drawbacks of their usage are the high average operating cost and high energy consumption compared with other solutions.

Sigfox is able to transmit data at very long distance up to 40 km in rural areas, but at very low data rate up to 100 bps. Its advantages are the low operational cost and the low energy consumption. Although it offers bidirectional communication, the downlink transmission occurs only after an uplink transmission. Moreover, it has a limited duty cycle, as it is restricted to 140 uplink messages per day with 12 bytes as a maximum payload per message.

LoRa works at an unlicensed spectrum and works at 433 MHz and 868 MHz in Europe. It can reach a distance of 20 km and

Table 2
Comparison of Wireless Sensor Networks.

	BLE	ZigBee	WiFi	3G/4G	SigFox	NB-IoT	LoRa
Frequency band	2.4 GHz	868/915 MHz 2.4 GHz	2.4 GHz 5 GHz	865 MHz 2.4 GHz	433 MHz 868 MHz 915 MHz	–	433 MHz 868 MHz
Data rate	2 Mbps	20–250 kbps	1.3 Gbps	1 Gbps	100 bps	250 kbps	50 kbps
Transmission range	100 m	20 m	100 m	Cellular Coverage	40 km	15 km	20 km
Energy consumption	Low	Low	High	Medium	Low	Low	Low
Cost	Low	Low	High	Medium	Low	High	Low

a speed up to a few KBytes per second. In addition, it offers low energy consumption with the theoretically expected life of sensors on batteries up to 10 years. Since it has no license cost, it has widely adopted within a few years.

NB-IoT is derived from Third Generation Partnership Project (3GPP) as a standard for cellular systems, aiming to service IoT devices with low data rate and low energy consumption. It is working in licensed cellular spectrum limited to few licensees which will belong to communication companies. Comparing with LoRa, NB-IoT can operate at higher distance up to 35 km, at higher data rate, lower latency, and reliability.

2.4. Discussion

The technologies described in this section aim to change the approach of how farmers and agronomists work in the field by reducing labor efforts, and by operating with accuracy on an everyday basis. UAVs could be the eyes of the farmers and help them to identify precisely diseases or areas with low production while UGVs can operate in the field in various tasks like seeding, weeding, spraying, or harvesting. Above these, a suitable WSN is mandatory to collect data from sensors and support the orchestration of all connected devices.

In the next decades, we will be spectators of the new era of Smart Farming, but until then, many obstacles should be overwhelmed. More specifically, although UGVs can operate continuously on an everyday basis, their operational speed is still very slow compared to manual work. In addition, their accuracy in some tasks like harvesting and weeding is still an open issue.

UAVs also have still some disadvantages, like energy consumption, which restrict them to operate more time in the field. Moreover, in order to be more autonomous, more research efforts should be spent on their usage without human intervention, and new regulation rules should be adopted on this basis.

Finally, WSNs will be the backbone of the whole infrastructure, so their characteristics will play a vital role in many factors. For example, reducing the energy consumption of the sensor nodes is mandatory since they operate with batteries. In addition, low latency is essential in tasks like control of UAVs or UGVs, especially in tasks where human protection is crucial.

3. Related research areas

In this section, we are analyzing the relevant research areas from ICT used in Smart Farming, namely Image Processing, Machine Learning, Big Data, and Cloud Computing. We are analyzing and discussing their characteristics and provide the main potential benefits from their usage in the agriculture section.

3.1. Image processing

Image Processing is one of the leading ICT technologies used in many operations in Smart Farming. Images captured from UGVs, UAVs, satellites, or ground sensors require image processing techniques before we can derive useful information. For this purpose, cameras in visible-spectrum, near-infrared, multispectral, hyperspectral, thermal, laser scanners, or synthetic aperture radar can be used depending on the desired application.

Image processing techniques are used to create two-dimensional maps from images taken from UAVs in various spectrums. These maps are valuable for crop monitoring and yield estimation, two of the most important applications in Smart Farming. Several vegetation indices are used in literature, namely NDVI, GNDVI, and SAVI for crop monitoring, and ARI, MARI, RGI, ACI, MACI, CI, and GRVI for estimating the leaf pigments [44]. The formulas of these indices are shown in Table 3.

Furthermore, three-dimensional models can be created from images or video captured from UAVs, which can be used for crop estimation as we can compare different 3D models taken at distinct times within a seasonal period or compare them with a previous seasonal period.

Similar applications for crop monitoring and yield estimation are also useful for UGVs, but their efforts are mainly in operating in the field. Thus, they are also equipped with more advanced Image Processing techniques as Computer Vision, enabling them to move through crops [45], detect diseases or insects [46], classify weeds [47], and detect fruits or vegetables ready to harvest [48]. In addition, Computer Vision gives UGVs the ability to perform operations in the field and relieve human from labor effort. Computer Vision is rarely used in UAVs nowadays since their purpose in most cases is limited in crop monitoring by capturing images over the field.

Finally, depending on the number of captured images and the necessity to be processed in real-time, a supporting platform is required based on Cloud Computing. Also, techniques for Big Data analysis should be considered in tough situations.

3.2. Machine learning

Machine Learning intends to bring significant advantages in every domain of ICT used. Its feature to give the machines the ability to learn without being previously programmed makes it a promising solution for many innovative applications. A typical Machine Learning algorithm starts with a learning process where the system is trained with multiple sets of values. After this procedure, classification and prediction rules are derived, which can be used in the future with new input parameters to predict the corresponding output, as shown in Fig. 1 [21].

The agriculture sector is one of the newest domains where Machine Learning promises a significant impact in the next decades. Many smart farming tasks accumulate an enormous amount of

Table 3
Vegetation indices [44].

Index name	Formula
Normalized Difference Vegetation Index	$NDVI = \frac{NIR-Red}{NIR+Red}$
Anthocyanin Reflectance Index	$ARI = Green^{-1} - RedEdge^{-1}$
Modified Anthocyanin Reflectance Index	$MARI = (Green^{-1} - RedEdge^{-1}) \times NIR$
Red–Green Index	$RGI = \frac{Red}{Green}$
Anthocyanin Content Index	$ACI = \frac{Green}{NIR}$
Modified Anthocyanin Content Index	$MACI = \frac{NIR}{Green}$
Chlorophyll Index	$CI = \frac{NIR}{RedEdge} - 1$
Green-Red Vegetation Index	$GRVI = \frac{Green-Red}{Green+Red}$
Soil-Adjusted Vegetation Index	$SAVI = \frac{(NIR-Red)\times(1+L)}{NIR+Red+L}$
Green Normalized Difference Vegetation Index	$GNDVI = \frac{NIR-Green}{NIR+Green}$
Difference Vegetation Index	$DVI = NIR - Red$

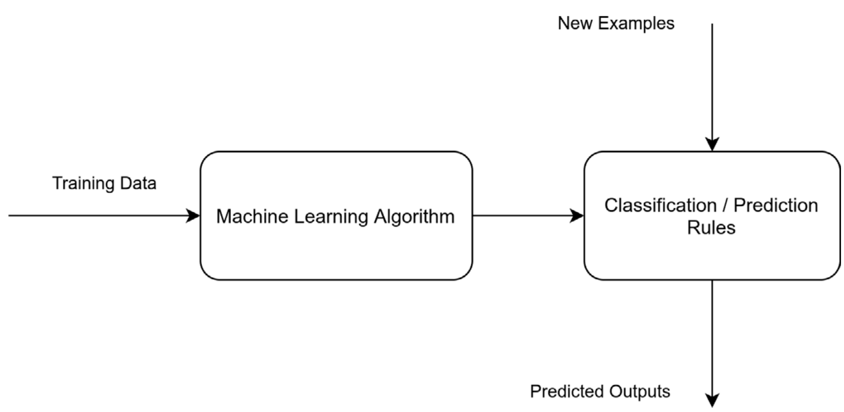

Fig. 1. A typical machine learning approach [21].

data from different sources, which require processing to derive useful information. Thus, Machine Learning based systems seems a suitable solution due to their capability of processing a large number of inputs and handle non-linear tasks [49]. In addition, Deep Learning was recently used in many research efforts offering modern techniques in image processing and data analysis, with promising results and large potential. Deep Learning is an extension of classical Machine Learning [22], and adds more complexity into the prediction models as well as transforms the input datasets using various functions that allow hierarchical representation, through several levels. These features result in larger learning capabilities and, thus, higher performance and precision.

