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Smart Farming Becomes Even Smarter With Deep Learning–A Bibliographical Analysis

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ABSTRACT Smart farming is a new concept that makes agriculture more efficient and effective by using advanced information technologies. The latest advancements in connectivity, automation, and artificial intelligence enable farmers better to monitor all procedures and apply precise treatments determined by machines with superhuman accuracy. Farmers, data scientists and, engineers continue to work on techniques that allow optimizing the human labor required in farming. With valuable information resources improving day by day, smart farming turns into a learning system and becomes even smarter. Deep learning is a type of machine learning method, using artificial neural network principles. The main feature by which deep learning networks are distinguished from neural networks is their depth and that feature makes them capable of discovering latent structures within unlabeled, unstructured data. Deep learning networks that do not need human intervention while performing automatic feature extraction have a significant advantage over previous algorithms. The focus of this study is to explore the advantages of using deep learning in agricultural applications. This bibliography reviews the potential of using deep learning techniques in agricultural industries. The bibliography contains 120 papers from the database of the Science Citation Index on the subject that were published between 2016 and 2019. These studies have been retrieved from 39 scientific journals. The papers are classified into the following categories as disease detection, plant classification, land cover identification, precision livestock farming, pest recognition, object recognition, smart irrigation, phenotyping, and weed detection.

INDEX TERMS Machine learning, internet of things, precision agriculture, artificial neural networks.

I. INTRODUCTION

Making agricultural activities more economically efficient has always been one of the main objectives throughout human agrarian history. However, this objective has not been achieved to the desired level due to the difficulty in establishing quality/cost balance. To get quality products, agricultural production areas need to be visited frequently, thus, it may be possible to affect all necessary precautions during crop production. As farmers spend time and resources on each visit, they increase the cost of the crop. Smart agriculture has become necessary, given that farmers spend much of their time monitoring and evaluating their crops. ''Internet of things'' (IoT)-based technologies offer remote and precise monitoring, making managing crops not only smart but also cost-effective [1].

However, real-time monitoring of agricultural activities is not enough to make agriculture smart. Smart agriculture should follow the cycle of observation, diagnosis, decision, and action. In this continuously repeating cycle, data should be collected and used quickly to make changes that optimize the farming process. During the observation phase, data can be obtained and recorded using sensors capturing features from natural resources like crops, livestock, atmosphere, soils, water, and biodiversity. During the diagnostic phase, the sensor values are transmitted to a cloud-hosted IoT platform based on predefined decision models that determine the state of the object under investigation. During the decision phase, the components based on machine learning techniques determine whether an action is required. During the action phase, the end-user evaluates the situation and applies the action. Then the cycle starts all over again [2].

In this century, it is not enough to have a passion for agriculture to be a farmer. Farmers need expert knowledge in agriculture, law, economics, accounting, and data analysis to achieve sustainable agriculture [3]. Since in some regions the majority of agricultural enterprises consist of family farms, an expectation of high levels of expertise is not realistic [4].

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In the 20th century, in most regions, growers continued to follow established farming methods, using more fertilizers and pesticides, causing irreversible effects on the environment [1]. With consciousness-raising, it became known that every plant should be treated by determining the need of plant, instead of dealing with every farm and crop in the same way. In recent years, farmers have increasingly sought the advice of experts, which is not always affordable. With the intelligent agricultural system consisting of IoT and machine learning techniques, it is possible for farmers to get such advice at an affordable price. These systems use the most advanced methods to automate crop monitoring and thus require minimum human intervention [4].

II. DEEP LEARNING

In the early days of artificial intelligence, it was discovered that mentally challenging problems for humans were simple for computers as long as they could be described as a list of mathematical and logical rules. As the field of artificial intelligence expands and evolves, to benefit from the experience, to recognize sound and image, and to make intuitive decisions became the focuses of research [5, p. 1]. Machine learning, which is a sub-branch of artificial intelligence, uses a self-learning approach to derive meaning from presented data. Instead of manually creating rules by analyzing large amounts of data, machine learning gradually improves prediction performance by capturing information in the data. This approach provides a more effective solution that can make evidence-based decisions [6, p. 2]. Machine learning, to extract meaningful relationships from data, uses learning rules such as supervised learning, unsupervised learning, reinforced learning, and hybrid learning [7].

Deep learning is a type of machine learning that uses artificial neural network principles. Deep networks are distinguished from neural networks by their depth. Before the big-data age, most machine learning techniques have been used in shallow architecture. These architectures generally consist of up to one or two layers containing nonlinear transformations. Shallow architectures are effective in solving well-structured problems, but they are inadequate for more complex real-world data applications such as images, human speech, natural voice, and language. With deep learning, it became possible to process these data [8, p. 205].

Single-layer artificial neural networks, which have been used as shallow architecture since the 1940s, lack the ability to process such data. Deeper architectures were needed to process more complex data. After the successful training of complex neural networks in the 1980s, it became possible to use neural networks effectively. This paved the way for designing more complex and deeper architectures. Since the application of neural networks has increased, it has gone through many changes. Currently, neural networks that use deep learning are of great interest [9, p. 165].

As its name suggests, artificial neural networks are computational networks that imitate the networks of nerve cells in the central nervous system [10, p. 1]. Simple processing units

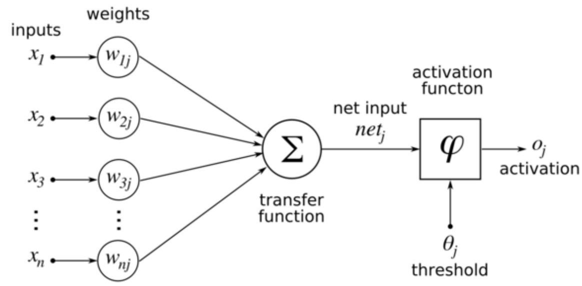

FIGURE 1. A schematic representation of an artificial neuron [81].

called artificial neurons, which communicate with each other, form an artificial neural network [11, p. 15]. The artificial neuron, after receiving binary or floating-point input from one or more sources, multiplies and aggregates with weights. The resulting total is transferred to the activation function to be transmitted to the output. Figure 1 shows a schematic representation of an artificial neuron [9, p. 31].

The data obtained from the output layer of one artificial unit can feed the input layer of the other artificial unit. The inputs are represented like $x_1, x_2, x_3, \ldots x_n$ as mathematical expressions [12]. The weights show how strongly the incoming data are transmitted to the output via the inputs. The mathematical expression of weights is shown as $w_1, w_2, w_3, \ldots w_n$ [13, p. 8]. The sum function produces net input by correlating each input value with the weights. The most commonly used addition function is the sum of each incoming input multiplied by its own weight. The mathematical form of the addition function is defined as [14]:

$$NetInput = \sum w_i x_i = w_1 x_1 + w_2 x_2 + \ldots + w_i x_i \tag{1}$$

The activation function sets limits for the output of the artificial nerve unit. Linear, threshold, sigmoid, hyperbolic, tangent, and softmax functions are the most commonly used activation functions. The selection of the activation function affects the data transmitted to the output [9, p. 48].

In feed-forward networks, the output is a value determined by the activation function, sent to another cell or outside world. In feedback networks, feedback is made by transmitting the output value to the input at the same time [12].

Assuming that in the learning process of the neural network, the desired output of the network is y and the network produces output ŷ, the difference between the predicted output and the desired output is ŷ-y. The difference value is converted to a metric known as the loss function (J) [15]. When the neural network makes too many errors, the loss is high, and when it makes fewer errors, it becomes low. The purpose of the training process is to determine the weight that minimizes the loss function in the training set [15]. During the training process, having a sufficient amount of data is important for the success of the network. With the development of the Internet, it has become easy to provide the amount of data required for training artificial neural networks. Large amounts of data provide an opportunity of developing many approaches to improve the learning performance of artificial neural networks. One of these approaches is the deep learning approach. An artificial neural network with more than one hidden layer is defined as a deep network and the learning style it exhibits is called deep learning [8, p. 206].

However, experimental studies have shown that it is more difficult to train deep architectures than shallow architectures. For example, as the architecture deepens the "local minimum" or "vanishing gradient" problem becomes more evident. Besides, as the architecture deepens, the training period takes more time. To overcome such problems in deep architectures, new solutions have been proposed in the literature [16, p. 34].

A rectified linear unit (ReLU) that produces particularly useful experimental results despite its simple structure became widely adopted with deep learning. The ReLU activation function is defined as $f(x) = \max(0, x)$. It gives zero for negative values and increases linearly for positive values [17, p. 68]. This activation function brings the predictions closer to the desired output more quickly. ReLU the activation function is considered an advantageous function in deep networks because it is relatively easy to calculate and does not suffer from the vanishing gradient problem due to its shape [15]. However, the ReLU activation function also has some disadvantages, later leaky ReLU, softplus, PReLU, ELU, swish activation functions were developed to overcome these disadvantages.

In deep networks to reduce training time and not to be trapped in a local minimum, several optimization techniques were developed [5]. Commonly used optimization algorithms in deep learning are the gradient descent algorithm and its faster version the gradient descent algorithm with momentum. Efforts to improve these algorithms led to the development of algorithms such as Nesterov accelerated gradient, Adadelta, AdaMax, Adam, Nadam, Adagrad, AMSGrad, RMSprop [18].

The challenges mentioned above are just a part of the work that should be done when deeper networks are used. Model selection is always a major challenge in deep networks because the model should be selected in such a way that it fits sufficiently. Inadequate compliance or overfitting of the model's data structure significantly influences predictions. To prevent problems such as inadequate learning and overfitting of the network, a trade-off between bias and variance is required [19, p. 102]. To solve the problem of over-fitting, more data can be collected to change the model. If data collection is not possible, the existing training set can be enhanced by data augmentation techniques [20]. In addition to data enhancement, terminating training early also solves overfitting problems. By looking at the performance of the validation set, the training should be stopped as soon as a decline occurs. To reduce the overfitting of the network it is also possible to apply regulation or dropout methods [21, p. 25].

III. METHOD

The bibliographic analysis in the domain based on databases of the Science Citation Index (SCI) included full-text papers published in peer-reviewed journals. A keyword-based search for these papers was done by using search terms, "deep learning", and "agriculture or farming". Through that query, 133 papers were obtained. Articles containing keywords "deep learning" but not related to the agricultural area have been eliminated. As a result of this search, 133 articles were identified, initially. Some articles were excluded due to the lack of meaningful findings and the initial number of papers was reduced to 130. Then review papers were excluded from the scope of the study, and the final number of papers was 120.

After collection of related work, a detailed review, and analysis of this work were undertaken. Considering the following research questions, the 120 papers selected were analyzed individually:

Q1: What are the topics, where deep learning is implemented in the agriculture domain?

Q2: What are the problems they addressed?

Q3: What approaches were employed to solve the problems?

Q4: What are sources of data used?

Q5: What is the benefit of deep learning relative to other solutions?

