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SURVEY

A Comprehensive Review of Deep Learning-Based Anomaly Detection Methods for Precision Agriculture

KONSTANTINOS GKOUNTAKOS[1,2], **KONSTANTINOS IOANNIDIS**[1], **KONSTANTINOS DEMESTICHAS**[2], **STEFANOS VROCHIDIS**[1], **(Member, IEEE), AND IOANNIS KOMPATSIARIS**[1], **(Senior Member, IEEE)**

[1]Information Technologies Institute (ITI), Centre for Research and Technology Hellas (CERTH), 57001 Thessaloniki, Greece
[2]Department of Agricultural Economics and Rural Development, Agricultural University of Athens (AUA), 11855 Athens, Greece

Corresponding author: Konstantinos Gkountakos (gountakos@iti.gr)

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ABSTRACT Anomaly detection is a challenging problem in various application domains of Artificial Intelligence, such as in video surveillance, the Internet of Things, and notably, precision agriculture. The effectiveness of anomaly detection in each field is intricately linked to the domain-specific data, adhering, at the same time, to the core objective of detecting outliers. In the precision agriculture domain, anomalies range from plant diseases in image data to fluctuating environmental conditions in time-series datasets. This review provides a detailed examination of deep learning-based anomaly detection methods within precision agriculture, adopting the PRISMA methodology for a structured and comprehensive analysis. We employ a novel taxonomy categorizing recent literature by agricultural application, anomaly relevance, data modality, deep learning architecture, supervision level, and dataset usage. Our findings highlight a predominant reliance on visual data and uncover a potential alignment between methods originally devised for classification or detection and the anomaly detection challenge. The review also signals a pressing need for large-scale datasets to address precision agriculture challenges effectively. By mapping the current landscape and suggesting directions for future research, our work aims to facilitate advancements in anomaly detection techniques, enabling enhanced decision-making and operational efficiency in precision agriculture.

INDEX TERMS Anomaly detection, deep learning, literature review, precision agriculture, taxonomy.

I. INTRODUCTION

The global population's significant increase in the last decades, with projections surpassing nine billion within the next three decades, underscores an urgent need for enhanced food production strategies [1]. To meet this demand, it is imperative not just to expand agricultural lands, but also to optimize crop yields through technological innovation. Precision Agriculture (PA) [2] is a management strategy, which integrates the Internet of Things (IoT) and Artificial Intelligence (AI), and stands at the forefront of this revolution, to offer a sustainable pathway to increase efficiency and precision in farming practices [3], [4]. As an example, using real-time input from Unmanned Ground Vehicles (UGVs), Unmanned Aerial Vehicles (UAVs) and other sensors, PA facilitates continuous monitoring and optimal management of soil, water, and air conditions, marking a significant leap from traditional methods [5], [6]. PA techniques can be applied in the whole cycle of farming, including the observation, diagnosis, decision and action, in order, for instance, to reduce the quantity of herbicides while effectively removing weeds, as well as to reduce main crop losses by keeping the farming cost low and decreasing environmental impact [7].

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Among AI technologies, Deep Learning (DL) represents a transformative approach, particularly in analyzing complex data such as satellite and aerial imagery for crop monitoring, disease detection, and environmental assessment. Unlike traditional Machine Learning (ML) techniques, DL can handle vast amounts of unstructured data, enabling more accurate and comprehensive analyses [8], [9]. This capability is crucial for PA, where the early detection of anomalies such as plant diseases or adverse environmental conditions can significantly mitigate risks and enhance crop yield [10]. Furthermore, DL applications extend to predicting weather patterns, optimizing irrigation schedules, and estimating crop yield, all of which contribute to reducing operational costs and environmental impact [11], [12], [13]. The following paragraphs illustrate recent studies that aim to categorize PA-related DL methods from different aspects.

In [10], the authors present a detailed categorization of 40 DL-based methods related to agriculture and food production. They define and classify the methods into 16 categories of agriculture areas while highlighting their performance and DL-related features. The same authors, in [14], summarize and analyze 27 methods related to agriculture based on Convolutional Neural Network (CNN) architectures, focusing on technical details of the employed models, their reported performance and data sources used. In [15], the authors present a short review of DL methods in the agriculture and food production domain by illustrating their performance compared to traditional AI models, while in [1], the authors carry out a short review of DL-based methods related to weed detection in five types of crops. In [16], the authors present a survey of DL-based techniques by categorizing the methods into 14 categories related to agriculture and reviewing the data employed, the DL architecture design, and the performance.

In [17], the authors propose a classification of DL methods based on the type of dense scenes encountered in agricultural contexts. Their classification into quantity-dense and inner-dense scenes provides a framework for assessing the suitability and effectiveness of different DL approaches in PA. Let us note that quantity-dense scenes refer to environments where the primary focus is on countable objects, such as fruits or vegetables, whereas inner-dense scenes describe environments characterized by the holistic view of plants, such as fields of wheat or canopy cover. In [18], recent ML and DL approaches related to plant phenotyping techniques for crop monitoring are reviewed. In [19], a statistical analysis of scientific studies -related to agriculture- published during the last two decades is presented. ML and DL techniques are analyzed and counted according to the number of citations gained, published country, applied framework, and category of the input data. In [7], the authors present a bibliographic analysis of 120 published scientific studies in the field of agriculture by categorizing them into nine domains of agriculture. In [13], the authors filter recent DL papers and review 32 of them by classifying them into three categories: plant, animal, and others; moreover, they report the technical details about the DL architecture used for each one.

In [20], the authors review robotic systems developed based on ML and DL algorithms to address typical agricultural operations, namely harvesting and cropping. In [21], the authors illustrate a detailed review of DL-based methods for yield prediction and estimation at an early stage. In [12], the authors survey the DL methods related to the crop yield prediction problem and illustrate their objectives, techniques used, and applied crop types. In [22], the authors review the recent advancements, challenges and prospects of DL methods applied in controlled environments, i.e. greenhouses and plant factories. In [23], the authors analyze 595 documents related to few-shot learning, with 27% of them found to be applied in the agriculture domain. Few-shot learning, recognized for its ability to learn from limited data, represents an evolution beyond traditional DL approaches, offering promise in scenarios where collecting extensive labeled datasets is impractical. Despite its distinct methodology, few-shot learning often relies on DL models as foundational backbones, benefiting from their robust feature extraction capabilities to perform with minimal examples.

In [24], the authors review the DL-based methods proposed over five years in the agriculture domain by characterizing the problem addressed, the dataset employed, the DL model used, the framework deployed, and the data augmentation technique applied. Finally, in [25], the authors develop a DL-based system to detect and classify tomato plant diseases from leaves observation related to the tomato diseases and analyse their performance across ten deep learning architectures.