Machine Learning and Deep Learning techniques are used in various tasks in agriculture and are expected to bring significant improvements. In more detail, they are used in crop monitoring [47], in water management [14], to identify diseases [50] and to classify weeds [51].

Machine Learning and Deep Learning will also improve Knowledge Managements Systems by manipulating the vast amount of gathered data which may originate from historical data and by combining them with recently aggregated data from ground sensors, satellite images, images from UAVs and local weather forecasts.

3.3. Big Data

Smart Farming will be responsible for the massive deployment of sensors in the next years, with an expected huge amount of produced data, measuring various characteristics such as soil moisture, humidity, and temperature. In addition, UAVs, UGVs, and even satellites will generate an enormous amount of images for agriculture purposes. Moreover, additional resources are data from weather stations, historical data gathered by governmental authorities, or open source datasets available via online repositories. All of these consist of a tremendous amount of heterogeneous data, which in most cases demand to be elaborated, transferred in real-time through wireless networks, and saved. This phenomenon is called Big Data in literature and should be addressed regarding Smart Farming [20,52]. A proper architecture to manipulate and store such an enormous amount of data is Cloud Computing [53].

As described by Y. Demchenko et al. [54], Big Data can be characterized from five dimensions, namely Volume, Velocity, Variety, Veracity, and Valorization, known as 5Vs. The authors A. Kalimaris et al. distinguished these dimensions in the needs of the agriculture domain and proposed another relevant "V" corresponding to the Visualization of data [52].

Based on [55] the Big Data chain refers to six steps, data capture, data storage, data transfer, data transformation, data analytics, and data marketing. In [20] S. Wolfert et al. analyze these steps regarding the agriculture domain of Smart Farming based on the Big Data state-of-the-art applications, as shown in Fig. 2. In more detail, the first step includes data aggregation captured from sensors, biometric sensing, UAVs, or already available open data. In addition, they can be genotype information or reciprocal data. In the second step, the gathered data should be stored probably in Cloud-based platforms. Hadoop Distributed File System (HDFS) is an appropriate solution while other hybrid storage systems also exist. Data transfer is the next step, where data is

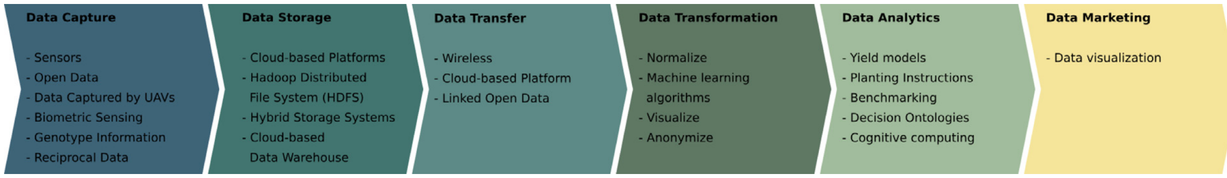

Fig. 2. The data chain of Big Data in Smart Farming [20].

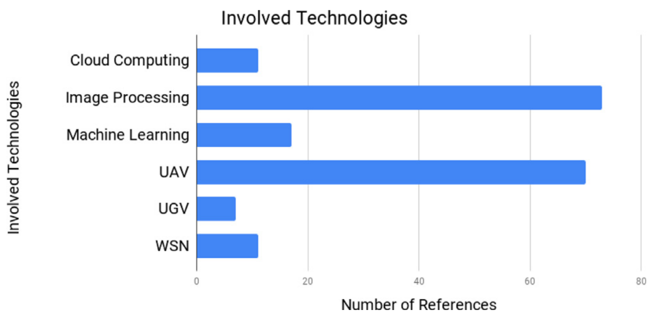

Fig. 3. Statistical analysis of research efforts in Europe for involved technologies based on Table 4.

transferred probably throw wireless connection, and supported from a Cloud-based platform. In the fourth step, data transformation occurs where appropriate algorithms are used for operations such as normalization, visualization, anonymization, or machine learning. The fifth step is where the data is analyzed in order to define new yield models, planting instructions, or create decision ontologies. Cognitive computing and benchmarking are also used in this step. Finally, to exploit the results of Big Data, visualization techniques are used for data marketing purposes.

Although Big Data in agriculture is still at an early stage, it has the potential to arise in many applications. Weather forecasting [56] is an important application for Smart Farming where local or global weather data should be processed to support decision making systems to help farmers. The produced amount of data regarding weather forecasting is enormous and should be analyzed and processed in real-time, which yields an extra complexity. Big Data is also present in crop production estimation [57], where global monitoring systems can be used to provide data analysis tools for crop-condition monitoring and production assessment. Weed discrimination [58] is another domain where a large amount of data should be analyzed, processed, and used by multiple machines in the field. In addition, newly gathered data should be used to evolve existing algorithms for weed control. Storage and querying this amount of data incurs significant challenges. Detailed knowledge of croplands based on accurate remote sensing technologies is an important key parameter for land management [59,60], which will result in improved productivity. All of the above applications can produce input parameters for decision making systems to help farmers with their decisions.

3.4. Cloud computing

For the elaboration and storage of the tremendous amount of data produced from the huge amount of sensors and the involved UAVs and UGVs in Smart Farming, an innovative infrastructure based on Cloud Computing is indispensable. As we had described in the previous subsection, Big Data and Cloud Computing are interdependent, since an enormous amount of data should be stored, processed, and always be accessible to end users. Sometimes the storage and processing should occur in real-time, which requires extra computational resources. Cloud Computing can provide on-demand computation and storage resources for various agricultural applications to support the work of farmers and agronomists [61]. In more detail, Cloud Computing can offer a plethora of storage and computational resources, and these resources are reliably available from any place at any time. In addition, an elastic model of resources can lessen the overall cost, as we can use the available resources only when we need them.

Nevertheless, Cloud Computing is not only useful when Big Data is present but is also suitable for many other occasions. For example, its centralized control is proper to aggregate data from the deployed sensors in the field and provide the derived information in a visualized form, easy to understand from the farmers or agronomists, on their phones or tablets from anywhere and at any time. In essence, Cloud Computing offers an abstraction layer able to provide multiple user-friendly services to final users. Applications like soil monitoring [62], smart irrigation [63], disease or insect detection [46], and Farm Management Systems (FMS) [64] are some examples of the services that can be provided from a Cloud Infrastructure at the edge devices.

FIWARE seems a suitable Cloud architecture to support Smart Farming applications, as it is open source with many available enablers for agriculture. Hence, it is used in many research papers in the literature [65,66]. Moreover, Fog Computing is a novel promising architecture, aiming to improve the services of Cloud Computing at the edge of the network. It promises low latency since Fog Nodes are at the proximity of edge devices [67]. Tasks, where UAVs and UGVs are co-operating, low latency, is essential for the immediate response to actions. Moreover, when farmworkers are working with heavily automated machinery, low latency and reliability are of paramount importance for their safety. In such scenarios, local Fog Nodes near the field can offer their computational and storage resources with low latency and reliability. In addition, Fog Computing can improve the reliability of the supported system [65] and reduce the amount of data transferred from the field to the Cloud. In particular, Fog Nodes can participate in computational efforts and accomplish tasks on the field while filtering the results before uploading them to the Cloud.

3.5. Discussion

The research areas analyzed in this section are aiming to transform traditional farming and to enrich it with new capabilities to help farmers with their work and their decisions. In addition, they constitute supporting techniques for UAVs, UGVs, and WSNs which are deployed in the field.

More specifically, Image Processing is valuable in many tasks in Smart Farming, as in analyzing the images taken from UAVs and UGVs, as well as to endow them with Computer Vision capabilities in order to operate and navigate autonomously in cultivation. Even though Image Processing has been sufficiently analyzed in research papers, there is still a need for research efforts in various domains and evaluation in real environments, in order to improve the capabilities of UAVs and UGVs, and new services arise.