IV. RESULTS

In the Appendices, a list of the 120 reviewed works is given, indicating the research domain, problem the research address, proposed methods for the solution, and sources of data used. The summary tables obtained from analyzes are given in Appendix A.

The highest number of deep-learning-based agriculture-relevant papers on the database of the SCI appeared in 2019 (76) and there were no papers before 2016. The time trend analysis given in Table 1, displays the eight most productive countries. With its rapidly growing publications in 2019, China was a leader throughout the period. Similarly, the growth rate of publications in the USA was much faster than the other six predominant countries. As shown in Table 1, the distribution of the topics focused in all countries is almost equal, expect papers by Chinese authors that concentrate on topics such as disease detection (6), land cover identification (6), object recognition (6), pest recognition (5), plant classification (4), and precision livestock farming (8). As shown in Table 2, those topics appear to be the most common topics. Therefore, it seems that China determines the trend of deep-learning-based agriculturally-relevant studies.

The full list of those topics obtained from the analysis of 120 articles for the deep-learning-based agriculture domain is given in Table 2. Disease detection and plant classification are the most common topics, with 19 records, followed by land cover identification with 18 records, and precision livestock farming with 13 records.

Table 3 was created to obtain information about the number of authors per article. Of the 120 papers, 48 (40%) were written by teams consisting of up to three authors whereas the remaining 72 (60%) were written by teams consisting of four or more authors. Algorithms created for deep learning study are complex and obtaining suitable data is also a laborious process, so it is natural that articles were written with the contribution of large teams. One hundred and thirteen papers (94%) were written by teams consisting of up to six authors. Notably, four articles of the remaining seven are written by Chinese authors. Especially the article written with a team of 14 authors is noteworthy.

A total of 39 journals published papers in this area during 2016-2019. The distribution of the 120 papers across these journals is given in Table 4 and shows that more than 63% of the deep-learning-based agriculture-relevant articles appear in the three journals.

Computers and Electronics in Agriculture is the journal with the most relevant articles (55), followed by *Sensors* with 11 articles, and *Remote sensing* with 10 articles. Deep learning appears to still be a slow-developing topic in some important journals in agriculture, such as *Plant Methods and Journal of the Science of Food and Agriculture*, which published only two relevant articles each. There are some other journals (not listed in Table 3) that published articles in a related domain. Those were *Oriental Insects, Journal of Arid Land, Genetics Selection Evolution, International Journal of Agricultural and Biological Engineering, Acta Agriculture Scandinavica, American Dairy Science Association, Acta Microscopica, Animals, Journal of Dairy Science, Field Crops Research, The Plant Journal,* and *Precision Agriculture.*

The distribution of 662 of keywords used in 120 articles is shown in Table 5. "Deep learning" is the most common keyword, with 68 uses, followed by "convolutional neural network" with 51 uses and "image processing" with 23 uses. The remainder of the list contains keywords related to area of use, such as "disease detection", "crop classification", "pest detection", "weed detection", "fruit detection", "unmanned aerial vehicle", "yield estimation", and "smart agriculture".

Since the majority of articles shown in Table 5 were published in journals with computer science perspective, there are also keywords related to techniques, such as "computer vision", "deep neural network", "machine learning", "transfer learning", "hyperspectral imaging", and "artificial intelligence".

Detailed information about how deep learning was applied to the most common domains is given in subtopics below, as well as in Appendix B.

A. DISEASE DETECTION

Plant diseases are among the important production losses in agriculture. It is critical to monitor the condition of the products and to control the spread of diseases. The prevention methods of plant diseases as well as disease diagnosis methods differ from plant to plant. The plant-specific disease detection methods are reported in the literature. Lu *et al*. [22] proposed a wheat disease diagnosis method that functions automatically in fields. Fuentes *et al.* [23] proposed a deep-learning-based detector for recognition diseases and pests in tomato plants. Kerkech *et al.* [24] proposed deep leaning approaches for vine diseases detection using vegetation indices and colorimetric spaces, applied to images collected by UAV. Hu *et al*. [25] proposed a low shot learning method for disease identification in tea leaves. Coulibaly *et al.* [26] proposed an approach for the identification of mildew disease in pearl millet, which is using transfer learning with feature extraction. Cruz *et al.* [27] proposed an artificial intelligence-based approach for detecting grapevine yellows symptoms. Deep convolutional neural network-based approach for crop disease classification on wheat images proposed by Picon *et al*. [28]. It was validated under real field conditions by deploying on a smartphone. These and other studies focusing on disease detection are given in Appendix B have made useful contributions to the prevention of plant diseases.

B. PLANT CLASSIFICATION

Harvesting is laborious and time-consuming task in fruit production, with harvesting mostly done manually, so new developments are directed towards automated harvesting robots. Since automation techniques cannot be generalized across crops, researchers focused on developing crop-specific systems. Grinblat *et al.* [29] proposed plant identification based on vein morphology. Rahnemoonfar and Sheppard [30] proposed automatic yield estimation based on robotic agriculture for tomato plants.

Veeramani *et al.* [31] and Altuntaş *et al* [32] applied deep convolutional networks (CNN) for sorting haploid maize seeds. Knoll *et al*. [33] proposed a self-learning CNN, to distinguish individual classes of plants using the visual sensor data in real-time. Häni *et al.* [34], Tian *et al.* [35], Gené-Mola *et al.* [36], and Kang and Chen [37] proposed detection and counting methods for apples in orchards. Yu *et al*. [38] proposed fruit detection for a strawberry harvesting robot. Koirala *et al.* [39] compared the performance of six deep learning architectures. Detection of mango fruit has been achieved using images of tree canopies [39]. Arad *et al.* [40] present the case study of robotic harvesting for sweet pepper. Further studies on plant classification are given in Appendix B.

C. LAND COVER IDENTIFICATION

Land cover and crop type maps have emerged as an area where deep learning could be used efficiently. Multi-source satellite images are often used to capture specific plant growth stages. Several studies used deep learning for land productivity assessment and land cover classification. Kussul *et al.* [41] present a workflow for developing sustainable goals indicators assessment using high-resolution satellite data. Persello *et al.* [42] combined a full CNN with globalization and grouping to detect field boundaries. Zhou *et al.* [43] presented a deep learning-based classifier that learns time-series features of crops and classifies parcels of land. Using these parcels, a final classification map was produced. Zhao *et al.* [44] proposed a method for rice mapping which combined a decision tree method and a CNN model.

Satellite data is not the only source of data for land cover classification. With development IoT-based technologies, unmanned aerial vehicles (UAV) have become an effective tool for crop monitoring. Yang *et al.* [45] present a deep CNN for rice grain yield estimation. This method using remotely sensed images collected by UAV is able to make estimations at the ripening stage. Dyson *et al.* [46] integrated a radiometric index with terrain height images for segmenting crops and trees over the soil. High-resolution images collected by UAVs were used in the study. Nevavuori *et al.* [47] applied CNNs to crop yield prediction using RGB and NDVI data collected by UAVs. More studies on land cover identification are given in Appendix B.

D. PRECISION LIVESTOCK FARMING

As a part of precision farming, managing the livestock is also one of the current challenges for agriculture and is considered as a special topic, precision livestock farming techniques. These techniques include monitoring of animal health indicators, such as the comfort of animal, pose estimation, and behavior detection, as well as other production indicators. Gorczyca *et al.* [48] used machine-learning algorithms for predicting skin, core, and hair-coat temperatures of piglets. Kvam and Kongsro [49] proposed a method for estimating the IMF on ultrasound images. A noninvasive *in vivo* method, constructed using deep CNNs, by (Huang *et al.* [50] and Yukun *et al.* [51] provided a low-cost method based on machine vision and deep learning for evaluation of body condition scores. Zhang *et al.* [52] proposed a real-time sow behavior detection algorithm based on deep learning. Li *et al*. [53] proposed deep cascaded convolutional models for estimating cattle pose. A full list of studies focused on precision livestock farming is given in Appendix B.

E. OBJECT RECOGNITION

Providing automation of processes in precision farming, the detection of anomalies that may occur in the system is a specific area of study. Anomaly detection can be defined as detecting unexpected items or unusual behavior in data sets, which differ from the normal situation. According to the notions in the field of agriculture, elements that are not natural for the environment are known as anomalies. An algorithm combining anomaly detection and deep learning proposed by Christiansen *et al.* [54] performed anomaly detection with the exploitation of the homogenous characteristics of a field. Ma *et al*. [55] proposed an unsupervised deep hyperspectral anomaly detector. Rong *et al.* [56] proposed two different CNN structures for automatic segmentation and detection of foreign objects of different sizes that can be either natural or man-made. The proposed structures were applied to walnut images. Rasmussen and Moeslund [57] trained CNN models for kernel fragment recognition in RGB images of silage.

Intelligent management and the automation of agricultural machinery is now a realistic option, with an increase in the level of agricultural mechanization. However, agricultural machinery recognition differs from plant recognition in the data acquisition methods used. For capturing agricultural machinery images vehicle terminal camera is used, so the images need preprocessing. Zhang *et al.* [58] designed and trained AMTNet network to automatically recognize agricultural machinery images that produced acceptable results.

F. PEST RECOGNITION

Although some insects are economically beneficial, some species can severely damage to agricultural production and products. These destructive insects, known as agricultural pests, need to be correctly identified and treated according to their species to minimize the damage they cause. Pest recognition is not just objected recognition; it is a more complex task that should be treated in a special way. Cheng *et al.* [59] performed pest identification via deep residual learning in a complex background. Ding and Taylor [60] and Zhu *et al.* [61] used deep learning techniques for the classification of moth images. Shen *et al.* [62] applied a deep neural network for the detection and identification of stored-grain insects. Partel *et al*. [63] utilized artificial intelligence to develop an automated vision-based system that can be used for monitoring pests, such as the Asian citrus psyllid. Thenmozhi and Reddy [64] and Dawei *et al*. [65] proposed techniques for the recognition of pests by image-based transfer learning. Li *et al*. [66] proposed an effective data augmentation strategy for CNN-based pest recognition and localization in the field.

G. SMART IRRIGATION

Due to the continuing decline of water resources available to the world, efficient use of water is an important concern for all countries. Many studies have been conducted to efficiently manage the irrigation process in agriculture and this has become a specific research area known as smart irrigation. For efficient management of the irrigation process, it is important to detect the water status of plants. AlZu'bi *et al.* [67] proposed image processing concepts, where IoT sensors work with machine learning methods to make smart irrigation decisions. Song *et al.* [68] proposed a novel model combining deep belief network with macroscopic cellular automata (MCA) approach to predict the soil moisture content over an irrigated cornfield. Sirsat *et al.* [69] used almost all available regression methods to predict four key soil nutrients and fertility indices for soil organic carbon. Zambrano *et al.* [70] predicted the reduction of drought-related agricultural productivity in Chile using rainfall estimates, and climate oscillation indices.

H. PHENOTYPING

Phenotype is a set of observable features that result from the interaction of an individual genotype with the environment.