The aforementioned research reviews are related to DL-based techniques proposed in PA and cover the domain from various aspects, i.e., through comparison of DL methods' performance, agricultural practice categorization, and classification of DL architectures used. However, none of them is designed to perform a categorization of the methods taking into account their primary objectives and their relevance to the anomaly detection problem, which typically aims to the separation of data samples into positive and negative categories. According to [26], [27], [28], [29], [30], and [31], an anomaly is defined as a data point or event that deviates from the data considered normal, an outlier, an abnormality, something unusual, irregular, inconsistent, unexpected, erroneous, or faulty, generally everything that generates nonconforming patterns. The methods and algorithms proposed to effectively observe, detect, extract, and identify these data points or events comprise the main objective of the anomaly detection domain. Such methods and algorithms are characterized by using unlabeled or few -labeled with anomalies- data.

In this work, we characterize and categorize the currently applied DL-based methods for anomaly detection in the field of PA by proposing a new taxonomy. We provide a detailed discussion and report the characteristics and datasets of all examined methods. Our contributions are summarized as follows:

(a) **A Novel Taxonomy for PA:** We introduce a novel taxonomy that categorizes DL methods based on their relevance to anomaly detection in PA. This taxonomy is unique in its consideration of both the nature of anomalies (e.g., plant diseases, environmental stresses, pests and weeds appearance, crop yield deviations) and the data types (e.g., satellite imagery, sensor data) used in their identification. Hence, we provide a framework that directly links the objectives of DL methods to their applicability in detecting agricultural anomalies.

(b) **Method Objective Categorization:** Our taxonomy classifies DL methods into specific categories, namely feature extraction, classification (binary, multi-class, pixel-wise), region proposal (object detection), instance segmentation, regression, and reward predictor depending on their final objective. We provide examples illustrating how these objectives support specific anomaly detection tasks in PA, like pixel-wise classification for stress identification in crops or instance segmentation for precise disease detection.

(c) **Characterization Across the Supervision Spectrum:** Recognizing the varied availability of labeled data in PA, our taxonomy includes methods spanning the entire supervision spectrum: unsupervised, semi-supervised, supervised, and reinforcement learning. This categorization underscores the potential of unsupervised and semi-supervised methods in scenarios where anomalies are rare or ambiguous, highlighting their importance for effective anomaly detection in PA.

(d) **Comprehensive Discussion on Categorization:** We offer an extensive discussion on the proposed categorization, addressing the effectiveness and challenges of applying these DL approaches to PA. This includes considerations of data availability, computational demands, and the integration of multi-modal data, providing a critical analysis of current methodologies and suggesting pathways for future research.

(e) **Evaluation of Datasets and Methodologies:** In addressing the critical role of datasets for training and evaluating DL models, we present an analysis of the datasets utilized by categorized methods, facilitating considerations of their diversity, quality, and relevance to different anomaly detection tasks. Moreover, our review highlights the approaches to cross-domain evaluation within the taxonomy, emphasizing its significance in assessing the robustness and generalizability of these methods across various PA scenarios.

The remainder of the paper is organized as follows: Section II specifies the methodology adopted for collecting the related literature and datasets. It includes our systematic approach to data collection, the criteria for inclusion and exclusion, and the process for categorizing content. Additionally, we articulate the research questions addressed through our analysis, laying the groundwork for a thorough investigation of the domain. Section III provides a foundational overview of DL concepts critical to understanding the subsequent analysis. Section IV introduces and explicates the proposed novel taxonomy for categorizing DL-based anomaly detection methods in PA. We detail each category within the taxonomy and discuss the rationale behind their creation, followed by an in-depth examination of the DL methods assigned to each category, highlighting their objectives, methodologies, and applications. Section V proceeds in a detailed discussion of the findings from our taxonomy linked to the corresponding subsections of section IV, including a statistical analysis of the methods categorized and the insights gained from this classification including computational resources demands of each DL approach. We explore emerging trends, identify gaps in the current research landscape, and discuss the implications of our findings for future work in the field. Finally, the conclusions are presented in section VI.

II. METHODOLOGY

The methodology followed to identify, screen, and include the methods reported in this survey is aligned with the guidelines reported by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology [32]. Specifically, PRISMA methodology addresses 27 relevant items from a predefined checklist and the actions are illustrated in the flowchart focusing on new systematic reviews, which included searches of databases and registers only. The actions for discovering the studies that will be reported and reviewed in this survey are based on the three steps: identification II-A, screening II-B, and inclusion II-C, as depicted in Fig. 1 for the collection, validation, and selection of the respective studies.

A. IDENTIFICATION-RECORDS COLLECTION

The step of "Identification" aims to collect the content for this survey by defining the databases and formulating the queries applied to the corresponding search engines. Thus, a combination of keywords and operators is required to formulate the queries to acquire the content that will be analyzed in this systematic review. The formulated queries were executed in two scientific databases: SCOPUS and Web of Science (WoS), as depicted in the list below:

- **Scopus**: *TITLE((agriculture AND "deep learning") OR (agriculture AND "artificial intelligence")) AND ABS ((agriculture AND "deep learning") OR (agriculture AND "artificial intelligence")) AND PUBYEAR > 2017 AND PUBYEAR < 2024 AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp"))*
- **Web of Science**: *(((((TI = (agriculture) AND TI = (deep learning)) OR (TI = (agriculture) AND TI = (artificial intelligence))) AND ((AB = (agriculture) AND AB = (deep learning)) OR (AB = (agriculture) AND AB =*