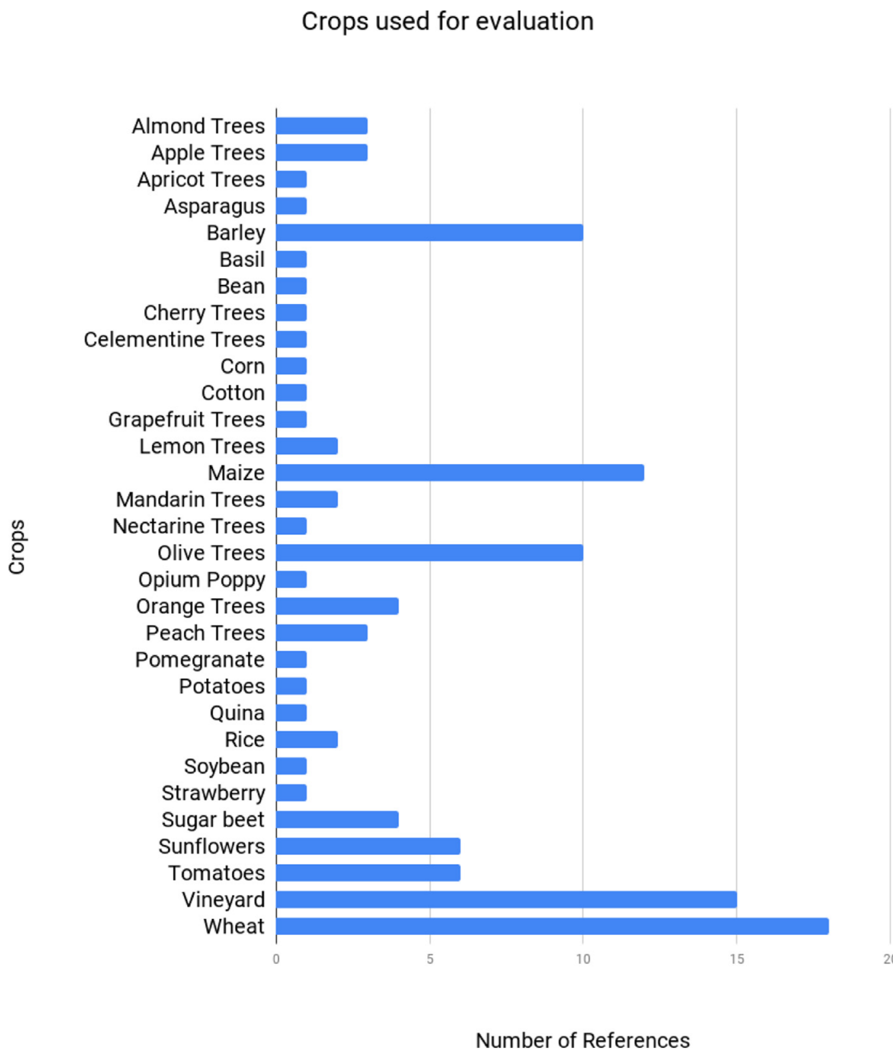

Fig. 4. Statistical analysis of research efforts in Europe for crops used for evaluation based on Tables 5.

Although it is not mandatory in every deployment of Smart Farming, Big Data should be taken into consideration, especially when an enormous amount of produced data is expected from the massive amount of connected devices. Until now, there are not many research efforts in the agriculture domain in Big Data, but in the next years, when more complex deployments will be implemented, we should confront the problems derived from this phenomenon.

Cloud Computing is aiming to be the central supporting system of the whole infrastructure offering its enormous amount of storage and high processing capabilities. It may be useful in many cases such as Knowledge Management Systems and Decision Support Systems, and it may also be indispensable in deployments with Big Data requirements.

4. Research efforts in Europe

In this section, we present an overview of the main research efforts in Europe in Smart Farming. We have used Google Scholar as a search engine with the following query :

"[TECH]" AND "Agriculture" AND ("experimental" OR "study area") AND "[COUNTRY]".

The keyword [COUNTRY] is one of the European countries while the keyword [TECH] is one of the following phrases: "UAV", "drone", "UGV", "robot", "WSN", "Big Data", "Cloud Computing", "Deep Learning", "Machine Learning".

Some criteria were used to filter the results, and we kept only useful manuscripts from research efforts in Europe. In more detail, we selected only conference papers or journal articles in which the presented results evaluated in real fields or greenhouses around Europe in the Smart Farming section. To reduce even more the results and keep the best papers, we selected those published within the last ten years with at least fifteen citations for those between 2010 and 2014, and at least ten citations between 2015 and 2017. We did not set such limitations for papers published in the last two years, but we selected them based on the reputation of the journal and the quality of the manuscript.

Under these criteria, we have selected 97 papers, which are provided in Tables 4, 5, 6, and 7. More specifically, Table 4 includes the recent technologies used in Smart Farming like WSN, UAVs, UGVs, Image Processing, Big Data, Cloud Computing, or Machine Learning. The Table 5, provides the research efforts categorized by cultivation crops in the experimental fields around Europe, such as maize, olives, tomatoes, lemon trees, almond trees, broccoli, barley, sugar beet, clover, or pomegranate. Moreover, Table 6 contains the field operations evaluated during the experimental study in outdoor fields or greenhouses. Finally, in Table 7, we are providing the countries from the corresponding experimental fields.

In Figs. 3, 4, 5, 6, we are presenting a statistical analysis depending on the research efforts in Europe from Tables 4, 5,

Table 4
Involved technologies in European research efforts.

Involved technologies	Refs
Cloud Computing	[65], [63], [68], [69], [70], [71], [72], [73], [74], [75], [76]
Image Processing	[77], [47], [78], [44], [79], [80], [81], [82], [83], [84], [85], [40], [86], [87], [88], [89], [50], [51], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101], [39], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [75], [123], [124], [25], [125], [126], [127], [128], [129], [130], [131], [27], [132], [133], [26], [134], [135], [136], [137], [138], [139]
Machine Learning	[47], [85], [50], [51], [91], [140], [71], [100], [102], [73], [14], [141], [114], [116], [142], [118], [143]
UAV	[77], [78], [44], [79], [80], [81], [82], [83], [84], [85], [40], [86], [87], [68], [88], [144], [90], [91], [92], [93], [94], [71], [95], [96], [98], [99], [101], [102], [103], [104], [105], [145], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [117], [119], [120], [121], [122], [146], [147], [123], [124], [25], [125], [126], [127], [128], [129], [130], [131], [27], [132], [133], [26], [134], [135], [148], [76], [137], [138], [139]
UGV	[84], [40], [38], [39], [116], [122], [136]
WSN	[15], [65], [63], [69], [70], [72], [73], [14], [74], [143], [76]

Table 5
Crops used in European research efforts.

Crops	Refs
Almond Trees	[63], [135], [148]
Apple Trees	[83], [147], [136]
Apricot Trees	[135]
Asparagus	[97]
Barley	[85], [144], [99], [103], [112], [117], [127], [128], [129], [26]
Basil	[70]
Bean	[74]
Cherry Trees	[76]
Clementine Trees	[106]
Corn	[130]
Cotton	[141]
Grapefruit Trees	[113]
Lemon Trees	[63], [135]
Maize	[47], [78], [84], [144], [51], [91], [92], [101], [104], [109], [121], [27]
Mandarin Trees	[111], [113]
Nectarine Trees	[106]
Olive Trees	[15], [84], [86], [68], [50], [89], [71], [98], [110], [25]
Opium Poppy	[115]
Orange Trees	[86], [106], [111], [135]
Peach Trees	[69], [106], [135]
Pomegranate	[81]
Potatoes	[140]
Quinoa	[88]
Rice	[75], [137]
Soybean	[122]
Strawberry	[143]
Sugar beet	[51], [107], [122], [146]
Sunflowers	[91], [93], [95], [116], [132], [133]
Tomatoes	[65], [38], [73], [14], [118], [138]
Vineyard	[77], [44], [79], [82], [90], [94], [38], [72], [96], [39], [105], [145], [119], [126], [138]
Wheat	[80], [84], [85], [40], [87], [144], [100], [108], [114], [142], [120], [122], [123], [124], [125], [131], [134], [139]

Table 6
Field operations in European research efforts.