Plant phenotyping, which can be defined as the identification and quantification of effects on the phenotype, is laborious and time-consuming because it is typically a manual task. Therefore, phenotyping of large populations in plant breeding programs have high costs. An automation of phenotyping tasks can bring great benefit to plant improvement. Uzal *et al.* [71] proposed a deep-learning-based computer vision method that estimates the number of seeds into soybean pods. Ampatzidis *et al.* [72] used small UAVs equipped with sensors for the rapid acquisition of phenotypic data. This method simplified the surveying procedure, decreased data collection time, and reduced the cost of phenotyping. Yang *et al.* [73] used deep CNNs and leaf images for the identification of the three *Cinnamomum* species. Milella *et al.* [74] proposed methods for automated grapevine phenotyping. Feng *et al.* [75] combined machine learning with hyperspectral imaging to develop a tool for salt-stress phenotyping.

I. WEED DETECTION

Weeds are undesirable plants that grow in agricultural crops and cause yield losses because they compete for the resources needed by the crop. Smartweed detection makes it possible to apply herbicide treatments specifically to detected weeds. Santos Ferreira *et al.* [76] used CNN to perform weed detection in soybean crop images and classify them as grass and broadleaf weeds. Moshia and Newete [77] proposed a deep learning neural network, for automatic identification of weeds from the main crop using row-guided robots. Bah *et al.* [78] proposed a learning method using CNN for weed detection from images collected by UAV that automatically performed unsupervised training dataset collection. Kounalakis *et al.* [79] combined classifier for weed recognition with transfer learning techniques for deep learning-based feature extraction. Partel *et al.* [80] designed and developed a smart sprayer using machine vision and artificial intelligence. This smart sprayer distinguishes target weeds from crop and precisely sprays the targeted weed.

V. DISCUSSION

In agriculture manual activities, such as yield monitoring, fruit counting, phenotyping, pest recognition and disease detection, are slow, labor-intensive, expensive, and error-prone, reducing real-time performance and increasing costs [60]. Considerable work has been done on automating these activities in recent years. This review of the relevant articles highlights that success has been achieved in many studies, especially with the use of deep learning approaches. When applying deep learning the user does not need to be an expert at detecting disease or having other specific knowledge [27]. The system does not need preprocessing of images, so this makes it more advantageous than the current standard techniques.

As a result of analyzing 120 articles, the topics of the studies were observed to change over time. Earlier studies compared manual, current methods, and deep learning techniques. The result of these studies showed that by applying deep learning approaches it is possible to obtain high order features or more accurate results [29], [30], [59], [76], [82]–[87]. However, there are some studies showing that the current methods are better than deep learning or give the same result, concluding that there is no value in applying complex structures [23], [31], [88], [90], [91]. Sometimes simple models that are formulated by carefully selecting the best estimators and then by examining a specific situation they give better results than complex models [70]. However, it is not always possible to have the necessary knowledge to examine specific situations. In these cases, the generalizing ability of deep learning architecture provides an advantage. Also, for the data that is too small to capture, the associated characteristics and variations, deep learning approaches are not meaningful [90].

It should be also noted that the data collection process, which is the basic condition for success in deep learning models, can also be time-consuming and laborious. As a technology that aims to address this issue, UAV-aided IoT networks have enormous potential in agriculture practices [24], [45]–[47], [78], [110], [128]. This approach reduces the technical workforce, is more cost-effective and consistent than the manual methods based on the expertise of existing staff [72]. Given that high maneuverability, high mobility, and low maintenance cost, UAVs were used in studies related to almost all topics. In addition to being an effective tool, UAVs can contribute to the change from current practices

TABLE 1. The most productive countries during 2016 – 2019.

Country	2016	2017	2018	2019	Total	%
China	2	3	5	30	40	33
USA		2	3	9	14	12
Spain			2	4	6	5
France			3	2	5	4
Australia			2	3	5	4
Turkey			1	4	5	4
Denmark	1	1		3	5	4
Italy			1	4	5	4
Others	2	6	10	17	35	29
Total	**5**	**12**	**27**	**76**	**120**	**100**

TABLE 2. The most productive subjects during 2016 - 2019.

Domain	Number Of Papers	%
Disease detection	19	16
Plant classification	19	16
Land cover identification	18	15
Precision livestock farming	13	11
Object recognition	12	10
Pest recognition	9	8
Smart irrigation	7	6
Phenotyping	7	6
Weed detection	5	4
Other	11	9
Total	**120**	**100**

TABLE 3. Number of authors per article for the most productive countries.

	Number of authors per article											
Country	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**14**	**Total**
China		3	6	7	10	10		1	1	1	1	40
USA	1	2	5	3	3							14
Spain		1		3	2							6
France			3	1				1				5
Australia	1	1	1	1	1							5
Turkey		2	1		1	1						5
Denmark		1	1	2					1			5
Italy			1	2	2							5
Others	3	10	5	7	8	1	1	0	0	0	0	35
Total	**5**	**20**	**23**	**26**	**27**	**12**	**1**	**2**	**2**	**1**	**1**	**120**
Cumulative Percentage	**4%**	**21%**	**40%**	**62%**	**84%**	**94%**	**95%**	**97%**	**98%**	**99%**	**100%**	

TABLE 4. The most productive journals during 2016 - 2019.

Journals	**Nunber Of Papers**	**%**
Computers and Electronics in Agriculture	55	46
Sensors	11	9
Remote Sensing	10	8
Remote Sensing of Environment	3	3
Symmetry	3	3
IEEE Access	3	3
GIScience & Remote Sensing	2	2
Soft Computing	2	2
BMC Bioinformatics	2	2
Plant Methods	2	2
IEEE Geoscience and Remote Sensing Letters	2	2
Computers in Industry	2	2
J Sci Food Agric	2	2
Others	21	18
Total	**120**	**100**

TABLE 5. The 20 most popular keywords in 120 articles.

Keywords	**Number of Usage**	**%**
Deep learning	68	10
Convolutional neural network	51	8
Image processing	23	3
Disease detection	20	3
Precision agriculture	19	3
Computer vision	17	3
Deep neural network	14	2
Machine learning	11	2
Agriculture	10	2
Crop classification	9	1
UAV (unmanned aerial vehicle)	8	1
Pest detection	8	1
Transfer learning	8	1
Hyperspectral imaging	8	1
Weed detection	7	1
Fruit detection	7	1
Yield estimation	6	1
Object detection	6	1
Smart agriculture	4	1
Artificial intelligence	4	1
Others	354	53
Total	**662**	**100**

to practices that protect the environment. Standard broadcast sprayers integrated with UAVs, treating the entire area, resulting in unnecessary application to areas that do not require treatment. With the AI-based UAVs, a fast and precise treatment can be applied to specific areas, which can significantly reduce the amount of agrochemicals used [80]. Therefore, UAV-aided studies were not analyzed as an independent topic, and UAV can be considered as an integral part of smart farming.

Although UAVs are a key technological advance, they have some difficulties in their use in agriculture. Given their high power consumption during their flight, the flight time of UAV is quite limited [84]. It is known that it takes much longer than the normal flight time to train a deep neural network system even on a very fast central processing unit. Therefore, UAVs have to be equipped with a graphics processing unit to speed up training, which brings extra costs [77].

This kind of tradeoff between accuracy and computational cost could be addressed in technologies supporting AI in agriculture. So when there are some limitations and speed constraints, the more important metrics should be taken into account and compared to help to choose the right method [79]. However, there are studies that improve the accuracy of detection and speed of processing to make these suitable for real-time applications [50], [52], [103].

Employment of Big Data for smart agriculture is a completely new concept [114]. Although Big Data applications in smart agriculture are not that common, they are meant for cloud computing and IoT-based smart agriculture application [67]. Systems that support reasoning from real-time sensor data have the potential to deliver digital data sources for online services, operations, farmers, and processes by integrating a large number of data sources [131]. Having the opportunity of direct access to infrastructures that support advanced data discovery and image processing services, researchers, farmers, or companies involved in smart farming could obtain value from these data.