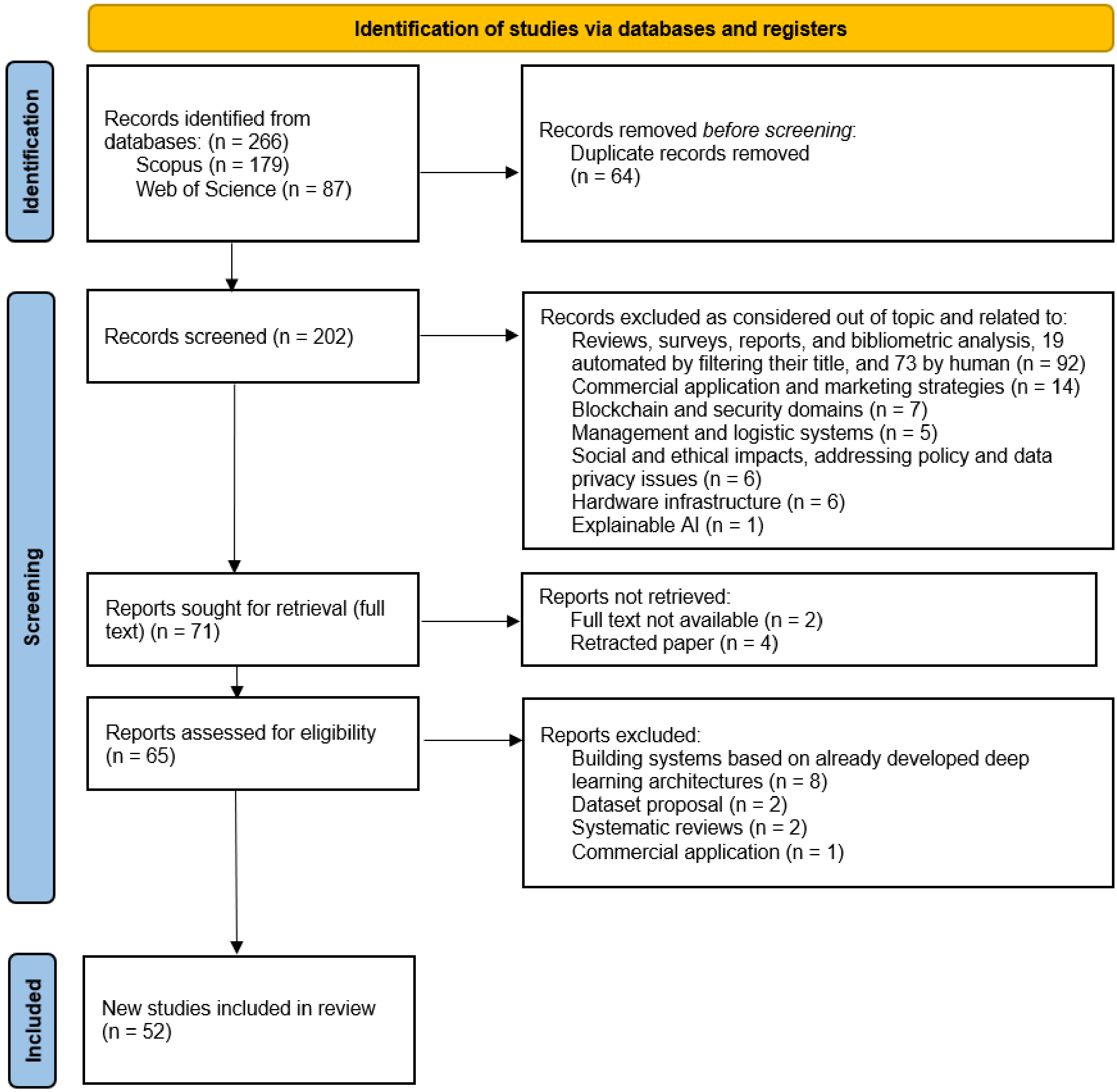


FIGURE 1. **PRISMA 2020 flow diagram for identification of studies via databases and registers.**

(artificial intelligence)))) AND PY = (2018-2023)) AND DT = (Article OR Proceedings Paper)) AND LA = (English)

The queries target to retrieve manuscripts in English and published only in conference proceedings or journals. The relevant publications must contain the words "agriculture" and "deep learning" or "agriculture", and "artificial intelligence" in their abstract and its title, while the publication time should be between 2018-23. We emphasized the use of generic keywords and logical operators in query formulation, an extended publication timeframe, and the inclusion of two databases to mitigate potential limitations and biases, in order to ensure greater transparency in the systematic review. In Fig. 1, are depicted 266 records have initially been identified from the two databases (last access: July 20, 2024), out of which 64 were duplicates and hence, were excluded, resulting in 202 records for the next step.

Fig. 2 illustrates the distribution of these collected publications over the examined years (after removing the duplicates). It is clearly illustrated that there is an increased interest from researchers in publishing DL-based scientific works related to precision agriculture year to year. This is also

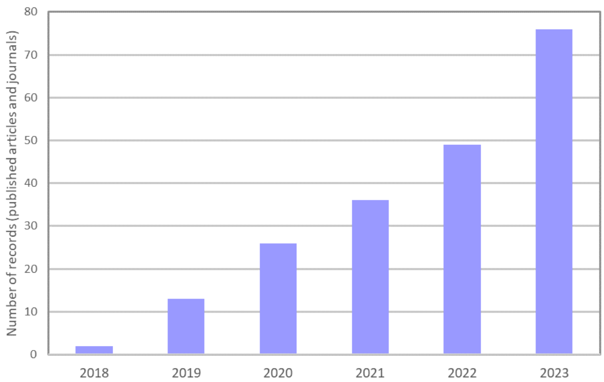


FIGURE 2. Number of published scientific works in SCOPUS and web of science from 2018 to 2023.

depicted in 2023 with more than 76 scientific works related to DL-based precision agriculture from a total of 202 published in the last six years.

B. SCREENING-RECORDS MASKING

In this step, the objective is to mask the data records that are not directly relevant to this systematic review by reporting the reasons and the eligibility criteria, firstly based on their title and abstract and then by reading their full texts. As depicted in Fig. 1, from 202 records, 19 are excluded because they are related to systematic reviews and surveys. These records contain the keywords "review" and/or "survey" in their titles, while another 73 records are excluded as reviews, surveys, reports, and bibliometric and scientometric analyses during the screening step. Moreover, 14 records [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46] are rejected, because they aim at illustrating commercial applications and marketing strategies, while 14 records [6], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59] are focused on non-relevant domains, such as blockchain, security, and explainable AI. Five records [60], [61], [62], [63], [64] are excluded because they are related to management and logistics systems rather than to the topic of this systematic review. Considering the goal of the present study, six records [65], [66], [67], [68], [69], [70] are not included, since they are related to social, ethical, policy or data privacy issues.

The remaining records (called reports from now on), which amounted to 71, were retrieved and then scrutinized for eligibility for this systematic review. From these 71 reports, two reports [71], [72] are not available as full text, and another four have been characterized as "Retracted", resulting in 65 being included in this review. Eight [73], [74], [75], [76], [77], [78], [79], [80] are related to infrastructure applications without a significant contribution to the DL analysis domain. These studies are typically focused on an incremental approach with the objective of building systems based on already developed DL architectures. In [81] and [82], two well-structured datasets are proposed; however, these studies have no focus on analysing DL models. The authors propose a commercial application in [83], while reports in [84] and [85] are systematic reviews. Hence, the reports mentioned above have been excluded from the analysis of this systematic review, resulting in a total of 52 studies considered for further analysis.