Field Operations	Refs
Crop Monitoring	[65], [63], [77], [47], [79], [80], [82], [83], [84], [85], [40], [87], [88], [144], [92], [71], [72], [95], [96], [98], [99], [102], [103], [73], [105], [145], [106], [107], [108], [109], [110], [111], [112], [113], [74], [114], [142], [117], [119], [120], [121], [122], [146], [75], [147], [123], [124], [25], [125], [127], [128], [129], [130], [131], [26], [134], [148], [76], [137], [138], [139]
Disease Detection	[44], [68], [89], [50], [97], [115], [118]
Harvesting	[136]
Pruning	[39]
Spraying	[79], [84], [86], [68], [38]
Water Management	[15], [65], [63], [81], [69], [90], [70], [107], [14], [112], [74], [143], [126], [135], [76]
Weed Management	[78], [84], [51], [91], [93], [104], [116], [124], [27], [132], [133], [134]
Yield Prediction	[140], [100], [101], [141], [121]

6, 7. More specifically, Fig. 3 provides the statistical analysis of participating ICT types, Fig. 4 applies to the kind of crops used for evaluation, Fig. 5 refers on operations used in the field, and Fig. 6 presents the countries where evaluation process took place.

5. Research projects in Europe

During the last decades, Europe tries to adopt various technological innovations in the field of agriculture, aiming to increase

Table 7
European countries involved in research efforts.

Country	Refs
Belgium	[109], [136]
Denmark	[99], [112], [139]
Finland	[85], [123]
France	[44], [80], [83], [51]
Germany	[87], [92], [101], [103], [142], [127], [128], [129], [130], [131], [26]
Greece	[81], [68], [97], [14], [141], [120], [75]
Ireland	[143]
Italy	[77], [78], [82], [89], [50], [70], [94], [38], [105], [145], [114], [115], [116], [75], [137], [138]
Lithuania	[108]
Netherlands	[88], [147]
Norway	[40]
Poland	[144]
Portugal	[69], [96], [39]
Russia	[73]
Spain	[15], [65], [63], [79], [84], [86], [90], [91], [93], [140], [71], [72], [95], [98], [102], [104], [106], [107], [110], [111], [113], [74], [117], [118], [119], [121], [146], [75], [124], [25], [125], [126], [27], [132], [133], [134], [135], [148], [76]
Switzerland	[122]
Turkey	[47]
United Kingdom	[100]

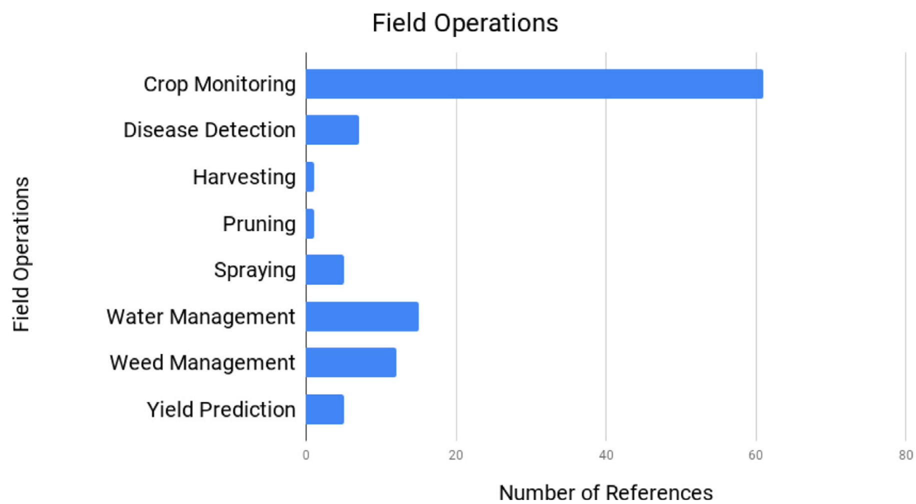

Fig. 5. Statistical analysis of research efforts in Europe for operations in the fields based on Tables 6.

production while reducing cost and improving the quality of products with minimal use of fertilizer or pesticides. In this vein, the European Union funds many research projects to support the evolution of the agriculture domain. As mentioned in the previous Sections 2 and 3, such technological innovations are Unmanned Aerial Vehicles, Unmanned Ground Vehicles, Wireless Sensor Networks, Image Processing, Machine Learning, Big Data, and Cloud Computing.

In this section, we are discussing the best European Union projects of the above technological fields in the agriculture sector. We are presenting them in classification in Table 8, and then we analyze each of them briefly. In more detail, in the column "Involved Technologies" of Table 8, we classify each project based on the technologies used in the field, namely Unmanned Aerial Vehicles, Unmanned Ground Vehicles, Wireless Sensor Networks, Image Processing, Machine Learning, Big Data, and Cloud Computing. In the next column, we are presenting the crop types used for testing and evaluation. Finally, we are providing the operations performed in the field for each project, namely harvesting, seeding, crop monitoring, water management, and weeding.

In the next subsections, we briefly describe each project of Table 8, and provide all the available information found.

5.1. ECHORD Plus Plus

ECHORD Plus Plus [149] was an EU project that tried to promote interaction between robot manufacturers, researchers, and users by facilitating the cooperation between academia and industry. A number of application-oriented research subprojects funded under ECHORD Plus Plus, of which seven focused in the area of Smart Farming, namely, GARotics, MARS, SAGA, GRAPE, CATCH, INJEROBOTS, and 3DSSC.

GARotics (Green Asparagus Harvesting Robotic System) subproject was aiming to develop a robotic system for green asparagus, with an improved automatic harvesting mechanism compared with existing solutions. The robot was able to detect and harvest with accuracy the final product in the field, thus relieving the need for seasonal workers.

MARS (Mobile Agricultural Robot Swarms) subproject was aiming to develop a mobile agricultural robot (Fig. 7), which had the ability to cooperate and work in swarms. The subproject MARS had focused on the seeding process for corn and had three main aspects. Firstly, it was aiming to reduce the need of seeds during the seeding process as well as reducing the need for fertilizer and pesticides. Secondly, since the developed UGV was small enough, it avoids the soil compaction as well as the major energy consumption from the existing heavy machinery. Finally,

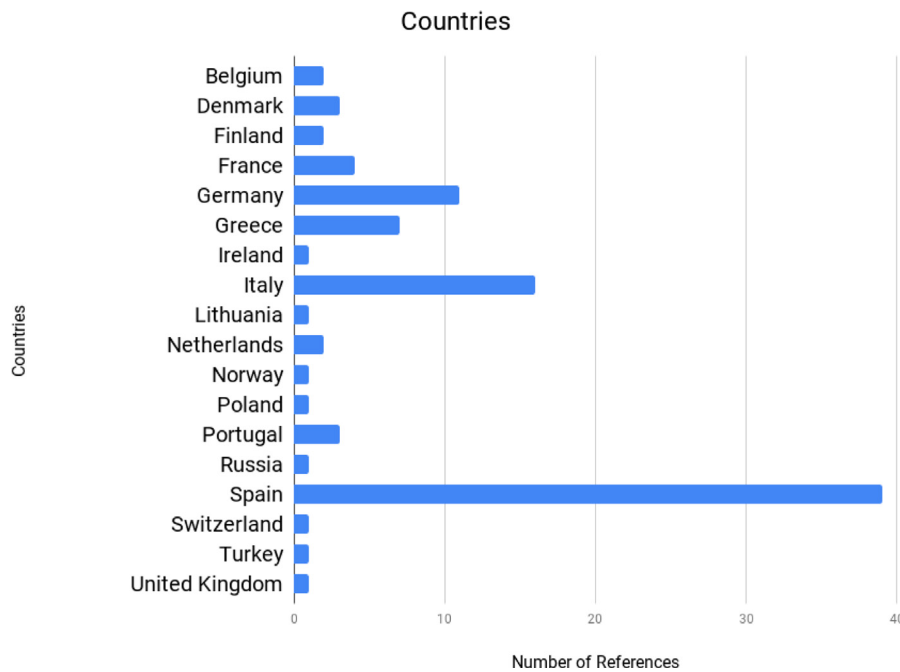

Fig. 6. Statistical analysis of research efforts in Europe for countries where evaluation process took place based on Tables 7.

Fig. 7. UGV from project MARS is able to work in swarms.

Fig. 8. UGV from subproject GRAPE suitable to operate in vineyards.

the provided solution was flexible, highly automated, and simple to operate, parameters which are essential in the Smart Farming era.

SAGA (Swarm Robotics for Agricultural Applications) subproject was intended to demonstrate technologies like cooperation and parallel operation of multiple robots. In this vein, a small number of UAVs have been exploited to monitor and map a large sugar beet field, to detect the presence of weeds and determine when a weeding procedure is necessary.