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
1	"DeepAnomaly: combining background Subtraction and deep learning for detecting obstacles and anomalies in an agricultural field"	Anomaly detection	DeepAnomaly is an algorithm that combines anomaly detection and deep learning to make the homogenous characteristics of a field and to perform anomaly detection	Sensor data	DeepAnomaly can detect humans at ranges between 45–90 m, which makes it more effective than Region-based convolutional neural networks (RCNN). It has faster processing time per image and needs a small computational cost.	[54]
2	"Automatic moth detection from trap images for pest management"	Pest management	An automatic deep learning based detection applied for identifying and counting pests in images collected by placing field traps	Commercial codling moth dataset	Compared to other techniques applied for pest detection, this approach needs minimal human effort and no pest-specific engineering knowledge.	[60]
3	"Hybrid deep learning for automated lepidopteran insect image classification"	Recognition of lepidopteran (butterfly) species correctly	An architecture combines Supported Vector Machines (SVMs) with deep convolutional neural network (DCNNs) to identify Lepidoptera species from their images.	A data-set of 1301 Lepidoptera images from 22 species.	Achieves an accuracy of 100% and it takes only about 200 ms to recognize insect species from an image. Outperforms LLC and CART method, as well as Local mean color feature-based method.	[61]
4	"Deep learning for plant identification using vein morphological patterns"	Plant identification using vein morphology	A deep convolutional network was used to develop a task-specific module.	White bean, red bean and soybean leaves dataset	A feature extractor that learns relevant features automatically provides the elimination of manual search. The study shows that the depth of the model make a positive effect on the final accuracy.	[29]
5	"Modeling spatio-temporal distribution of soil moisture by deep learning-based cellular automata model"	Precise irrigation scheduling	A model using deep belief networks (DBN) for predicting the soil moisture content (SMC) was applied to an irrigated corn field	Data from 172 sensors	A multi-layer perceptron (MLP) was compared to DBN. Compared to the MLP-MCA model, the DBN-MCA model caused a reduction in RMSE by 18%.	[68]
6	"An in-field automatic wheat disease diagnosis system"	Implementing effective management with controlling the spread of diseases	An automatic diagnosis system for disease detection and localization for disease areas in wheat fields. A weakly-supervised deep learning framework was trained with only image-level annotation.	Wheat Disease Database	Using the same amount of parameters, the proposed system was compared to conventional CNN architectures. Two different deep learning architectures with the mean recognition accuracies of 97.95% and 95.12% respectively, outperformed two conventional CNN frameworks with the results of 93.27% and 73.00%.	[22]
7	"Automatic image-based plant disease severity estimation using deep learning"	Yield loss prediction and disease management	Deep convolutional neural networks for diagnosing the severity of the disease	An open access database of 50,000 images (PlantVillage)	The performances of deep models and shallow networks were evaluated. Trained with transfer learning, deep VGG16 was the best model, having an overall accuracy of 90.4%.	[83]
8	"A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition"	A fast and accurate detection of diseases and pests	A deep-learning architecture for diseases and pests recognition was developed. Diseases and pests detection was performed in tomato plants using various resolution camera images captured in-place.	Dataset contains images with several diseases and pests in tomato plants.	Comparisons were made using Region-based Fully Convolutional Networks (R-FCN), Faster R-CNN, and Single ShotMultibox Detector (SSD). The plain networks performed better than deeper networks, but with data augmentation, deeper networks showed a performance of more than 90%.	[23]
9	"Super-resolution of plant disease images for the acceleration of image-based phenotyping and vigor diagnosis in agriculture"	Disease classification and accelerate image-based phenotyping	CNN-based classification of the diseases applied on super-resolution, high-resolution, and low-resolution images	Plant Village dataset	The proposed method speeds up images capturing tasks in the tomato field. Furthermore, it secures the accuracy of these images for the following analysis. Making better spatial resolution enhancement of tomato disease images, the proposed method outperformed conventional image scaling methods.	[84]
10	"Deep learning classification of land cover and crop types using remote sensing data"	Better discrimination of certain summer crop types	A multilevel Deep Learning approach for land cover and crop types classification	Multitemporal multisource satellite imagery	In the study, a traditional fully connected MLP and random forest (RF) were compared with CNNs. Overall classification accuracies for MLP, RF, 1-D and 2-D CNNs were 92.7%, 88.7%, 93.5%, and 94.6%, respectively.	[85]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
11	"Estimation of the botanical composition of clover-grass leys from RGB images using data simulation and fully convolutional neural networks"	Automatic analyze images acquired from fields	A pixel-wise classification was performed using a fully convolutional neural network. The network was trained to classify weeds, clover, and grass, in RGB images of clover-grass mixtures.	Simulated top-down images of clover-grass fields	Manual annotation of real images for training task takes more than 3000 h, where the use of simulated images reduces the manual labor to a few hours. The network was tested on images with different amounts of clover and grass. An overall pixel classification accuracy achieved was 83.4%.	[86]
12	"Pest identification via deep residual learning in complex background"	To prevent damage caused by agricultural pests	Development of an agricultural pest identification system using deep residual learning	Pest image database	Traditional BP neural networks, SVM, and plain CNN were compared to the deep residual network. Classification accuracies for SVM, BP NN, and plain CNN were 44.0%, 42.67%, and 86.67%, respectively. The ResNet-101 model had an accuracy of 98.67%.	[59]
13	"Deep count: fruit counting based on deep simulated learning"	Estimation of tree, fruit, and flower numbers for improving decision making	Automatic yield estimation based on robotic agriculture a simulated deep convolutional neural network for yield estimation	Synthetic and real data	In the study area-based counting, shallow networks were compared to deep networks. Accuracies for area-based counting, shallow network and proposed method were 66.16%, 11.60% and 91.03%, respectively. The average time for one test image for manual counting is 6.5, for the area-based method is 0.05 and for the proposed method is 0.006 seconds.	[30]
14	"DeepSort: deep convolutional networks for sorting haploid maize seeds"	Discriminate diploids from haploids maize seeds	Application of a deep convolutional network (DeepSort) for the sorting of haploid seeds	Dataset consists of 4731 RGB images of corn seeds	DeepSort is compared to RF, SVM, Logistic Regression (LR) and test accuracies were 96.8%, 84.5%, 87.6%, 77.5%, respectively. Results show that the performance decreases the number of the layers decreases.	[31]
15	"In vivo prediction of intramuscular fat using ultrasound and deep learning"	Intramuscular fat (IMF) Prediction	A method for estimating IMF using deep convolutional neural networks on ultrasound images.	3037 animal images	In vivo ultrasound estimation of intramuscular fat based on deep learning compared to images from the real world or previous studies using ultrasound data. The method performs best on moderate to low IMF images <6% giving a correlation of R = 0.82.	[49]
16	"Heterogeneous sensor data fusion by deep multimodal encoding"	To improve inference and prediction	A multimodal data fusion framework, the deep multimodal encoder (DME), based on deep learning techniques for sensor data compression, missing data imputation, and new modality prediction under multimodal scenarios.	Real-world dataset collected from anagriculture sensor network	DME can detect intramodal correlations in initial layers, as well as the enhanced intermodal correlations in deeper layers. The non-linear transformations and the higher-order features increase robustness to missing data. DME is capable of filling missing data even with a 90% missing rate.	[87]
17	"Weed detection in soybean crops using ConvNets"	Weed detection in agricultural crops	Using Convolutional Neural Networks (ConvNets or CNNs) to perform weed detection in soybean crop images and classify these weeds among grass and broadleaf	4500 weed images	In the study ConvNets, Support Vector Machines, AdaBoost and Random Forests were compared. Precision values were 99.5%, 98.0%, 98.2%, 96.0%, respectively. Training time was 528.16, 0.78, 16.28, 2.33 seconds, respectively. Memory usage of the algorithms was 1715 MB, 329 MB, 283 MB, 623 MB.	[76]
18	"Optimized Wishart network for an efficient classification of multifrequency PolSAR data"	Disaster prediction in agriculture	Single-hidden layer OWN and extended OWN for classification of multi-frequency, and single frequency PolSAR data	PolSAR images	The proposed single-hidden layer network outperforms deep architecture involving multiple hidden layers because it takes polarization information of the PolSAR data into consideration, while deep learning-based architecture considers the PolSAR data like any general data.	[88]
19	"Deep leaning approach with colorimetric spaces and vegetation indices for vine diseases detection in UAV images"	Detection of symptoms in grape leaves	Method based on CNN and color information to detect symptoms in the vineyards	UAV system with RGB sensor were used for data acquisition	Using different color spaces and vegetation indices performances of CNNs were compared. The obtained results give the best accuracy of more than 95.8%.	[24]
20	"Deep learning models for plant disease detection and diagnosis"	Plant disease detection and diagnosis	CNN models were developed to perform plant disease detection and diagnosis using simple leaves images of diseased and healthy plants	An open database of 87,848 images, containing 25 plants	Several deep architectures were trained, with the best performance of 99.53% success rate in classifying diseased and healthy plants.	[89]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
21	"Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification"	Automatic recognition of plant diseases	The application of deep learning with a focus on CNNs	An image database composed of 12 plant species	A dataset that contains various image capture conditions, plant species, and diseases are not suitable for CNN, because it has a low number of samples in each class, which makes it difficult to capture the characteristics of each class.	[90]
22	"Approximate Bayesian neural networks in genomic prediction"	Genome-wide prediction	A tool for the detection of single nucleotide polymorphisms (SNPs).	Pig dataset comprising 3534 individuals	NNs of different complexities were combined to compare the shallow models to complex models and confirmed that the shallow model performs better than more complex models.	[91]
23	"Estimation of vegetation indices for high-throughput phenotyping of wheat using aerial imaging"	Estimate vegetation index (VI) from multispectral image	Deep neural networks based estimation of a vegetation index using RGB color images	A 3DR Solo drone was used with a custom platform	The proposed approach accurately estimates VI using deep neural networks at a low cost. The results show that RGB images contain information that is sufficient for VI estimation.	[92]
24	"An explainable deep machine vision framework for plant stress phenotyping"	Identification of abiotic and biotic stresses in crop	A machine learning framework for the identification and classification of foliar stresses in soybean	4,174 images for healthy leaves	The authors found a classification accuracy (94.13%) using a large dataset for the testing tasks. With no need for detailed symptom annotation by experts, a model can accurately identify and quantify foliar stresses.	[93]
25	"A two-branch CNN architecture for land cover classification of PAN and MS imagery"	Monitoring of the earth's surface at fine-scale	Direct deep learning based classification of images without preprocessing methods like image sharpening or resampling process	Reunion Dataset, Gard Dataset	The proposed method (MultiResoLCC) outperforms recent classification methods for optical Very High Spatial Resolution (VHSR) images.	[94]
26	"Targeted grassland monitoring at parcel level using sentinels, street-level images and field observations"	Improving accuracy in parcel level crop monitoring	Deep learning classification method for identification of grassland-declared parcels	BRP datasets of 770,000 parcels	In the study, parcels declared as grassland were valuated using Sentinel-1- and -2-derived (S1 and S2) markers. By combining S1 and S2, the best marker with a precision of 98% was obtained.	[95]
27	"DecoFungi: a web application for automatic characterisation of dye decolorisation in fungal strains"	Measurement of dye decolorisation applied to fungal strains	Deep-learning model applied to characterize dye decolorization level of fungal strains automatically	The dataset consists of 1204 images	DenseNet, Resnet 50, GoogleNet, OverFeat, VGG16, VGG19, Inception and Xception networks were used in the study. The 6 classifiers such as Extremely Randomised Trees, MLP, Nearest Neighbor Pattern Classification, LR, RF, and SVM were used. The best method with an accuracy of 96.5% is obtained when Resnet 50 is used as a network, and SVM is employed.	[96]
28	"Classification of high resolution hyperspectral remote sensing data using deep neural networks"	Analyzing hyperspectral remote sensing data	The DNN is combined with a stacked autoencoder and a softmax classifier.	Hyperspectral remote sensing data	DNN classifier is able to make accurate identification of different land covers such as natural forest, agricultural area, buildings, roads, etc.	[97]
29	"Apple flower detection using deep convolutional networks"	Estimate bloom intensity	A pre-trained convolutional neural network is improved for flower detection.	Dataset is composed of a total of 147 images	The proposed method (CNN+SVM) was compared to the three baseline methods such as HSV, HSV+SVM, and HSV+Bh. It outperforms these approaches precision rates higher than 90%. AUC-PR for HSV, HSV+Bh, HSV+ SVM, CNN+SVM are 54.9%, 61.6%, 92.9%, 97.7 %, respectively.	[98]
30	"An unsupervised deep hyperspectral anomaly detector"	Anomaly detection	DBN based anomaly detection	The dataset downloaded from NASA	The proposed method outperforms the Collaborative Representation detector, global Reed-Xiaoli detector, and the local RX detector.	[55]
31	"Large-scale oil palm tree detection from high-resolution satellite images using two-stage convolutional neural networks"	Remote sensing-based quantitative detection of oil palm trees	A two-stage convolutional neural network (TS-CNN) developed for oil palm detection using high-resolution satellite images	QuickBird satellite image	The proposed approach is compared with existing methods for oil palm detection. F1-scores for single-stage CNN, SVM, RF, Artificial Neural Network (ANN) and for proposed method are 87.95%, 81.80%, 80.61%, 78.35%, and 94.99%, respectively.	[99]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
32	"Detection of stored-grain insects using deep learning"	Detection of stored-grain insects	Application of deep neural network for stored-grain insect detection and identification	The images taken by the OITD system 1944×2592 pixels.	Developed to extract feature maps, the improved inception network with a precision of 87.99 outperformed inception network and VGG16 with a precision of 81.39, 82.66, respectively.	[62]
33	"Seed-per-pod estimation for plant breeding using deep learning"	Phenotyping of large populations	Deep learning based computer vision method for estimation of seed amount per soybean pod	7853 + 10325 images	Features extraction (FE) followed by SVM and CNNs methods. Test accuracies of 50.4% for FE+SVM and 86.2% for FE+CNN show that deep learning outperforms the classic machine vision approach.	[71]
34	"Building a globally optimized computational intelligent image processing algorithm for on-site inference of nitrogen in plants"	To analyze nitrogen status in wheat plants	Analysis of nitrogen status in wheat plants using image processing with computational intelligence	A dataset of 4,800 samples of RGB color and binary values	LR, MLP, deep learning MLP (DL-MLP), the Gray world (GW), white patch (WP) were compared in the study. Euclidean error (ΔE) of DL-MLP method is 3.67, which is lower compared to the error of LR, MLP, GW, WP, and MLPs fusion (11.03, 4.85, 22.30, 13.74, 4.10).	[100]
35	"Automatic classification of plant electrophysiological responses to environmental stimuli using machine learning and interval arithmetic"	To test different methods of automatic classification	Different methods of automatic classification were tested. Different environmental cues causing specific changes in the electrical signals of plants were identified.	145 signals after osmotic stress, 118 signals after low light stress, 76 signals after cold stress, 342 signals in ideal conditions	Machine learning algorithms as ANN, CNN, Optimum-Path Forest (OPF), k-Nearest Neighbors (k-NN), and SVM and interval arithmetic were compared. The experiments suggested supervised classifiers and Interval Arithmetic are more suitable than deep learning.	[101]
36	"Improving efficiency of organic farming by using a deep learning classification approach"	To distinguish the individual classes of plants using the visual sensor data	A self-learning convolutional neural network was used for the classification	The dataset consists of 4742 plants (50% carrots, 50% weed)	Proposed classifier is found to be better in all parameters than random forest classifiers. The accuracy of random forest classifier is 93.8%, while the accuracy of the deep-learning approach is over 98%.	[33]
37	"Application of deep learning architectures for accurate and rapid detection of internal mechanical damage of blueberry using hyperspectral transmittance data"	Detection of internal mechanical damage of blueberries	Classification of hyperspectral blueberry samples into sound and damaged groups using deep CNN	737 blueberry samples collected from Chile	LR, RF, Sequential Minimal Optimization (SMO), Bagging MLP methods are compared with deep CNN. Classifiers SMO, LR, RF, Bagging, MLP, and CNN obtain accuracy of 80.8%, 76.1%, 73.1%, 71.1%, 78.3%, and 88.4% respectively. Deep models are better in classification than the traditional machine learning methods.	[102]
38	"Automatic recognition of lactating sow postures from depth images by deep learning detector"	Automatic detection of posture using computer vision	Identification of five postures like sitting, standing, lateral, sternal, ventral recumbences with Faster R-CNN based deep learning framework	Data images were recorded using a Microsoft Kinect v2 sensor	A detector which detects about 20 frames in a second could be adequate to be used in real-time monitoring for livestock breeding. With emergency measures inserted to system abnormal behavior could be detected in a short time.	[103]
39	"Machine learning algorithms to predict core, skin, and hair-coat temperatures of piglets"	To predict surface temperatures of livestock	Machine learning algorithms for predicting physiological temperatures, such as hair-coat surface (Th), skin-surface (Ts), and rectal (Tr)	Sensor data at 200 data points	Four machine learning algorithms were tested. The best prediction for Tr was performed by DNN, with an error of 0.36%, for Ts was performed by a gradient boosted machines with an error of 0.62%, for Th was performed by random forests with an error of 1.35%.	[48]
40	"Automatic prediction of village-wise soil fertility for several nutrients in India using a wide range of regression methods"	An automatic prediction of fertility indices	Fertility indices for soil organic carbon and four soil nutrients such as manganese, zinc, iron, and phosphorus pentoxide were used in available regression methods	Data include 372 geo-referenced patterns	A collection of 76 repressors like Deep Learning, ANN, SVM, RF, quantile regression, partial least squares, generalized additive models bagging, and boosting were compared. The most accurate prediction of five nutrients and soil fertility indices was achieved by ExtraTrees	[69]
41	"Prediction of drought-induced reduction of agricultural productivity in Chile from MODIS, rainfall estimates, and climate oscillation indices"	Early season forecasts on drought occurrence and severity	Deep learning (DL) architecture for early prediction of drought occurrence	Moderate Resolution Imaging Spectroradiom eter (MODIS)	Two prediction approaches as optimal LR and DL were compared. The mean variability explained (Rcv 2) values for one, two, three, four, five, and six months lead time were 0.96, 0.84, 0.65, 0.54, 0.46, 0.38 for DL, and for OLR were 0.95, 0.83, 0.68, 0.56, 0.46.	[70]