C. INCLUSION-META-ANALYSIS STUDIES

The final step of the PRISMA methodology consists of the systematic reading and meta-analysis of the reports -a total of 52- (from now on, called studies), to respond to the following questions:

- How is anomaly detection in precision agriculture through DL? (Subsection IV-A)
- Do the examined studies address the imposed challenges as an anomaly/outlier detection problem? (Subsection IV-A1)
- What topics of agriculture (from now on, called categories) are more relevant to the detection of anomalies? (Subsection IV-A2)
- What are the types of anomalies related to each category? (Subsection IV-A3)
- Except from RGB imagery, do the examined studies applied in agriculture rely on additional modalities; and if yes which? (Subsection IV-B)
- What are the data types of the examined studies rely on? (Subsection IV-B1)
- What are the training objectives of the proposed DL architectures, and what is their supervision spectrum? (Subsections IV-C1, IV-C3)
- What is the structure of the proposed frameworks, and what types of DL networks do they rely on? (Subsections IV-C, IV-C2)
- What are the datasets used in the agriculture domain? (Subsection IV-D)
- Do the authors rely on widely used datasets or propose their own - Do they report cross-domain evaluation? (Subsection IV-D)

III. THEORETICAL BACKGROUND

In this section, the fundamental characteristics of Artificial Neural Networks (ANNs) are presented. ANNs aim to simulate the human brain's processing procedures by employing neurons and inner connections to recognize patterns and relationships extracted from features learned by the trained data [86]. A special category of ANNs is the Deep Neural Networks (DNNs) that employ multiple layers -named hidden layers- in a sequence to encode the given data more effectively. Both ANNs and DNNs are deployed with at least one input layer that feeds the network with the input data and the output layer that generates the output adapted to the objective of the problem [13].

A particular category of DNNs is the Convolutional Neural Networks (CNNs) that report impressive results when applied to various tasks, including Computer Vision (CV) and Natural Language Processing (NLP). CNNs typically consist of an input layer followed by multiple sequential convolutional layers stacked with fully connected layers before the output layer. In addition, CNNs consist of pooling layers aiming to reduce the encoded information after each convolutional layer, activation layers that deploy activation functions (i.e., ReLU [87], Sigmoid [88], etc.) after each layer and cost functions that are employed for optimizing network parameters (weights) and error-calculation during training [89]. Well-known CNN architectures include but not limited to AlexNet [90], LeNet-5 [91], VGG [92], and ResNet [93].

In the field of CV, CNNs have been used in various domains to encode visual features with the main objectives being but not limited to binary, multi-class or multi-label classification. Although these tasks represent a large part of the CV needs, there are additional relevant needs, such as detecting anomalies, reconstructing images, generating segmentation masks, and detecting objects of interest. Hence, various and famous CNN-based architectures have been proposed to address these objectives: Stacked Auto-Encoders [94], U-Net [95], Faster R-CNN [96], among others.

However, the aforementioned architectures do not report effective performance when aiming to encode spatiotemporal data streams, such as video frames, that are typically the input for activity recognition [97] and surveillance systems [98]. Thus, architectures such as 3D-CNNs have been designed to learn the network parameters given a sequence of input frames and apply the convolutional function to 3D space simultaneously [99]. A more effective network to deal with spatiotemporal data is a variation of a basic neural network, namely the Recurrent Neural Network (RNN). RNNs are effective when processing time-series data, such as audio, NLP and sequences of images. RNNs have proved to be effective in this respect, as they can address the gradient problem (which may result in overfitting during learning [100]), and are modelled by Long-Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). Finally, BiRNNs are employed for LSTM and GRU to effectively capture the sequence of data in both forward and backward directions [101].

IV. PROPOSED TAXONOMY

This section presents the proposed taxonomy of the studies included in this review, in this point we have to clarify that a study may utilize multiple methods, resulting in 64 examined methods from the 52 studies. A high-level representation is illustrated in Fig. 3, where the studies/methods are summarized considering the key-examined attributes of the proposed taxonomy for simplicity purposes. From left to right, the relevant agriculture categories, their possible mapping to anomalies, the corresponding type of anomalies, the data modalities employed, the type of deployed architectures and the training objectives are presented, visualizing their detected interrelations as "path-flows" in the chart (the larger a path-flow the stronger the interrelation). More details are given in subsection V-E.

To provide a more focused investigation, the schema proposed in this paper is divided into four sub-taxonomies describing distinct characteristics: a) agriculture categories and their relevance with anomalies, b) data modalities and their types, c) training objectives and their deployed architectures, and d) datasets and evaluation. The meta-analysis of the studies considering each sub-taxonomy is presented in the following subsections.

A. AGRICULTURE CATEGORIES AND THEIR RELEVANCE WITH ANOMALIES

The main objective of this sub-taxonomy is related to capturing the primary intent of the presented work. For each of the studies analyzed in this review, the agriculture category is depicted in Table 1, followed by its relevance with anomalies and the corresponding type of anomaly, if applicable. The agriculture categories related to each study are depicted in the rows, classified into one of three possible types of relationships: "**Yes**" means that a study explicitly models and addresses its primary objective as an anomaly detection problem; "**No**" means that a study does not model and address its primary objective as an anomaly detection problem; and "**Could be**" means that a study could be modified straightforwardly to model and address its primary objective as an anomaly detection problem. The columns represent the categorization of the studies according to their type of anomalies. Specifically, there are three possible types of anomalies: point anomalies, contextual anomalies, and group anomalies. The studies that have "No" connection to anomalies are included in the column "N/A" in Table 1.

1) AGRICULTURE CATEGORIES

This subsection includes the proposed categories related to the analyzed studies. Specifically, 13 agriculture categories have been extracted - Disease detection, Weather prediction, Land cover classification, Plant pest/disease recognition, Crop monitoring, Crop size and mass estimation, Object/fruit/crop/obstacle detection, Soil moisture prediction and soil type/quality classification, Crop/weed classification, Crop yield prediction, Crop quality classification, Weed resistance assessment, Land coverage optimization- which collectively cover all the agricultural topics of the studies examined. The "Plant pest/disease recognition" category refers to detecting and recognizing pests and diseases. In contrast, the "Disease detection" category is limited to detecting whether a plant is potentially diseased. In addition, the "Crop/weed classification" category is related to classifying weeds and crops into a range of possible types. Finally, studies belonging to the category of "Land cover classification" aim to distinguish various types of land cover, e.g. forest and water, in contrast to studies belonging to the "Land coverage optimization" category, aiming to optimize the coverage of the land using onboard sensors,