GRAPE (Ground Robot for vineyArd monitoring and ProtEction) subproject was aiming to develop a UGV (Fig. 8) able to execute semi-autonomous vineyard monitoring and farming tasks. For example, the UGV was able to use biological techniques in a vineyard like green pruning, bunch-tip thinning, and precise spraying with respect to traditional practices. Such innovative concepts in a vineyard can reduce chemical usage and improve the cost-effectiveness of products.

CATCH (Cucumber Gathering — Green Field Experiments) subproject was targeting to develop a flexible, reconfigurable and cost-effective UGV which can help in harvesting in outdoor fields. In particular, the developed UGV has been tested on harvesting cucumbers.

INJERROBOTS (Universal Robotic System for Grafting of Seedling) subproject has proposed to develop two flexible, cooperative robotic arms that can perform grafting for horticultural plants like tomatoes, peppers, eggplants, cucumbers, melons, and watermelons.

5.2. WaterBee

WaterBee [150] (Low cost, easy to use Intelligent Irrigation Scheduling System) was an EU project aiming to reduce water wastage by wisely manage it in the agriculture sector. To achieve that, an intelligent irrigation system was designed using soil moisture sensors, integrated into low-cost sensors networks, and managed with intelligent software. In more detail, a ZigBee wireless sensors network was deployed into the growing area, providing continuous measurements for the actual real-time soil-moisture conditions, that was more accurate and in higher density than any other known method before. Combined with

Table 8
Research projects in Europe.

Ref	Acronym (Start Date) (End Date)	Involved Technologies	Crop	Field Operations
[149]	ECHORD Plus Plus (01-10-2013) (30-09-2018)	Cloud Computing Image Processing Machine Learning UAV UGV	Asparagus Corn Cucumber Eggplant Melons Peppers Sugar Beet Tomatoes Vineyard Watermelons	Crop Monitoring Grafting Harvesting Pruning Seeding Spraying Weed Management
[150]	Water-Bee (01-10-2008) (30-09-2010)	WSN	–	Water Management
[151]	SMART-AKIS (01-03-2016) (31-08-2018)	–	–	KMS
[152]	SWEEPER (01-02-2015) (31-10-2018)	Image Processing UGV	Peppers	Harvesting
[153]	VINEROBOT (01-12-2013) (31-05-2017)	Image Processing Machine Learning UGV	Vineyard	Crop Monitoring Disease Detection Water Management
[154]	VINBOT (01-02-2014) (31-01-2017)	Cloud Computing Image Processing UGV	Vineyard	Crop Monitoring Yield Prediction
[155]	FIGARO (01-10-2012) (30-09-2016)	WSN	–	Water Management
[156]	Flourish (01-03-2015) (31-08-2018)	Image Processing UAV UGV	Sugar Beet Sunflower	Crop Monitoring Spraying
[157]	PANtHEOn (01-11-2017) (31-10-2021)	Big Data UAV UGV WSN	Hazelnuts	Crop Monitoring Water Management
[158]	FOODIE (01-03-2014) (28-02-2017)	Cloud Computing	–	KMS
[159]	ERMES (05-09-2013) (01-03-2017)	Big Data Cloud Computing UAV WSN	Rice	Crop Monitoring
[160]	ENORASIS (01-01-2012) (31-12-2014)	WSN	Apple Trees Cherry Trees Corn Cotton Grapefruit Maize Potatoes Raspberry	Water Management
[161]	FRACTALS (01-09-2014) (31-08-2016)	Cloud Computing WSN	Olive Trees	Crop Monitoring Disease Detection Fertilization
[162]	MISTRALE (01-01-2015) (31-12-2017)	Image Processing UAV	Potatoes Vineyard	Crop Monitoring Water Management
[163]	GATES (01-01-2017) (30-06-2019)	–	–	Educational
[164]	ROMI (01-11-2017) (31-10-2021)	UAV UGV	–	Crop Monitoring Weed Management
[165]	WEAM4i (01-11-2013) (30-04-2017)	Cloud Computing WSN	–	Water Management
[166]	CHAMPI-ON (01-02-2011) (31-08-2013)	Image Processing Machine Learning	Mushrooms	Harvesting

historical and forecast meteorological data, intelligent software decides more precisely about the water needs of the crop.

WaterBee DA (WaterBee Demonstration Action) was the next phase of the successful project WaterBee. The developed prototype has been tested and evaluated for 15 months across Europe, in real agricultural fields with various crops. The aforementioned demonstration action has taken place in 12 fields in Estonia, Italy, Malta, Sweden, Spain, and the United Kingdom.

During the evaluation at those trials with various crops and in different growing conditions, the following benefits for the farmers involved: (a) achieved 21% on average, with a maximum of up to 44% on irrigation water savings, (b) reduction up to 23% on irrigation events, (c) excellent return of investment (ROI), as repaid period for a WaterBee system is expected to be 5 years for small farms as 1.5 ha.

5.3. Smart-AKIS

The EU project Smart-AKIS [151] (European Agricultural Knowledge and Innovation Systems (AKIS) towards innovation-driven research in Smart Farming Technology) was aiming to collect and disseminate the best practices around Europe in the area of Smart Farming. In more detail, its main concept was to implement a self-sustainable Thematic Network containing existing scientific knowledge as well as best practices and provide them in an understandable and easy to use format for agricultural practitioners. In this vein, SMART-AKIS was trying to bridge the gap between research and the final users in agriculture. The project was based on results from five EU projects, namely VALERIE, SOLINSA, PRO-AKIS, FRACTALS, and AGRISPIN.

After almost three years, SMART-AKIS Thematic Network over 200 Smart Farming solutions showcased and assessed in the online platform, and over 50 solutions were adopted by farmers and agronomists.

5.4. SWEEPER

The EU project SWEEPER [152] (Sweet Pepper Harvesting Robot) was targeting on developing a UGV able to harvest peppers in greenhouses, relieving thus farmworkers from an uncomfortable and repetitive task. In particular, the developed robotic system tried to overcome obstacles of the previous implementations in the domain, such as the slow speed and the low success rate of around 33% on picking the right fruit.

The implemented UGV (Fig. 9) has been designed and tested on pepper harvesting; however, it can be easily modified to suit other crops and tasks, such as harvesting apples and grapes or spraying. The SWEEPER project was based on a previous EU-funded project, named CROPS, on which harvester technology was implemented for peppers, such as localization and fruit maturity detection.

5.5. VINEROBOT

VINEROBOT [153] (VINEyardROBOT) was an EU project aiming to develop a novel UGV capable of monitoring grape growth. More specifically, the UGV would have the obligation of vineyard management such as grape yield, vegetative growth, water stress, and grape composition in order to achieve better grape synthesis and wine quality. Such an automation approach is able to deliver better results than the existing traditional methods with hand-held equipment. In addition, comparing to aerial monitoring from planes or UAVs, it provides better results with better image quality.

The developed VINEROBOT (Fig. 10) was supplied with artificial intelligence and machine learning techniques in order to continuously improve its abilities in vineyard management.

Fig. 9. The SWEEPER is designed to harvest peppers in a greenhouse.

Fig. 10. The VINEROBOT is capable of monitoring grape growth.

5.6. VINBOT

The EU project VINBOT [154] (Autonomous Cloud-Computing Vineyard Robot to Optimize Yield Management and Wine Quality) has developed a UGV which is responsible for vineyard monitoring and management. It was charged with tasks such as decision making in grape yield estimation and relevant canopy features, generating maps of the crop, and record the state and location of the assets. In addition, it is equipped with sensors allowing it to roam autonomously in the vineyard and monitor grapes and bunches to predict future yields with no human intervention. All the generated information is uploaded in the cloud, and the derived results are provided with an easy to use way to winegrowers, giving them the opportunity for accurate decision making.

VINBOT (Fig. 11) is not intended for individual winegrowers since it is still expensive, whereas it may be suitable for service providers and wine producers.

5.7. FIGARO

FIGARO [155] (Flexible and PrecIse IrriGation PlAtform to Improve FaRm Scale Water PrOductivity) was an EU-funded project focused on water management in order to reduce fresh water usage. The proposed implementation consisted of a cost-effective precision irrigation management system based on newly precision technologies and tested simultaneously in many countries around Europe. In more detail, soil, water, and plant sensors positioned around the field, and their measurements combined with information from local meteorological stations uploaded to FIGARO irrigation management platform. Based on the analysis of this information, the developed decision support system provides specific and accurate recommendations for farmers, on how much and when to irrigate their crops.