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42	"DeepDendro – A tree rings detector based on a deep convolutional neural network"	An automatic detection of tree-ring boundaries	An automatic detector for tree-ring boundary using the CNN	Testing dataset contained over 2500 of tree-ring boundaries	The method is based on CNN, which is claimed to be the first application of CNNs in the area of dendrochronological analysis. The proposed approach detection rate was at the level of 96%.	[104]
43	"Mexican poppy (argemone mexicana) control in cornfield using deep learning neural networks: a perspective"	Site-specific weed control	Automatic identification of weeds based on deep learning neural networks trained on real-time image acquired by row-guided robots	Real-world dataset collected from agriculture sensor network	Training DL takes longer on the Central Processing Unit (CPU), therefore for high-performance training Graphics Processing Unit (GPU) is needed to finish work quickly.	[77]
44	"Deep learning with unsupervised data labeling for weed detection in line crops in UAV images"	Automatic weed detection	Appling CNNs to unsupervised training dataset in order to perform fully automatic weed detection	Datasets for bean and spinach fields.	CNNs, SVM, and RF were applied to features extracted from the datasets. The models were applied to two types of data and found to be comparable for three classification methods with a maximum difference of about 6% in both fields.	[78]
45	"A comparative study of fine-tuning deep learning models for plant disease identification"	Plant disease classification	Plant disease classification applied to images using deep CNN	54,306 images form PlantVillage database	The DL architectures as Inception V4, VGG 16, DenseNets with 121 layers, ResNet with 50, 101, and 152 layers were compared. DenseNets outperforms the rest of the architectures, achieving an accuracy of 99.75%.	[105]
46	"A low shot learning method for tea leaf's disease identification"	Identification of disease in tea leafs	A low shot learning method for identification of disease in tea leafs in order to monitor tea leaf's diseases precisely and timely	40 images of tea diseases for each type	Deep learning based architecture (C-DCGAN+VGG16), SVM, and Decision Tree RF were compared. Deep architecture outperforms classical learning methods having an accuracy of 90%.	[25]
47	"Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild"	Precise identification of the specific infection	An adapted Deep Residual Neural Network-based algorithm to deal with the detection of multiple plant diseases in real acquisition conditions	8178 images of three relevant European endemic wheat diseases	Results from previous work were enhanced by making use of a Residual NN that included several improvements on the augmentation scheme and on the tile cropping. The balanced accuracy improved from 0.78 up to 0.87 under exhaustive testing.	[28]
48	"Deep neural networks with transfer learning in millet crop images"	Detection and diagnosis of Mildew disease	Identification of mildew disease in pearl millet using transfer learning with feature extraction	124 images manually downloaded from internet	Due to the experimental result accuracy of 95.00%, the precision of 90.50%, the recall of 94.50% and the f1-score of 91.75% was obtained.	[26]
49	"Detection of grapevine yellows symptoms in Vitis vinifera L. with artificial intelligence"	Grapevine yellows disease detection	CNN applied for end to-end detection of Grapevine yellows (GY) in red grape vine, using color images of leaf clippings.	Leaf clipping images acquired from internet	ResNet-101, ResNet-50, AlexNet, Inception v3, GoogLeNet, and SqueezeNet were compared. The best of tested architectures was ResNet-50 with a sensitivity of 98.96% and specificity of 99.40%. Expensive sensing equipment and expert knowledge in GY detection are not required.	[27]
50	"PD2SE-Net: Computer-assisted plant disease diagnosis and severity estimation network"	Development of diagnosis system for plant diseases.	Applied ResNet50 architecture as the basic model and combined with shuffle units as the auxiliary structures formed the proposed PD2SE-Net50.	Synthetic dataset that was Global AI Contest and the synthetic dataset	ResNet18, ResNet34, ResNet50 and ResNet101 were tested. SGD optimizer integrated PD2SE model based on ResNet50 the best accuracies of 91%, 98%, and 99% for disease severity estimation, plant disease classification, and plant species recognition, respectively.	[106]
51	"Pixel-level aflatoxin detecting based on deep learning and hyperspectral imaging"	Detect of Aflatoxin in peanut	Electric displacement platform, SCOMS, grating module, and camera were used to design a CNN besed hyperspectral imaging system.	146 images cubes of 73 peanut samples (before and after aflatoxin)	Traditional identification models such as K-NN, RF, RBF-SVM, BP-ANN were compared to DL. DL was the best on pixel level and kernel level, with the recognition rate is higher than 96% and 90%, respectively.	[107]
52	"Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease"	Development of effective method for disease and symptoms diagnosis	Proposed multilayer CNN classifies Mango leaves infected by fungal disease.	A real-time dataset of 1070 images of the Mango leaves	The proposed method, having accuracy of 97.13%, outperformed SVM, Particle swarm optimization (PSO), and Radial basis function neural network (RBFNN) that have accuracies of 92,75%, 88.39%, 94.20%, respectively.	[108]
53	"Plant disease identification using explainable 3D deep learning on hyperspectral	A soil borne fungal disease called charcoal rot	A 3D deep CNN applied to the hyperspectral data	The training dataset consists of 1090 images.	The proposed model classifies hyperspectral data with an accuracy of 95.73%. The most sensitive pixel locations were visualized using the concept of a saliency map.	[109]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
	images”					
54	“Quantitative phenotyping of Northern leaf blight in UAV images using deep learning”	Northern leaf blight (NLB) disease detection	Segmentation of NLB disease lesions in unmanned aerial vehicle (UAV) images with a mask R-CNN model.	3000 aerial images and 5234 lesion instances.	An average precision of 0.96 was obtained. Being robust to variation in image scale, the proposed method demonstrates the potential for integrating a deep learning-based approach with UAV technology.	[110]
55	“Solving current limitations of deep learning based approaches for plant disease detection”	Plant disease detection	A neural network architecture with two-stage focused on a real environment for plant disease classification	Dataset containing 79,265 images	One-stage and two-stage detectors were tested. Proposed two-stage architecture called PlantDiseaseNet showed better performance with an accuracy of 93.67%.	[111]
56	“Plant disease and pest detection using deep learning-based features”	Diagnosis of plant diseases	Different approaches of nine powerful deep architectures for plant disease detection were evaluated.	eight clusters containing 1965 real pest images and plant disease	Feature vectors were obtained from deep learning networks like AlexNet, ResNet101, ResNet50, SqueezeNet, GoogleNet, VGG19, VGG16, Inception ResNetV2, and InceptionV3. The traditional classifiers of KNN, ELM, and SVM were used in the classification phase. ResNet50+SVM model produced the highest accuracy of 97.86%.	[112]
57	“End-to-end sequence labeling via deep learning for automatic extraction of agricultural regulations”	Altering human-oriented regulations with computer-oriented rules	8 different deep learning architectures to develop an end-to-end sequence labeler for phytosanitary regulations.	2426 PDF	The best system is a NN that uses Softmax, character embeddings, and Bidirectional Long short-term memory It achieves a performance of 88.3% F1 score.	[113]
58	“Interpolation of greenhouse environment data using multilayer perceptron”	Greenhouse environments analysis using big data	Statistical methods like spline and linear interpolations were applied. Linear models like RF and MLP were selected as machine learning methods.	Temperature, atmospheric pressure, relative humidity, light intensity, CO2 concentration	Short-term missing data and random extraction data were estimated with high accuracy. The machine learning method with stable accuracy was robust to experimental period changes. MLP showed high accuracy in all experiments among the other deep learning models.	[114]
59	“A workflow for sustainable development goals indicators assessment based on high-resolution satellite data”	Yield assessment and land productivity analysis	Assessment of land productivity using deep learning methodology	Satellite data	Thanks to the high resolution of remote sensing products and deep learning methodology the capacity to evaluate SDG indicators can be increased.	[41]
60	“Characterization of food cultivation along roadside transects with Google Street View imagery and deep learning”	Crop identification	A deep CNN were trained with Google Street View imagery two software tools for crop identification was tested	57,079 panoramas discovered in Nong Chang	The 40% of images were identified with an accuracy of 99.0% and the area under the ROC curve of 0.9905. The study shows good performance in detecting banana plants.	[115]
61	“Crop yield prediction with deep convolutional neural networks”	Remote sensing based yield prediction	CNNs based model for crop yield prediction was applied to NDVI and RGB data acquired from UAVs.	The data acquired from single Airinov Solo 3DR UAV	CNN models are at yield estimation trained with RGB images. CNN architecture performs better with RGB images than NDVI images.	[47]
62	“Deep convolutional neural networks for rice grain yield estimation at the ripening stage using UAV-based remotely sensed images”	Crop yield estimation	Discovery of important features related to rice grain yield using CNN architecture and low-altitude remotely sensed imagery.	800 management units in a 160-hectare site	Using UAV-based imagery, a deep CNN technique better than the vegetation index (VI) regression model for rice grain yield estimation. The performance of deep CNN at the ripening stage was better and more stable.	[45]
63	“Deep learning based multi-temporal crop classification”	Development of deep learning based classification framework for remotely sensed time series	Classification of summer crops using Landsat Enhanced Vegetation Index (EVI) time series. One-dimensional convolutional (Conv1D) layers and Long Short- Term Memory (LSTM) models were designed for this purpose.	Latest survey for Yolo County in year 2014.	XGBoost, RF, and SVM were compared to two types of deep learning models LSTM and Conv1D. LSTM showed the lowest accuracy of 82.41% of among all the classifiers, XGBoost was the best with an accuracy of 84.17% among non-deep learning classifiers. The highest accuracy of 85.54% was achieved by the Conv1D.	[116]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
64	"Delineation of agricultural fields in smallholder farms from satellite images using fully convolutional networks and combinatorial grouping"	Accurately detects sparse field contours	Detection of field boundaries using a fully CNN in combination with grouping and globalization	Field boundary data, comprising over 500 field polygons	gPb-owt-ucm, Single-scale Combinatorial Grouping (SCG), Multiscale Combinatorial Grouping (MCG) and deep models based on Fully Convolutional Network (FCN), SegNet were compared. FCN-based techniques showed better results than shallow techniques. SegNet-W provides more accurate results than FCN-DK6.	[42]
65	"Deep learning for automatic outlining agricultural parcels: exploiting the land parcel identification system"	Automatic outlining of agricultural plot boundaries	Outlining of agricultural plot boundaries using CNNs, applied to orthophotos over large areas with a heterogeneous landscape.	The open data from the Land Parcel Identi caption System (LPIS)	gPb-ucm (global probability of boundary followed by ultrametric contour map) method was compared to the CNN model. The proposed approach fit the GT boundaries better than boundaries detected by the gPb-UCM method.	[117]
66	"Long-short-term-memory-based crop classification using high-resolution optical images and multitemporal SAR data"	Parcel-based crop classification	Discovering of time-series features of crops using deep learning-based LSTM, to classify parcels and produce a final classification map.	high-resolution ZY-3 images and multitemporal Sentinel-1A SAR data	The proposed LSTM-based method was compared to RF and SVM. Overall accuracy scores for LSTM, SVM, and RF are 80.71%, 72.64%, and 74.19%, respectively.	[43]
67	"Mapping rice paddies in complex landscapes with convolutional neural networks and phenological metrics"	Estimating cropyield and performing land management	An innovative method for rice mapping by combining a convolutional neural network (CNN) model and a decision tree (DT) method with phenological metrics.	HJ-1 A/B charge-coupled device (CCD) images	The proposed classification method (93.56%) outperformed three other classification techniques, such as backpropagation neural network (BPNN), original CNN, pre-trained CNN applied to HJ-1 A/B charge-coupled device (CCD) images.	[44]
68	"CropDeep: the crop vision dataset for deep learning based classification and detection in precision agriculture"	Crop Classification and Detection	CropDeep species classification based on deep-learning technology	Detection dataset, consisting of 31,147 images	The proposed method was compared to VGG, ResNet, DenseNet, Inception, and SqueezeNet. The ResNet50 was the best model with an accuracy of 99.81% on the CropDeep datasets.	[118]
69	"Deep learning for soil and crop segmentation from remotely sensed data"	To correctly identify and separate crops from the soil	A strategy for integrating terrain height (DSM) images with radiometric index (NDVI) to segment crops and tree objects over soil through the use of high-resolution images from UAVs.	High resolution Digital Surface Model (DSM) data	The results demonstrate that the method potentially enables the correct segmentation of soil. It is shown that the DSM/NDVI index produces an improvement of about four times compared to its baseline NDVI marker.	[46]
70	"Smallholder crop area mapped with a semantic segmentation deep learning method"	Crop area mapping	WorldView-2 (WV-2) images with RGB bands were used to confirm the effectiveness of the proposed semantic classification framework for information extraction and the crop area mapping task.	WorldView-2 (WV-2) images	The proposed approach has Overall Accuracy of 95% of crop area classification, which is better than other deep semantic segmentation networks such as U-Net, PspNet, SegNet, DeepLabv2, and traditional machine learning methods, such as Maximum Likelihood (ML), SVM, and RF.	[119]
71	"A microbial image recognition method based on convolutional neural networks"	Design of microbial image recognition model	Mixed microbial image recognition model using Convolutional Neural Networks	The microbial data set	Image features are extracted through AlexNet, CNN, and then the classification task was completed through the traditional RF algorithm. The experiment result proves that the mixed microbial image recognition model proposed in this paper is effective.	[120]
72	"Automatic characterisation of dye decolourisation in fungal strains using expert, traditional, and deep features"	Measuring dye decolourisation of fungal strains	A systematic evaluation of different image-classification approaches considering traditional computer vision features, ad hoc expert features, and transfer-learning features obtained from deep neural networks.	235 images of dye decolourisation assays	The six classifiers that are considered in this work are extremely randomized trees (ERT), KNN, LR, MLP, RF, and SVM. For features are extraction DenseNet-ERT, GoogleNet-SVM, Inception-LR, Resnet-SVM, OverFeat-SVM, VGG16-ERT, VGG19-LR, and Xception-LR were used. The best model was Resnet-C-SVM with an accuracy of 96.5%.	[121]
73	"Classification of rubberized coir fibres using deep learning-based neural fuzzy decision tree approach"	Identify of coir fibre quality in mattress-manufacturing company	An intelligent method for classification and prediction of raw materials quality using deep learning	Central Coir Research Institute Dataset	A fuzzy extension of the back-propagation algorithm was compared to decision tree-based classification algorithms, such as Naive Bayes, C4.5, CART, ID3, fuzzy, MLP, and showed the best accuracy of 98.75%.	[122]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
74	"Classification of tree species and stock volume estimation in ground forest images using Deep Learning"	Identification of the number of trees contained in the image.	Estimation of the growing stock volume with the nonlinear mixed effect model	3000 ground forest images captured by Canon EOS 700D camera	VGG16 was used form pre-training of the UGG network, to segment the trunk part of each tree in the ground forest image. Using the UNET network structure, the accuracy rate was 96.03%,	[123]
75	"Computer vision detection of foreign objects in walnuts using deep learning"	Rapid detection of foreign objects	Automatic detection of different-sized man-made and natural foreign objects using two different CNN applied to walnut images	Experiments consisted of a total of 781 images	The proposed method succeeded to segment 99.5% of the object regions in test dataset, and to classify 95% of the foreign objects in the validation dataset. The processing time needed for segmentation and detection tasks is shown to be less than 50 ms per image.	[56]
76	"Deep learning-based automatic recognition network of agricultural machinery images"	Recognition of agricultural machinery images	Automatic recognition of agricultural machinery images using a network called AMTNet	200 machine images	AlexNet, GoogLeNet, ResNet, and VGGNet were compared for insect classification. Fine-tuning of the pre-trained model was made by applying transfer learning. As a result CNN architecture could learn deep features of the insect images and achieved an accuracy of 97.47%, giving better results than handcrafted features.	[58]
77	"Synthetic bootstrapping of convolutional neural networks for semantic plant part segmentation"	Image segmentation in agriculture	Machine learning methodology to reduce the need for manually per pixel level annotation of images	50 empirical and 10,500 synthetic images	It is stated that adding conditional random fields (CRF) only improved performance on the synthetic data. A performance was improved with the increasing size of the dataset. For the synthetic dataset, learning stabilizes around 3000 images. The generalization to other related datasets proved possible.	[124]
78	"Fast spectral clustering for unsupervised hyperspectral image classification"	Hyperspectral image classification	A spectral clustering method to improve classification of large-scale hyperspectral image without any prior information.	Synthetic datasets and Hyperspectral images (HSI) datasets	The proposed improved algorithm provides an efficient solution for large-scale HSI classification where the traditional spectral clustering has no capability to deal with them.	[125]