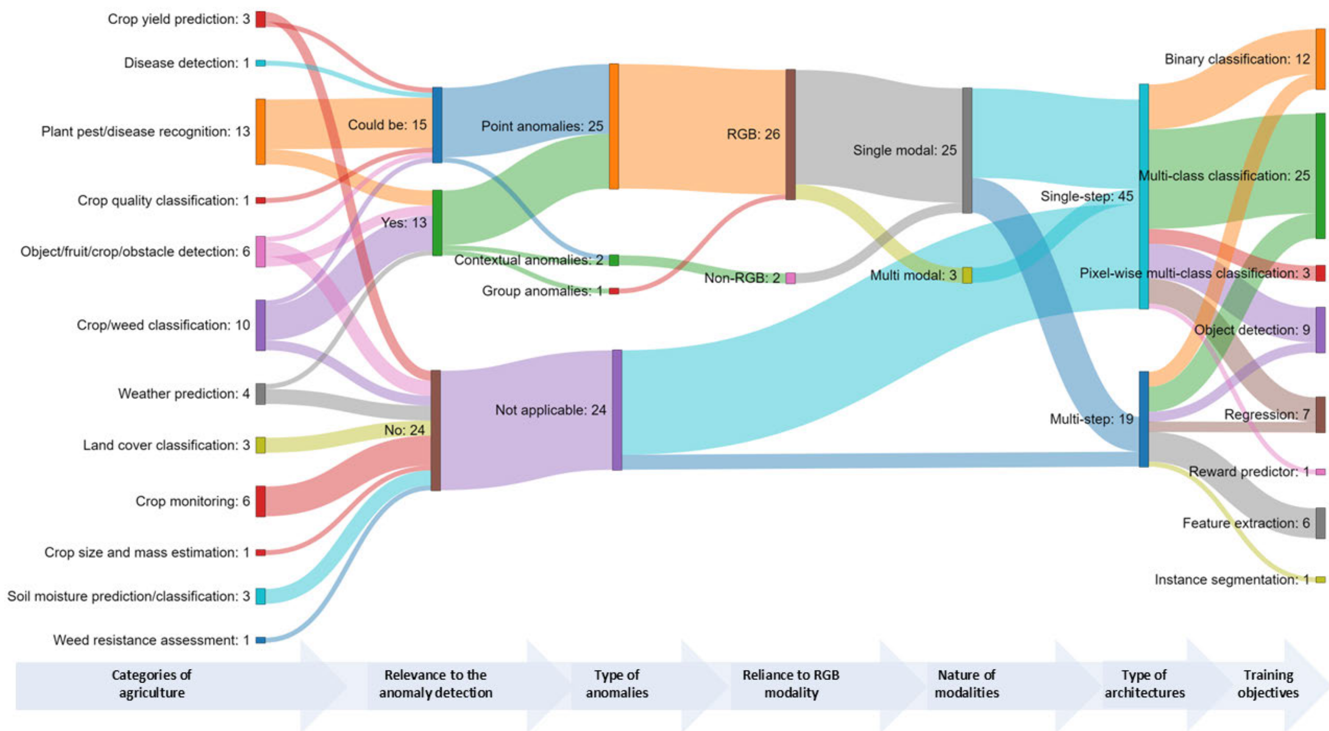
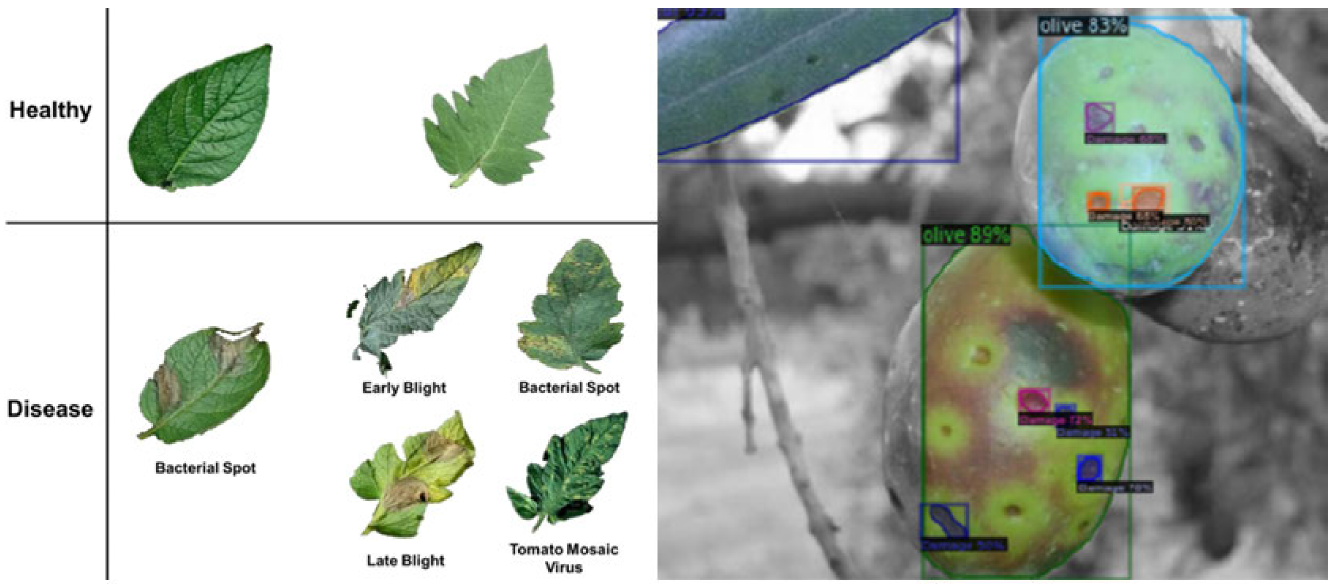


FIGURE 3. A flow-based representation of the key values extracted from the examination of the 52 studies and mapped to 64 DL training objectives. From left to right, the various categories of agriculture and their relevance to the anomalies as well as their mapping to the types of anomalies. Next, the reliance on the RGB modality, the nature of modalities and the architecture of the employed pipelines. On the right, are depicted the various training objectives.



(a) Point anomalies. (b) Group anomalies.

FIGURE 4. Image samples for illustrating the different types of anomalies. (a) Point anomalies [154] and (b) group anomalies [110].

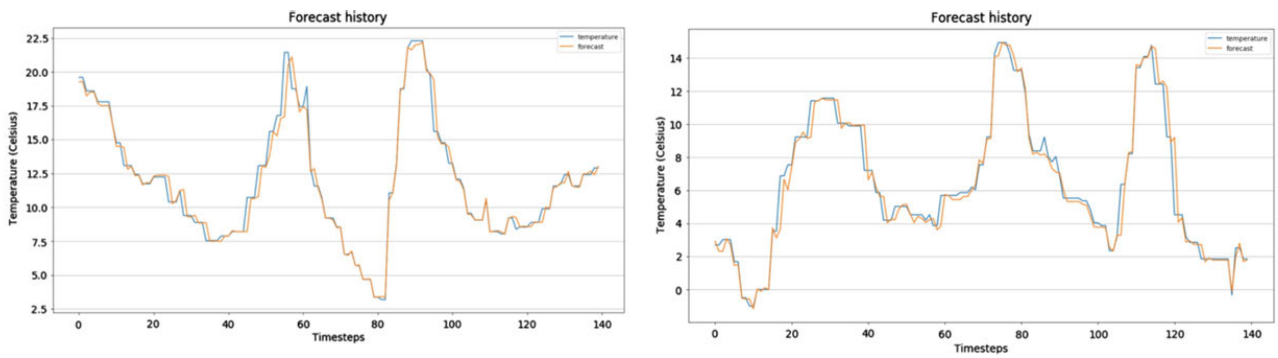
typically UAVs equipment with cameras. In case a study can be mapped to more than one agriculture category (due to employing more than one method), then the secondary category is marked with an "S" inside Table 1.