Fig. 11. The VINEBOT is responsible for vineyard monitoring and management.

5.8. Flourish

The EU funded project Flourish [156] (Aerial Data Collection and Analysis, and Automated Ground Intervention for Precision Farming) aimed to bridge the gap between the existing and the desired capabilities of autonomous robotics solutions. In this vein, Flourish proposed and developed a combined robotic solution with an autonomous small multi-copter UAV and a multi-propose UGV (Fig. 12). The developed UAV can provide the appropriate information from aerial views while the UGV can perform targeted tasks. For example, the UAV can survey the field and identifies regions where a weeding process is necessary. This information is used from the UGV for navigation to the area of interest in the field, and after a precise scanning of the crops, it classifies every plant and spraying only on detected weeds. The Flourish project has been tested and evaluated in fields with sugar beet and sunflowers.

5.9. PANtHEOn

PANtHEOn [157] (Precision Farming of Hazelnut Orchards) is an ongoing EU-funded project which is aiming to develop an agricultural equivalent of an industrial Supervisory Control And Data Acquisition (SCADA) system suitable for use in precision farming agriculture. The consortium will use a limited number of UGVs and UAVs (Fig. 13) properly to collect information at the resolution of a single plant and perform typical farming operations. All the acquired data will be collected in a central operative unit where it will be analyzed, and automatic operations will be performed in the field, such as regulation of the irrigation system. Moreover, the system can be used from agronomists as support to their decisions. The proposed SCADA infrastructure

Fig. 12. The developed UAV and UGV from Flourish project are able to cooperate in order to accomplish various tasks in the field.

will be tested and evaluated in large orchards hazelnuts, and the expected results are, (a) increase in hazelnut productions, (b) decrease in pesticides usage, (c) environmentally-friendly water usage, and (d) simplified management of large orchards.

5.10. FOODIE

The EU-funded project FOODIE [158] (Farm-Oriented Open Data in Europe) was aiming to develop an open platform hub based on Cloud Computing in order to provide computing and storage resources for data management related to the agricultural section. Existing open datasets, data publications, and data linking from heterogeneous data sources are used to provide services to any interested stakeholder. More specifically, FOODIE platform contains farming data such as maps, sampling data, yield, and fertilization. Moreover, public open data like land satellite images, agro-food statistical indicators, nature data, soil data, hydrometeorological data, as well as commercial data, like VHR satellite images and orthophotos, will also be available. Finally, the platform contains voluntarily collected data e.g. from agriculture production and OpenStreetMap.

FOODIE is targeting four primary groups of users, namely stakeholders from the agriculture sectors, the public sector, researchers interesting in large-scale experimentation on real data, and ICT companies.

5.11. ERMES

ERMES [159] (An Earth obseRvation Model based RicE information Service) was an EU-funded project which was aiming to provide services dedicated to the rice sector at the regional and local scale. Firstly, the Regional Rice Service (RRS) has been developed as a service to public authorities for regional planning. More specifically, a customized agro-monitoring system was used to contribute to monitoring crop status and regional estimation of yield as well as for alerting potential biotic and abiotic risks. Secondly, to support the private sector, the Local Rice Service (LRS) is providing information such as yield variability pattern, crop damage, and potential biotic and abiotic risks. The data used as input from ERMES project was coming from satellite images, from aerial views from UAVs as well as from in-situ measurements.

Fig. 13. The developed UAV and UGV from PANtHEOn project are able to collect information at the resolution of a single plant.

5.12. ENORASIS

The EU-funded project ENORASIS [160] (ENvironmental Optimization of IRrigAtion Management with the Combined uSe and Integration of High PrecisIon Satellite Data) was targeting on optimization of water usage from farmers by providing intelligent management tools and services. In particular, the benefits from the project concerning farmers, were the reduction of operational cost, improvement of property value, and the elimination of water runoff pollution. Moreover, the impact of ENORASIS for water companies were the increment of operational planning capacity, smart water pricing models, and long-term decisions in investment planning. To achieve that, the consortium of the project has developed and tested a number of innovative technologies, methodologies, and models, such as weather prediction systems based on satellite observations, smart irrigation systems with optimization techniques, and wireless sensors networks for field measurement and monitoring.

5.13. FRACTALS

The EU-funded project FRACTALS [161] (Future Internet Enabled Agricultural Applications) was intending to support ICT SMEs to take advantage of FIWARE platform and implement innovative applications suitable for the market in the agriculture sector. After an Open Call for proposals from European companies, 46 of them were awarded for receiving funding and creating their market-ready applications. Between them, three were in the area of Smart Farming, namely N-eXpert, Smart-Plant, and OLIWES. In particular, they intended to implement Farm Management Information Systems to support farmers in their decision making.

In particular, N-eXpert was aiming to reduce resource inputs and consequently cut down production costs. Based on the spatial pattern of the differences in nutrient status and demands of the field, a Farm Management Information System was implemented to help farmers in planning their fertilization strategy based on recent fertilization regulations. Thus, using the specified amount of nutritious when and where needed, they produced optimal yield formation and minimize losses of nutrients.

Smart-Plant subproject was aiming to help farmers to optimize their production by using the implemented ICT online solution. This solution was able to provide in real-time, possible risks of the appearance of pests and diseases based on data gathered from the field.

OLIWES subproject has developed a Farm Management Information System to support farmers to prevent diseases, reduce damages, and decrease the usage of pesticides on olive farms. The system uses historical and geo-located data, bulletins, and algorithms to create a complete scenario for any individual situation.

5.14. MISTRALE

The EU-funded project MISTRALE [162] (Monitoring of SoIl moiSture and wateR-flooded Areas for agricuLture and Environment) was aiming to provide relevant information to farmers for soil moisture of their fields. For this purpose, it has been developed a GNSS Reflectometry sensor integrated into a dedicated Remotely Piloted Air System (RPAS). Collected images are used to create soil moisture maps, and flooded areas monitoring. The developed system was tested and evaluated in vineyard and potatoes fields. In vineyard fields, the results were not satisfactorily, since the depth of the roots of wines is beyond the penetration depth of GNSS-R.

5.15. GATES

The GATES [163] (Applying GAming TEchnologies for training professionals in Smart Farming) was an EU-funded project aiming to develop a game-based training platform, and to educate agronomists and agriculturist on the applicability of Smart Farming in agriculture. In particular, they are being taught on available equipment and the economic benefits as well as the environmental impact of Smart Farming. The developed game has an easy to use interface with playable and enjoyable gaming experience, and it is available on various platforms, like Android, iOS, Windows, and Web. It has three different game modes, "Main Story", "Become an Expert", and "Simulation" game mode. More specifically, the first game mode focuses on increasing player's awareness of existing Smart Farming technologies and the benefits derived from their application. The second game mode concentrates on more complex scenarios to deepening players in various aspects such as sensors, machinery, software, and services. Finally, in the third game mode, real data such as weather data, yield data, and soil data from previous years from different climate zones around Europe are used. Thus, users are trained in simulation mode with real data in the crop of their choice in a specific area. At the end of the season, they are able to compare their performance with other players. The game is targeting to various user groups like agronomy students, agricultural advisors, sales-force agents, and farmers.

5.16. ROMI

The EU-funded project ROMI [164] (RObotics for MIcrofarms) is an ongoing project targeting in microfarms. The consortium is aiming to develop a UGV capable of performing tasks such as weeding, crop monitoring, and gathering detailed information on any individual plant. The UGV will also be supported by a UAV responsible for acquiring global information from the whole crop. An advanced 3D plant analysis from in-field data acquisition will provide useful information that will help the farmers on their decisions. ROMI will utilize novel adaptive learning techniques to deal with unpredicted situations. The expected benefits for the farmers are the reduction of manual labor by 25%, as well as the increase of productivity.

5.17. WEAM4i

The EU-funded project WEAM4i [165] (Water and Energy Advanced Management for Irrigation) was targeting on developing a smart grid system to reduce the water and energy consumption in smart irrigation systems. Moreover, one additional objective of the project was the implementation of an ICT cloud platform to provide Decision Support System (DSS) applications for the existing irrigation systems in the local fields. Demonstrations of the proposed techniques were performed and evaluated in three EU countries, and the results were satisfying in water usage and energy consumption.