79	"Maize silage kernel fragment estimation using deep learning based object recognition in non-separated kernel /stover RGB images"	To determine the quality of harvested crop	Two deep learning-based methods adopted for kernel processing prediction without stover and kernels separation step before capturing images.	1393 images containing just over 6907 manually annotated kernel instances	Bounding-box detection was performed with Region-based Fully Convolutional Network (R-FCN) and instance segmentation was performed with Multi-task Network Cascade (MNC). Kernel Processing Score (KPS) calculation became to be done in minutes by removing the requirement of kernel/stover separation.	[57]
80	"Double-DQN based path smoothing and tracking control method for robotic vehicle navigation"	Automatic path tracking	A path-tracking algorithm based on Double Deep Q-Network (Double DQN) for an automated robotic vehicle in a simulated virtual environment.	The software acquired the GPS and IMU data by RS232 serial communicatio n.	The performance of the proposed method was compared Pure-Pursuit Control (PPC) algorithm. While tracking curved paths overshoot and settling time could be reduced by Double DQN-based control at a minor cost of slightly increased rising time.	[126]
81	"A deep learning model to recognize food contaminating beetle species based on elytra fragments"	Identification of pests	CNN based solution for automatic identification of 15 beetle species that frequently detected in storage products	Dataset of 6900 microscopic images of elytra fragments	The proposed model with PX448 and SGD optimizer was compared to ANN or SVM. Accuracies of ANN, SVM and proposed method are 79%, 85%, and 83.8%, respectively.	[127]
82	"Automated vision-based system for monitoring Asian citrus psyllid in orchards utilizing artificial intelligence"	Detection of psyllids from other insects	Utilization of machine vision and artificial intelligence for an automated system that monitors the Asian citrus psyllid (ACP) in groves	Six high resolution USB cameras was used	Detection of ACPs on a sample of 90 young citrus trees was performed with precision and recall of 80% and 95%, respectively.	[63]
83	"Crop pest classification based on deep convolutional neural network and transfer learning"	Classification of insect species	CNN with deep architectures are used for automatic feature extraction. Method is able to learn complex high-level features in image classification applications.	NBAIR, Xie1, Xie2 insect dataset.	AlexNet, VGGNe, ResNet and GoogLeNet was trained for insect classification. The highest classification accuracy of 96.75%, 97.47%, and 95.97% were achieved for NBAIR, Xie1 and Xie2 insect dataset respectively.	[64]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
84	"An effective data augmentation strategy for cnn-based pest localization and recognition in the field"	Pest classification and counting	Pest recognition and localization methods based on CNN with an effective data augmentation strategy	4400 images split into training subset and validation subset at ratio of 9:1	The proposed method was compared to DAG-CNN, and HR, Feature Pyramid Network (FPN). Mean Average Precision for proposed method, DAG-CNN, HR, and FPN, were 83.23%, 73.76%, 76.77%, 68.74%, respectively. The experimental results show the effectiveness of the proposed data augmentation method.	[66]
85	"Recognition pest by image-based transfer learning"	Reliable pest identification	Transfer learning is used to develop diagnostic system for pest detection and recognition.	Less than 500 images	The proposed transfer learning method was compared to human experts and traditional neural network models (SIFT-HMAX and CNN). The experimental results show that the proposed method performed better than four human experts. It achieved an accuracy of 93.84%, which outperform SIFT-HMAX (85.50%) and CNN (90.41%) models.	[65]
86	"Citrus rootstock evaluation utilizing UAV-based remote sensing and artificial intelligence"	The rapid acquisition of phenotypic data	Reduction of cost, data collection time and facilitation of surveying procedure by equipping small UAVs with various sensors	Data collected by UAV	Correlation between UAV collected data and the manually collected data is high. Data collected by AI and UAV-based techniques could be used instead of the manual methods.	[72]
87	"Differentiating between morphologically similar species in genus Cinnamomum (Lauraceae) using deep convolutional neural networks"	Differentiating between the three species on the basis of their appearance	Three Cinnamomum species were identified using leaf images and deep CNN	Approximately 500 leaves were sampled from 1 to 3 individuals for each species	Score fusion was then applied to improve the performance of classifiers based on deep CNN models (VGG16, Inception-V3, and NASNet). The fused CNN classifiers reached an accuracy of 96.7%, which is higher than accuracy of SVM classifiers (74.6%).	[73]
88	"In-field high throughput grapevine phenotyping with a consumer-grade depth camera"	Methods for automated grapevine phenotyping	AlexNet, GoogLeNet, VGG16, and VGG19 were tested for segmentation of visual images into multiple classes and recognition of grape bunches in images acquired by the RGBD sensor.	An Intel RealSense RGB-D R200 imaging system	VGG19 model reached accuracy of 91.52%, despite the poor quality of the input images. Data acquired by the Intel RealSense R200 was used in automatic grapevine phenotyping in the field.	[74]
89	"Hyperspectral imaging combined with machine learning as a tool to obtain high-throughput plant salt-stress phenotyping"	The rapid selection of salinity-tolerant crops	Deep learning based image segmentation for leaf and plants applied RGB images extracted from HSI imaging	The public CVPPP 2015 dataset and the image segmentation challenge dataset.	Deep learning based image segmentation for leaf and plants achieved result score of 0.94 for plant segmentation and score of 85.4 for leaf segmentation. Results show that the proposed approach could replace traditional time-consuming laboratory-based methods.	[75]
90	"UAV-based high Throughput phenotyping in citrus utilizing multispectral imaging and artificial intelligence"	Low-cost and automated high-throughput phenotyping technique	Deep CNN, multispectral imaging, and UAVs were combined to develop technique for data acquisition and image processing to evaluate phenotypic characteristics on citrus crops.	UAV images.	Detection and counting of citrus trees in a grove were performed with precision and recall of 99.9% and 99.7%, respectively. Estimation of canopy size was performed with an accuracy of 85.5% and detection of tree gaps was performed with precision and recall of 100% and 94.6%, respectively.	[128]
91	"A comparative study of fruit detection and counting methods for yield mapping in apple orchards"	Fruit detection and counting methods	A novel semantic segmentation-based approach for fruit detection and counting using deep learning	Data sets are composed of a total of 2,874 images	The results of thestudy show that Gaussian Mixture Models based semi-supervised method is better from fruit detection and deep learning-based approach is better for fruit counting. With combining both methods estimation accuracies achieve range 95.56% to 97.83%.	[34]
92	"Analysis of transfer learning for deep neural network based plant classification models"	Classification of plant species	The automated classification of plant species using Deep Neural Networks (DNNs)	Flavia, Swedish Leaf, UCI Leaf, Plantvillage datasets	Four different transfer learning models for deep neural network-based plant classification were tested on four public datasets. The study shows that automated plant identification can benefit from transfer learning.	[129]
93	"Apple detection during different growth stages in orchards using the improved YOLO-V3 model"	Real-time apple detection in orchards	YOLO-V3 model for apple detection during different growth stages of apples in orchards	480 images later expanded to 4800 images using data augmentation methods	YOLOV3-dense model the original YOLO-V3 model and the Faster R-CNN. The average detection time of the model is 0.304 s per frame, which means that model could be used for real-time apple detection in orchards.	[35]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
94	"Fruit detection for strawberry harvesting robot in non-structural environment based on Mask-RCNN"	Fruit detection for a strawberry harvesting robot	Mask Region Convolutional Neural Network (Mask-RCNN) was used for improving performance of machine vision in fruit detection	2000 strawberry images	Resnet50 was combined with the Feature Pyramid Network (FPN) architecture to perform feature extraction. It achieved a precision rate of 95.78% and showed better results than four traditional fruit detection algorithms.	[38]
95	Fully automatic segmentation method for medicinal plant leaf images in complex background	Identification of medicinal plants	Fully automatic segmentation method for medicinal plant leaf images in complex background is proposed by taking vein enhancement and extraction.	Self-built database with 1600 species of medicinal plants	The accuracy of the proposed method, having a precision of 96.02%, is better than many main fully automatic image segmentation methods including deep learning Feature Pyramid Network (FPN) architecture.	[130]
96	"Grapevine variety identification using "Big Data" collected with miniaturized spectrometer combined with support vector machines and convolutional neural networks"	Identification of grapevine varieties	SVM and CNN were built for separating Touriga Nacional from 63 other varieties	35,833 spectra from leaves of 626 plants from 64 varieties	The classifiers compared were SVM and CNN. In the case of Touriga Nacional, the SVM provided better test results than the CNN. For Touriga Franca it was the CNN that gave the best results having correct classification percentage 93.82%.	[131]
97	"Identification of haploid and diploid maize seeds using convolutional neural networks and a transfer learning approach"	The selection of the haploid seeds	Automatic recognition of haploid and diploid maize seeds using CNN and transfer learning approach	1230 haploid and 1770 diploid maize seed images	The most effective of compared modes was VGG-19 with accuracy of 94.22%. The other CNN models also show promising results (AlexNet 92.67%, VGG-16 92.78%, GoogLeNet 90.89%, ResNet-18 92.44%, ResNet-50 90.89%, ResNet-101 91.11%.).	[32]
98	"Multi-modal deep learning for Fuji apple detection using RGB-D cameras and their radiometric capabilities"	Fruit detection and localization	The Faster R-CNN model was adapted for use with fivechannel input images: color (RGB), depth (D) and range-corrected intensity signal (S).	KFuji RGB-DS database of 967 multi-modal images containing 12,839 apples	After adding depth and range-corrected intensity channels, the model showed an improvement of 4.46% in the F1-score. When all channels are used F1- score and precision became 0.898 and 94.8%, respectively.	[36]
99	"Using Deep Convolutional Neural Network for oak acorn viability recognition based on color images of their sections"	Assessment of the viability of oak seeds	Visual assessment of the viability of oak seeds with DCNN	5 Mega-Pixel CCD digital machine vision camera images	DCNN outperformed manual assessment of the viability of oak seeds with an accuracy of 85%. Despite the long training procedure, the recognition task takes only 68 ms on average.	[132]
100	"Identification of wheat kernels by fusion of RGB, SWIR, and VNIR samples"	Improving the categorization of wheat kernels.	Assessment of robustness of a VGG16 deep learning tool and improving the categorization of wheat kernels.	40 classes, with 200 samples in each class	Simulations with 6400 training and 1600 testing samples showed accuracy rates higher than 98%, which is higher than almost all the state-of-the-art techniques.	[133]
101	"Deep learning for real-time fruit detection and orchard fruit load estimation: benchmarking of MangoYOLO"	Detection of mango fruit	Detection of mango fruit in images of tree canopies with deep learning architectures	1300 training, 130 validation and 300 test images	YOLOv3 and YOLOv2 were integrated to create MangoYOLO, which was compared to Faster R-CNN and Faster R-CNN. The proposed method achieved Precision and F1 score of 0.983 and 0.968, respectively, outperforming other algorithms.	[39]
102	"Controlled lighting and illumination-independent target detection for real-time cost-efficient applications. The case study of sweet pepper robotic harvesting"	Sweet Pepper detection	Low-cost and robust target detection with Flash-No-Flash (FNF) controlled illumination acquisition protocol	The database includes 156 scenes with 468 images containing a total of 344 yellow sweet peppers.	The color-based algorithm achieved precision and recall of 95% on FNF images and 99% precision at a 69% recall for Flash-only images. Deep learning techniques achieved a precision of 84% Flash-only and 83.6% for FNF images.	[40]
103	"Fruit detection and segmentation for apple harvesting using visual sensor in orchards"	Real-time fruit detection	A multi-function network for semantic segmentation of apples and branches and real-time detection by using the visual sensor in orchard	800 images from the orchards were collected	The comparison of the DasNet and the other state-of-the-art works in object detection and semantic segmentation was included. The DaSNet with ResNet-101 backbone outperformed state-of-the-art methods in both object detection and semantic segmentation, with an F1 score of 87.6% and 77.2% on the segmentation of apples and branches, respectively.	[37]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
104	"An improved single shot multibox detector method applied in body condition score for dairy cows"	Body condition scores evaluation	Low cost Body condition scores evaluation method based on deep learning	8972 image samples	The improved SSD method achieved an accuracy of 98.46% and 89.63% for classification and location, respectively. Compared to original SSD and YOLO-v3, it has a smaller model size with 23.1 MB and faster detection speed with 115 fps.	[50]
105	"Automatic monitoring system for individual dairy cows based on a deep learning framework that provides identification via body parts and estimation of body condition score"	Individual identification and BCS assessment	An automatic system for identifying individuals and assessing body condition score (BCS) using a deep learning framework	Sensor data	The selected linear regression model had a high coefficient of determination value (0.976), and the correlation coefficient between manual Body condition score (BCS) and ultrasonic BCS was 0.94. The finding of improved model performance for thin cows with the addition of phase congruency and gray channels in a CNN suggests that a minor improvement in the average accuracy may be achievable within the absolute accuracy error range.	[51]
106	"A computer vision system to monitor the infestation level of Varroa destructor in a honeybee colony"	Determine the number of bees and mites	A Computer vision system for monitoring the infestation level of the Varroa destructor mite	Video sequence with 1775 bees and 98 visual mites	The algorithm achieved an F1-score of 0.97 for counting bees and an F1-score of 0.91 for detecting varroa mites. The results show that the traditional methods, which require the killing of bees can be replaced with the proposed computer vision system.	[134]
107	"Automated pig counting using deep learning"	Pig counting	A deep learning solution for pig counting problem	Herd dataset containing nearly 30,000 pigs	A modified Counting CNN model according to the structure of ResNeXt was used. The proposed method gets a mean absolute error of 1.67 in real-world data.	[135]
108	"Deep cascaded convolutional models for cattle pose estimation"	Cattle pose estimation	A robust cattle pose estimation with deep cascaded CNN and RGB images captured under real cattle farm conditions.	2134 images of 33 dairy cattle and 30 beef cattle	The convolutional heatmap regression model, convolutional pose machine model, and the stacked hourglass model were tested. The stacked hourglass model outperformed other two, reaching a 90.39% PCKh mean score at the threshold of 0.5 for 16 joints.	[53]
109	FLYOLOv3 deep learning for key parts of dairy cow body detection	Accurate detection of the key parts of dairy cows	Detection of key parts of dairy cows with FilterLayer based YOLOv3 in complex scenes	1000 cow images	The proposed method FLYOLOv3, was compared to the YOLOv3 algorithm and Faster R-CNN and. FLYOLOv3 outperforms other methods with an accuracy of 99.18%, the recall rate of 97.51%, the average frame rate of 21 f/s, and the average precision of 93.73%.	[136]
110	"Prediction of sheep carcass traits from early-life records using machine learning"	Prediction of intramuscular fat, fat depth, computed tomography lean meat yield	Deep Learning (DL), Gradient Boosting Tree (GBT), K-Nearest Neighbour (KNN), Model Tree (MT), and RF were employed to predict HCW, IMF, GRFAT, LW and CTLEAN	Sensor data	RF and MT were the first two methods outperformed all other learning algorithms for all the traits and scenarios and the least efficient methods were LR and KNN. In this study, DL showed different efficiency for all the traits and scenarios.	[137]
111	"Real-time sow behavior detection based on deep learning"	Detecting sow behavior	A Real-Time Sow Behavior Detection Algorithm based on Deep Learning (SBDA-DL) is proposed	A 3 million pixel infrared network camera was used to collect 1912 images	SBDA-DL outperformed traditional detection algorithms (Haar+AdBoost, HOG+SVM) with an average precision of 96.5%, 91.4%, and 92.3% for drinking, urination, and mounting behaviors detection, respectively. Compared to commonly used deep models, the SBDA-DL can maintain the same category accuracy but with a much faster detection speed.	[52]
112	"A Multi-Feature Fusion Based on Transfer Learning for Chicken Embryo Eggs Classification"	Chicken Embryo Eggs Classification	A novel multi-feature fusion based on Deep Convolutional Neural Network (DCNN) architecture in a small dataset	1000 training and 1000 testing samples of chicken embryo images	The proposed transfer learning has better classification performance (accuracy rate of 98.4%) and superior generalization for small-scale agricultural image samples.	[138]
113	"Fast Pig Detection with a Top-View Camera under Various Illumination Conditions"	The fast detection of pigs	A method for fast detection of pigs under various illumination conditions using complementary information from the depth and infrared images	Sensor data	The detection accuracy was measured as 54% (YOLO9000 method), 79% (DeepLab method), and 79% (proposed method). The authors proposed an image processing-based method that guarantees a fast execution time. Having the same accuracy with the DeepLab method the execution time of the proposed method is only 8.71 ms.	[139]