2) RELEVANCE WITH ANOMALIES

This subsection explains the approach followed for characterizing each study as relevant or not to anomaly detection. Specifically, we have defined three groups for determining

TABLE 1. Studies categorization according to their agriculture category, relevance with the anomaly detection problem, and anomaly type.

Anomaly relevance / Agriculture category	Type of anomalies: Point	Contextual	Group	N/A
Yes				
Crop/weed classification	[102] [103] [104] [105] [106] [107] [108] S: [109]			
Crop quality classification	S: [104]			
Object/fruit/crop/obstacle detection	[109]		[110]	
Plant pest/disease recognition	[111] [112] [113]		S: [110]	
Weather prediction		[114]		
No				
Crop monitoring				[115] [116] [117] [118] [119] [120]
Crop size and mass estimation				[121]
Crop yield prediction				[122] [123]
Crop/weed classification				[124] [125]
Land cover classification				[126] [127] [128], S: [129]
Land coverage optimization				S: [126]
Object/fruit/crop/obstacle detection				[130] [131] [129]
Soil moisture prediction and soil type classification				[132] [133] [134]
Weed resistance assessment				[135]
Weather prediction				[136] [137] [138]
Could be				
Crop quality classification	[139]			
Crop yield prediction		[140]		
Crop/weed classification	[141]			
Disease detection	[142]			
Object/fruit/crop/obstacle detection	[143]			
Plant pest/disease recognition	[144] [145] [146] [147] [148] [149] [150] [151] [152] [153], S: [141]			



(a) Temperature data at Cieza location.

(b) Temperature data at Moratalla location.

FIGURE 5. Image samples for illustrating the contextual anomalies comparing temperature values in different locations inspired by [114]. (a) Temperature data at Cieza and (b) at Moratalla locations.

the relationships of presented studies to the problem of anomaly detection. The first group includes the studies that explicitly solve their identified problem as an anomaly detection problem, i.e. typically through the detection of outliers. The second group involves studies that usually perform classification; hence, with an adaptation, they could be considered studies associated with the detection of anomalies. For example, this group involves studies that aim to recognize plant diseases in a collection of images that also include healthy samples. Finally, the studies that cannot be considered or adapted to be characterized as anomaly-related are included in the last group. Specifically, the studies in this group usually aim to monitor crops or classify only 'healthy'/'normal' data points.

3) TYPE OF ANOMALIES

For the studies classified into one of the groups "Yes" or "Could be", the type of anomaly is specified, whereas for the studies that are categorized as "No" the type cannot be specified. According to [27], the different types of anomalies are point, group, and contextual. To clarify the different types, inspired by [27], examples are illustrated in Fig. 4 and Fig. 5. These image samples acquired and adapted from [110], [114], and [154] help in distinguishing the different types of anomalies. Point anomalies refer to individual data points that are deviant from the rest of the data points in a dataset, as illustrated in Fig.4 (a); there are a few leaves that are affected by disease compared to healthy leaves. Group anomalies are related to single data points that can be considered normal but, in a group, are considered abnormal, as illustrated in Fig. 4 (b); there are a few damages on the olives that are normal, but as a group of damages is considered abnormal probably effected by disease or pest. Finally, contextual anomalies are data points that can be considered normal in a specific context; however, if they are observed in another context, they could be considered abnormal. According to Fig. 5 (a) the temperature values at timestep 80 are low and can be considered normal compared to Fig. 5 (b) that are higher and can be considered as abnormal.

B. DATA MODALITIES AND THEIR TYPES

In this subsection, the data modalities and the corresponding data types used in the studies of this systematic review are presented. For each study, we have annotated the following columns and rows according to Table 2: the first column divides the studies into two main categories, "**Non-RGB**" and "**RGB**" for the characterization of each study with yes or no, depending on whether it relies on RGB data or not. Regarding the rows, the "**Nature of modalities**" represents the type of modalities each study relies on. If a study processes only one modality, for example, images or video frames, it is considered as single-modal. Otherwise, if it relies on multiple modalities, e.g. images and temperature data, it is considered multimodal. The column "**List of modalities additional to RGB**" includes a list of additional to RGB modalities separated by a semicolon for each of the studies depicted in column "**Studies**". Since RGB-related and single-modal methods cannot incorporate additional modalities, the cells of Table 2 for both Non-sequential and Sequential data types remain empty. Finally, the "Data types" column shows the data types of each study, namely: Sequential, Non-sequential, Both, or Not described. This is further explained in subsection IV-B1.

1) DATA TYPES

This subsection explains each data type mentioned in Table 2. The nature of the data determines the type of the data. i.e., temperature data are usually time series-based data, as they typically involve temperature values periodically over time. Another example is video data streams, which are almost always time-series data, as they capture a series of frames in video footage. Such data types are declared as **Sequential** and include time-series-based data; other examples include humidity-related data and speech data.

Conversely, **Non-sequential** data are data that are not time-dependent or do not follow a specific sequence; thus, still images and data acquired from sensors as alarms -without performing a periodic monitoring process- belong to this category. The declaration of **Both** is related to multimodal approaches that process sequential and non-sequential data in different modalities. Finally, in case the authors do not give sufficient details related to the nature of the data, **Not described** is specified in Table 2.

C. TRAINING OBJECTIVES AND THEIR DEPLOYED ARCHITECTURES

This sub-taxonomy encompasses details from the analyzed studies regarding the training objectives of the proposed DL architectures and the types of networks employed. It provides insights into their pipeline architectures and illustrates the range of supervision applied during the learning process. Table 3 presents a four-level classification that includes pipeline types, supervision spectrum, training objectives, and DL network types. Specifically, the first column (of Table 3) separates the studies according to their pipeline architecture into "**Single-step**" approaches that typically follow an end-to-end training approach to reach their final objective and "**Multi-step**" approaches that rely on multiple and separate stages of training to reach their final objective. The single-step studies listed in Table 3 are presented with only their final objective, except for the study [129], which is also marked with an "S" for its secondary objective, aiming to learn object detection and binary classification in a single step. This is evident in the multi-step approaches, which consistently include a secondary training objective. A particular case is depicted in [138] where the final objective of regression is deployed in multiple steps using CNN and LSTM architectures. The studies are categorized by their "**Supervision Spectrum**" during training into one of the following options: unsupervised, supervised, and reinforcement learning. More details are provided in subsection IV-C3.