5.18. CHAMPI-ON

The CHAMPI-ON [166] (Fully Automatic System for Picking and Handling Mushrooms for the Fresh Market) was an EU-funded project which has developed an automated robotic mechanism for picking and handling "agaricus - bisporus" mushrooms. In particular, the robotic system equipped with a camera capable of identifying the next mushroom with the appropriate level of growth. Then a robotic arm takes over to harvest it and place it to a tray. In order to accomplish this task, image processing algorithms have been used to identify mushrooms of size 38–60 mm and not to blemish the selected mushroom or the neighboring ones. Benefits from the developed system are the reduction of labor efforts by 80% as well as the prevention in damage or blemish of the white skin of the mushrooms compared with other automated mechanisms.

In Figs. 14, 15, 16, 17, we are presenting a statistical analysis depending on the European Projects from Table 8. More specifically, Fig. 14 provides the statistical analysis of participating ICT types, Fig. 15 applies to the kind of crops used for test and evaluation, Fig. 16 refers to operations used in the field, and Fig. 17 presents the participating countries of the project.

6. Trends and challenges

Traditional farming will evolve in a new era with less labor efforts and, hopefully, with products produced with less pesticides and fertilizers. The recent evolution in ICT promises to bring Smart Farming in its climax in the next decades. UAVs and UGVs seem to be in the first line of this evolution, promising many innovative solutions in fields. WSNs will support the whole infrastructure by connecting all devices together while Cloud Computing can be at the central role for their orchestration. In addition, Image Processing, Machine Learning, and Big Data are research fields with significant involvement in Smart Farming. Nowadays, numerous research efforts can be found in every research domain of Smart Farming, trying to set the basis of this evolution.

In the near future, UAVs will have a significant impact on how we will collect information about the status of cultivation in order to translate it into risk and knowledge management for the farmers. For that reason, UAVs on their own is a research challenge with high importance among researchers. For example, potential challenges in this area include disease recognition for various cultivations, developing of fully autonomous UAVs, develop and orchestrate of a swarm of UAVs, as well as privacy and security concerns for people and property around the flight area.

In addition, another part of mechanical innovation is UGVs which may replace heavy machinery in the field, or at least supplement it in some tasks. Researchers are trying to make them useful in numerous tasks like seeding, spraying, weeding, and harvesting. Thus, they might face various challenges, such as improving accuracy and speed in harvesting, improving navigation in the field, and protecting people from accidents while operating. Finally, another challenge is setting up UGVs in swarms in order to complete complex tasks through cooperation.

Moreover, wireless connectivity among involved devices will be required on an everyday basis. Thus, WSN will also have a significant impact on the whole system. Recent technologies in communications were developed, taking into consideration various requirements which are suitable in Smart Farming or other applications of the Internet of Things. For example, some applications require low latency and high bandwidth, while others require low energy consumption. Furthermore, since most devices on the field operate on batteries, the reduction of energy consumption at minimum levels is still a research challenge, on which many researchers work.

Recent research trends required UAVs and UGVs to become smarter during their operation, such as detecting diseases in the cultivation or deciding whether there is a need for watering. Thus, image processing techniques are widely used in such tasks. Moreover, Computer Vision, a specific branch of Image Processing, will make even clever UAVs and UGV, being able to recognize specific objects and navigate them securely in the cultivation or detect whether a fruit is ready for harvesting.

Machine Learning can also leverage intelligence in complex tasks of Smart Farming. For example, novel algorithms can improve disease detection accuracy, which is of paramount importance, as early detection of diseases can help the prevention with the appropriate treatment and reduce the overall amount of pesticides. In addition, weed detection can be benefited from machine learning algorithms, as images captured from UAVs or UGVs can be used as input, and the results can supply the appropriate information the automated mechanisms of UGVs in weeding. Finally, another machine learning application is yield prediction to help farmers estimate the production of their cultivation in the upcoming season.

The numerous involved devices are expected to produce an extreme amount of data that should be processed and stored. Researches are being concerned more and more about this phenomenon called Big Data. Manipulation of such amount of data, especially when real-time processing is needed, is a big challenge. Big Data is mainly present in applications that cover extensive cultivation areas. Thus, it is often present in governmental projects which cover the cultivations of a specific region of their territory. Moreover, large agricultural associations may face with Big Data when they want to supply their supported farmers with innovative technologies in ICT.

Cloud Computing can support the whole infrastructure of a Smart Farming solution with its enormous amount of storage and processing capabilities. One of its primary roles is having the central control of all devices and offering multiple services to support and extend their capabilities. Especially when we are dealing with Big Data, Cloud Computing seems the ideal platform. Researchers should face challenges in these scientific areas and implement new solutions for Smart Farming purposes.

The biggest challenge for researchers will be to combine all the involved technologies and implement a complex infrastructure to support every task of modern cultivation. Although such an approach is optimistic for now, there are already few research works that are trying to promote it. For example, the projects PANtHEOn [157] suggests co-operation between UAVs and UGVs in order to perform complex tasks in the field, while Cloud Computing supports them.

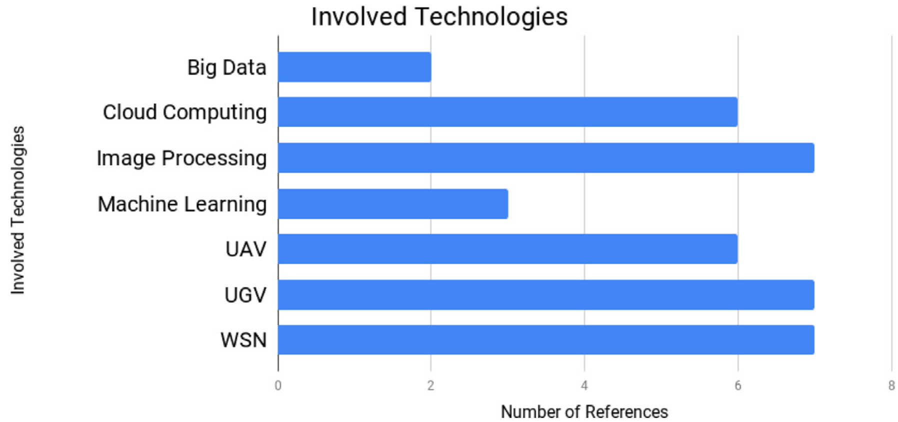

Fig. 14. Statistical analysis of European Projects for involved technologies used based on Table 8.

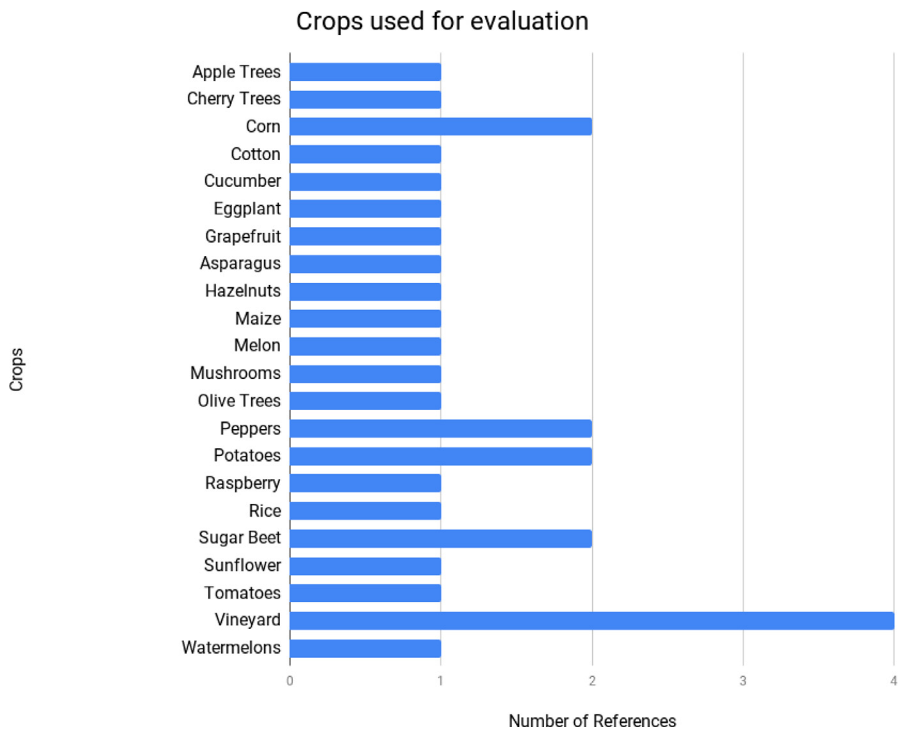

Fig. 15. Statistical analysis of European Projects for crops used for evaluation based on Table 8.