N	Article name	Problem	Proposed methods	Source of data	Results and advantages	Ref
114	"Hyperspectral demosaicking and crosstalk correction using deep learning"	To reduce crosstalk and to increase spatial resolution.	End-to-end demosaicking and crosstalk-correction of a 4 × 4 raw mosaic image using CNN based similarity maximization framework	A 10 bit, 4 × 4 mosaic sensor is used to make a dataset of 2500 aerial images.	Similarity maximization framework for demosaicking outperformed standard bilinear interpolation or Bayer demosaicking. Increase in the number of layers and the addition of nonlinearity, improved results to achieve a median structural similarity (SSIM) index of 0.86 between original and upscaled images.	[140]
115	"An efficient employment of internet of multimedia things in smart and future agriculture"	Efficient management of irrigation process	Exploitation of IoT sensors and machine learning methods for image processing task to make the irrigation decision	Sensed Multimedia Data	SVM, CNN, and RF were compared. CNN outperformed the other classifiers with a precision of 0.96. Among the models, CNN was the slowest model. SVM, it also proved to be a high performing classifier with high accuracy and short training time.	[67]
116	"Land parcel-based digital soil mapping of soil nutrient properties in an alluvial-diluvia plain agricultural area in China"	Accurately and precise soil nutrient mapping	Extraction of land parcels from high-resolution remote sensing images using CNN based automatic extraction model	Land parcel boundaries were extracted from GF-2 fusion data	RF, ANN, ordinary kriging, and cokriging combined with the land-parcel-based DSM framework. The ANN model performs the worst, and land parcel-based RF performs the best in four models.	[141]
117	"Reference evapotranspiration estimation and modeling of the Punjab Northern India using deep learning"	To estimate evapotranspiration because it plays a pivotal role in irrigation water scheduling	DL, Generalized Linear Model (GLM), RF, and Gradient-Boosting Machine (GBM) were evaluated for the overall ability to predict future ETo.	Daily meteorological data 31 years for Hoshiarpur and 38 years for Patiala is considered for study	DL model showed great capabilities for ETo estimation and outperformed RF, GLM and GBM models. DL model had good accuracy on training, validation, and testing respectively because it was able to avoid overfitting. Robustness of the proposed model was higher than the robustness of conventional approaches.	[142]
118	"Mapping irrigated areas using Sentinel-1 Time Series in Catalonia, Spain"	Irrigation mapping	A method to map irrigated plots using S1 SAR (synthetic aperture radar) time series	Open access Sentinel-1 (S1) and Sentinel-2 (S2) data	The overall accuracy obtained using the NDVI in RF; classifier reached 89.5% while that in the CNN reached 91.6%. By applying the CNN approach to SAR data, the overall accuracy of 94.1% was obtained.	[82]
119	"Deep learning-based visual recognition of rumex for robotic precision farming"	Recognition of the Broad-leaved dock in grasslands	A classifier for weed recognition was combined with transfer Learning techniques for deep learning-based feature extraction	An image dataset from a dairy farm containing broad-leaved docks.	The discriminatory capabilities of features extracted using various deep CNN architectures and their combination with classifiers were evaluated. Result shows that the proposed method outperforms other recognition methods inaccuracy, but not in false-positive rates.	[79]
120	"Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence"	Weed detection	Machine vision and artificial intelligence were utilized to develop smart sprayers for distinguishing target weeds from non-target objects in order to precisely spray on the desired target/location.	1000 images of targets and non-targets labeled manually for each target position on the images.	Traditional broadcast sprayers usually treat the entire field and apply agrochemicals areas that do not require treatment. AI-based weed mapping and precision spraying systems, with spraying to a specific area can significantly reduce the quantity of agrochemicals required for treatment.	[80]