Additionally, the objectives pursued in each study during training and applied during inference are detailed in the rows of Table 3, subsection IV-C1. The corresponding DL network types for each study are shown in the columns, as described in subsection IV-C2. When a study relies on multiple DL network types, these are declared sequentially with the letters (a, b, c). In [142], the letter "b" appears twice because it employs a two-stream (rather than a sequential) approach, specifically LSTM + CNN-LSTM.

1) TRAINING OBJECTIVES

This subsection outlines the various training objectives pursued in the reported studies, as shown in Table 3. Typically, a DL network aims to classify the given input based on extracted encoded features. Therefore, the training objectives generally focus on learning features for extraction and/or classification, including binary, multi-class, and multi-label classification. A specific classification category includes semantic segmentation approaches, which aim to classify an image at the pixel level. This involves segmenting the image to classify some or all pixels into one or more categories. This can be further extended to instance segmentation [155], panoptic segmentation [156] and referring segmentation [157]. Moreover, DL network objectives often involve generating region proposals for object detection tasks, which typically include both the localization and classification of depicted objects into their respective categories.

TABLE 2. Studies categorization according to their data modalities and their types.

	Nature of modalities Data types	Studies	List of modalities additional to RGB
Non-RGB	**Multimodal**		
	Sequential	[133] [134]	Volumetric soil moisture, soil temperature, climate data (air temperature, air humidity, and rainfall); pH, OC (Organic Carbon), Potassium, Phosphorous
	Single modal		
	Non-sequential	[126]	Grid cell data (localization, region data)
	Both	[123]	State name, district name, crop year, seasons, crop type, rainfall, wind speed, humidity, area under irrigation, area, production
	Not described	[116]	Soft sensor
	Sequential	[114] [115] [137] [140] [120] [138]	Temperature, humidity, wind speed; Temperature, humidity, ultraviolet; Temperature, humidity; Production; Temperature; Temperature, humidity
RGB	**Multimodal**		
	Both	[142] [132] [117] [135]	Temperature, humidity, pressure, soil moisture; Textual moisture (rainfall); Color-InfraRed (CIR); Hyperspectral, structural (Canopy Height Model)
	Non-sequential	[143] [139] [127] [129]	Depth; Thermal images; Color-InfraRed (CIR); Color-InfraRed (CIR)
	Sequential	[128]	NIR
	Single modal		
	Non-sequential	[144] [121] [145] [146] [130] [147] [148] [136] [149] [102] [124] [125] [141] [103] [122] [104] [109] [112] [105] [131] [113] [110] [106] [150] [151] [152] [107] [153] [108]	
	Sequential	[118] [119] [111]	

TABLE 3. Studies categorization according to pipeline types, supervision spectrum, training objectives and deep learning network types.

	Supervision spectrum Training objective	CNN	RNN GRU	LSTM	BiLSTM	RNN	RBF	Caps Net	WONN	SAE	ANN	ENN	KERNEL ELM	N/D
Single-step	**Reinforcement learning**													
	Reward predictor	[126]												
	Supervised													
	Binary classification	[142]b* [140] [118] [128]a S: [129] [108]		[142]a [142]b* [114]	[128]b		[115]						S: [107]	
	Multi-class classification	[144] [147] [148] [136] [132]c [149] [124] [125]a [104] [139] [112] [113] [106] [123]a [150] [151] [152] [153]	[132]b [125]b	[132]a [125]c			[122]							
	Object detection	[130] [143] [103] [131] [129] [107] [108]												
	Pixel-wise multi-class classification	[102] [117]												[127]
	Regression	[135]	[137]	[119] [133]			[120]							
Multi-step	**Supervised**													
	Feature extraction	[141] [105] [111]						[145] [146]						
	Binary classification											S: [105]	S: [109]	
	Multi-class classification	S: [141] [110]	S: [146]		S: [145]	S: [111]								
	Instance segmentation	[121]												
	Regression	[138]a		[138]b							S: [121]			
	Object detection	[109] [110]												
	Unsupervised													
	Feature extraction								[116]					
	Binary classification									S: [116]				

Finally, a deep neural network's objective might be to solve a regression problem or to minimize or maximize a penalty or reward during reinforcement learning.

2) DEEP LEARNING NETWORK TYPES

In addition, the various types of deployed deep neural network architectures are noteworthy. The corresponding type for each study is presented in the columns of Table 3. Specifically, the types for each study include one or more of the following: CNN, RNN (GRU, LSTM, BiLSTM, RNN), RBF, CapsNet, WONN, SAE, ANN, ENN, Kernel ELM, as well as N/D, which stands for "Not described" if the authors do not provide this information. For RNNs, we also include the option of "RNN" when the specific type of RNN architecture is not detailed by the authors.

3) SUPERVISION SPECTRUM

The supervision spectrum of the reported studies is one of the key components that should be further analyzed. In general, DL-based approaches use data to learn and "encode" input features to perform specific tasks, i.e. classification and detection, effectively. To this end, the training process requires a large amount of annotated data, following a supervised learning approach. On the contrary, approaches that do not require annotated data and are trained without

TABLE 4. Datasets and evaluation.

Dataset range	Pre-trained dataset					
Dataset name	COCO	ImageNet	PASCALVOC	Trained from scratch	N/D	Cross-domain dataset
Introduced						
Apple leaf disease				[145]		
Bale	[130]					Bale synthetic
Carrot disease					[147]	
Cieza+Moratalla				[114]		
Coconut leaf disease				[146]		
Dubai			[129]			
Food crops and weed images				[109]		
FruitGB				[104]		
Indian crops					[123]	
Indian meteorological department				[133]		
KARC, AARC					[124]	KARC, AARC & vise versa
Mango					[139]	
Morocco				[117]		
Mushroom				[131]		
National Bureau of China				[140]		
Not described				[126]	[115] [116] [125]	
Pea and strawberry					[103]	
Punjab, India					[127]	
SeedsGermination				[118]		
Soil					[132]	
Taiwan				[120]		
Tamil Nadu				[134]		
Temperature and humidity, Baldia Town				[138]		
Temperature and humidity, China Ningxia				[137]		
Tomato	[121]					
Tomato Growth				[119]		
UAV weeds					[108]	
Weed					[105]	
Wheat crop				[122]		
Xiangyang farm				[135]		
Yogyakarta				[128]		Mengwi
Existed						
Coffee leaf disease					[152]	
Cotton crop					[106]	
Crop/Weed			[107]			
CWFID				[102]		
Fruit-360, PlantVillage		[141]				
INRIA person, PennFudanPed				[143]		
Kaggle potato leaf dataset		[150]				
Kaggle, PlantVillage, DiaMOS				[111]		
Paddy disease					[153]	
PlantVillage and its variants	[110]	[144] [149] [110]		[142]* [151]	[148] [112] [113]	*Coffee Leaf Rust
WEAPD				[136]		

supervision, are known as unsupervised learning. These are often associated with tasks like image reconstruction or anomaly detection.