In the near future, an expected optimistic scenario would be the co-operation of a swarm of UAVs with a swarm of UGVs, while deployed sensors in the field are collecting various information like temperature and soil humidity and this information is aggregated through a WSN to a Cloud Computing infrastructure. The collected data from sensors, UAVs, and UGVs, should be processed based on Big Data techniques. Especially for image data acquired from UAVs and UGVs, real-time Image Processing, and Machine Learning techniques running in Cloud Computing are required, as the results and decisions should be returned with low latency back to the field.

7. Conclusion

Smart Farming is aiming to be the new revolution in the agriculture domain and bring significant changes in how agriculturists and agronomists work on the field. The use of innovative methods and the involvement of ICT technologies like Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), Image Processing, Machine Learning, Big Data, Cloud Computing, and Wireless Sensor Networks (WSNs) will impact positively in the sustainability and efficiency of the agriculture by increasing the productivity and reducing the need of inputs in the field, like nutritious and pesticides. In addition, the intensive use of automated mechanisms will lessen the labor effort needed and relieve farmers from many ordinary tasks.

Europe is aiming to become a leader in this upcoming era in the agriculture domain, spending a lot of effort and investments in this direction. Many research projects have been funded under the European Union in the agriculture domain, and many researchers from Europe have a significant contribution in this sector. Such evolution is substantial for the sustainability of the agriculture domain in European countries to protect them against the globalization of trade and economy.

Due to the multiple technologies involved in Smart Farming, scientists from different scientific areas should cooperate to boost the progression of innovative methods in the agriculture domain. To support their work, we presented the state-of-the-art research efforts in Smart Farming tested and evaluated in fields around the

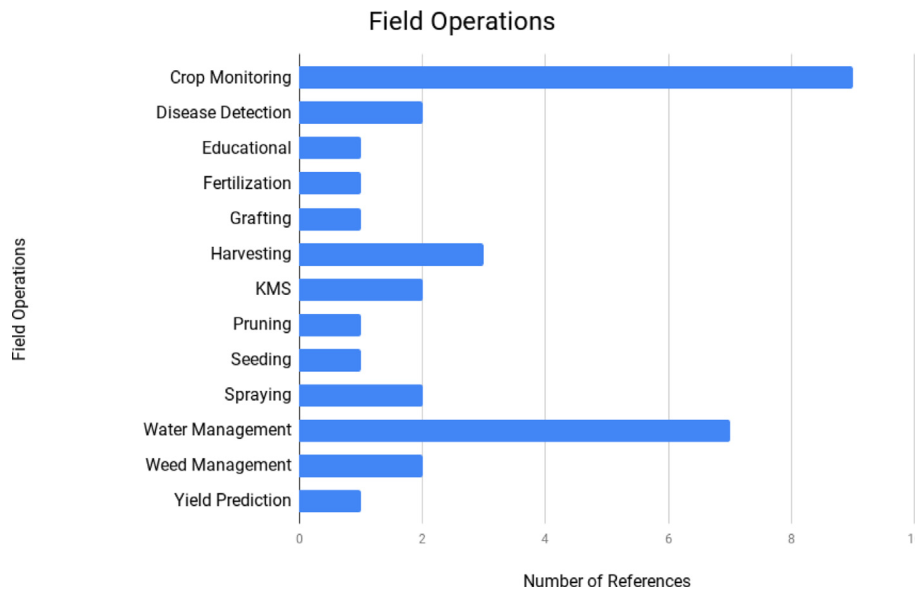

Fig. 16. Statistical analysis of European Projects for operations in the field based on Table 8.

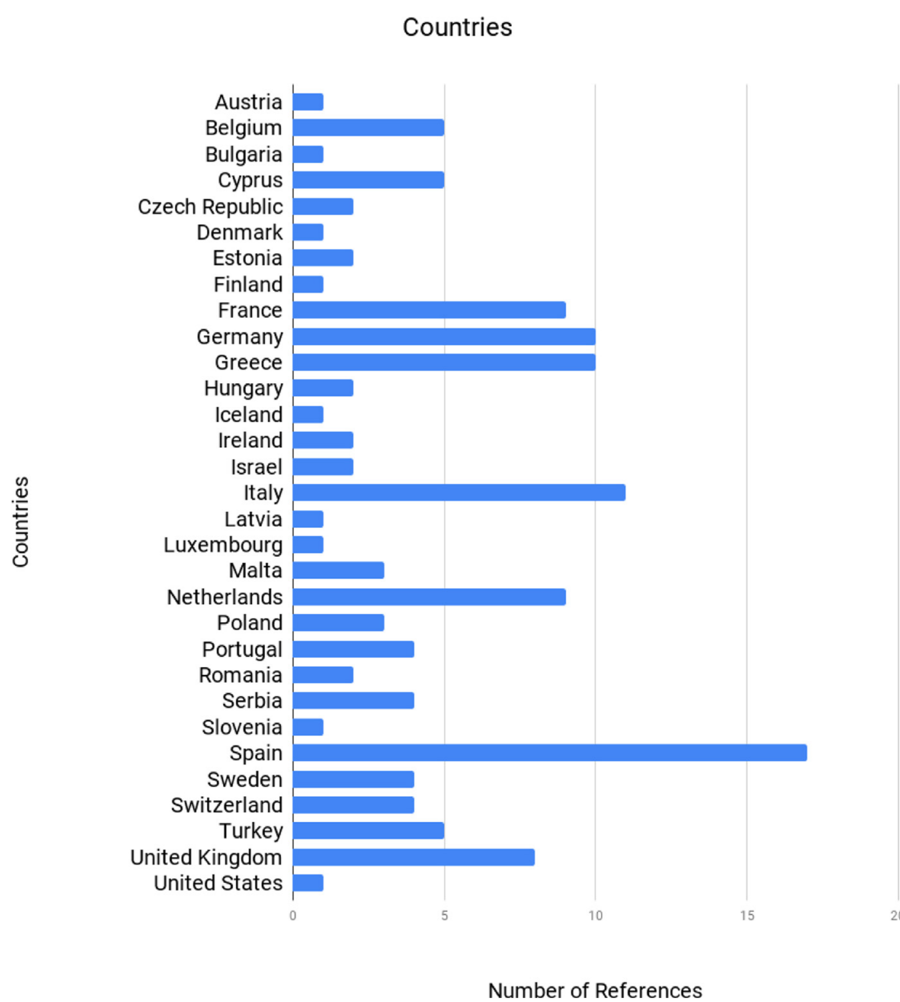

Fig. 17. Statistical analysis of European Projects for countries where evaluation process took place based on Table 8.

European region. We have discussed them and give information on the involved ICT technologies and their impact on the field. In addition, we tried to summarize the most significant projects funded in Europe and give information about the involved ICT technologies, the kind of crop they tested in and evaluated, and the operations advancing on the field.

It is apparent that with the advent of Smart Farming, a lot of things will be changed in the agriculture section, such as how farmers are working on the field, as well as the expected quality and quantity of production. Smart Farming will retain the sustainability of agriculture and will continue to support the livelihood of human species. It is expected that UAVs and UGVs will become integral equipment in the field along with the traditional heavy machinery. In addition, services from ICT like Big Data, Cloud Computing, Image Processing, Machine Learning, and wireless communication will be integrated into the whole infrastructure, supporting the decision making of agronomists and agriculturists.

Complex solutions combining two or more of the above ICT technologies, such as the cooperation between UAVs and UGVs are also a common issue and will boost the sustainability of agriculture even more. In addition, integrated solutions that combine crops, livestock farming, and forestry, along with weather predictions, are promising to reduce the overall cost production and reduce Greenhouse Gas (GHG) emission.

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.

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