VI. CONCLUSION

Using bibliographic methods, the characteristics of deep-learning-based agriculture-relevant literature from 2016 to 2019 based on the SCI database were examined. The study reveals that the literature on deep learning has grown exponentially over the past 2 years. China was revealed to be an important contributor to the deep learning literature with the highest number of publications (40), followed by the USA (14). The study also found that three core journals, namely *Computers and Electronics in Agriculture, Sensors* and *Remote sensing* published about 63% to the articles on deep-learning-based agriculture. Disease detection, plant classification, land cover identification, and precision livestock farming were found to be the key subjects with the deepest learning publications in the agricultural domain. The most common agriculture-relevant keywords used were "disease detection", "crop classification", "pest detection", "weed detection", "fruit detection", "unmanned aerial vehicle", "yield estimation", and "smart agriculture".

UAV-aided IoT networks have enormous potential for application in agriculture. Given their high maneuverability, high mobility, and their low maintenance cost, they were used in studies related to almost all topics. Therefore, UAV-aided studies were not analyzed as an independent topic and UAV can be considered as an integral part of smart farming. With the integration of UAVs into smart farming, equipped with sensors and cameras, the articles tended towards artificial intelligence applications that produce faster results working with real-time data. In addition to datasets collected with sensors and cameras, in deep learning studies there are also other data sources like satellite data, open-access databases, and synthetic datasets.

The focus of this study was to identify where deep learning has been used for improving various agricultural practices, to rank the topics in order to help new researchers in this area, and to emphasize practices that could direct future research. This survey should motivate more researchers to focus on deep learning topics, related to data analysis, image analysis and computer vision, applying it for classification or prediction in smarter farming.

APPENDIX A

The summary tables obtained as a result of analyzes made in this article.

APPENDIX B

The list of the 120 identified relevant works and answers to research questions. (See Table.)

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