Finally, reinforcement learning is applied to complex decision-making problems. In this approach, an agent interacts with an environment to gain knowledge by minimizing or maximizing penalties or rewards, meeting predefined programmed conditions [158]. While reinforcement learning can be considered unsupervised due to its lack of reliance on labeled data, it also incorporates elements of supervised learning by using unlabeled data to learn features based on specific conditions. This ambiguity has led to the recognition of reinforcement learning as a distinct category within the supervision spectrum.

D. DATASETS AND EVALUATION

This sub-taxonomy provides a detailed examination of the datasets and their evaluation domains. In Table 4, the categorization of studies based on their dataset range is illustrated, along with the specific dataset name for each study. The category "**Introduced**" includes all datasets that were first introduced by the authors in the corresponding study. On the other hand, the category "**Existed**" includes datasets that are widely used in the relevant literature, including those that have been proposed previously, as well as their subsets or extensions. The columns of the table also depict the datasets used in pre-trained models and map them to the corresponding studies. "Trained from scratch" is indicated when an approach does not rely on a

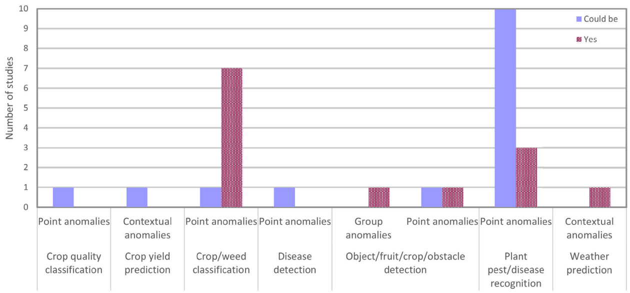


FIGURE 6. Statistical analysis of reported studies according to their agriculture category and type of anomaly. Studies that cannot be adapted to address their objectives as an anomaly detection problem have been excluded from this analysis.

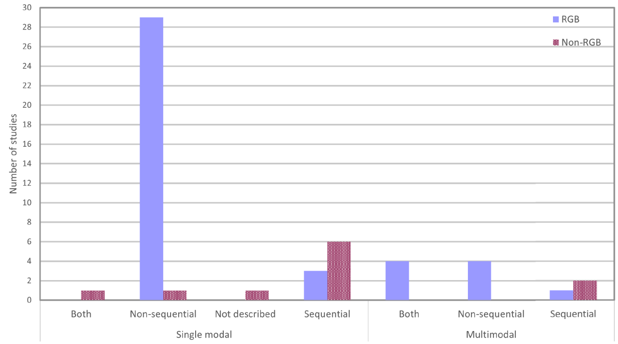


FIGURE 7. Statistical analysis of the reported studies according to data modalities, nature of modalities and data types.

pre-trained dataset, and "N/D" is assigned to studies where the authors do not provide this information. A special case is noted for study [110], which uses both COCO [159] and ImageNet [160] datasets in the pre-trained models. This study relies on COCO weights for object detection and on ImageNet weights for classification tasks. Additionally, the column "Cross-domain dataset" specifies whether a study performs a cross-domain evaluation and lists the dataset used, it is worth mentioning that only 4 studies evaluated using cross-domain datasets. Finally, an asterisk (*) denotes the name of a cross-domain dataset used for evaluation by study [142].

V. DISCUSSION

In this section, the characteristics of the studies under investigation are presented and discussed according to their agriculture category, data modalities, types, training objectives, datasets, and evaluation methods.

A. AGRICULTURE CATEGORIES

Table 1 categorizes the studies according to their relevance to anomaly detection and the types of anomalies addressed. We have focused on the studies that are classified as "Yes" (dark red), which means that solve their problems as anomaly detection issues, as well as on those that "could be" (purple) adapted in order to address their objectives as anomaly detection problems. Hence, Fig. 6 depicts the 28 studies that address or could be adapted to address their objectives as anomaly-related problems based on point, group, or contextual anomaly types. Specifically, two studies align with or could be adapted to address their objectives as contextual anomalies: (a) the crop yield prediction category, which leverages historical yield data across various crops to identify anomalies, and (b) the weather prediction category, which analyzes specific contextual data (e.g., area and season) to detect anomalies in weather patterns. Furthermore, one study focuses on detecting group anomalies by identifying small damaged regions on crop leaves potentially indicating a disease.

From Fig. 6, it is clear that most studies (25) are relevant to point anomalies. The majority of studies (21) fall into two categories: "Crop/weed classification" and "Plant pest/disease recognition". Both categories involve problems related to anomaly detection; for example, a disease is a deviation from a healthy plant and is thus considered an anomaly. Moreover, studies focused on classifying crops and weeds are more likely to address the problem as an anomaly-related issue compared to those aimed at recognizing plant pests and diseases, which could often be adapted for anomaly detection. This difference may be due to the nature of the objectives in each category, as anomaly detection typically involves separating samples into positive and negative classes rather than recognizing specific categories of anomalies.

B. DATA MODALITIES AND THEIR TYPES

Table 2 categorizes the examined studies (52) according to their data modalities, the nature of these modalities and their type. Considering all the research studies, Fig. 7 provides a summary of the studies according to a triple-level hierarchy. This starts with the usage of the RGB modality, then classifies according to the nature and type of the modalities.

The vast majority of studies rely on processing data within the visual spectrum (41), (purple). In addition, most of these studies (29 in total) rely on a single modality with their data types being Non-sequential. This indicates that computer vision techniques play a significant role in agricultural applications.

Finally, as shown in Fig. 7 (right), it is observed that most studies unrelated to visual analysis modalities (8 compared to 4 related to RGB), (dark red) anticipate sequential data types. This was expected, as some studies take into account time-series data such as temperature, humidity, and moisture.

C. TRAINING OBJECTIVES

Table 3 presents the sub-taxonomy of the examined studies based on the type of architecture (pipeline), supervision spectrum, training objectives, and the type of DL network employed. Only one study relies on unsupervised learning,

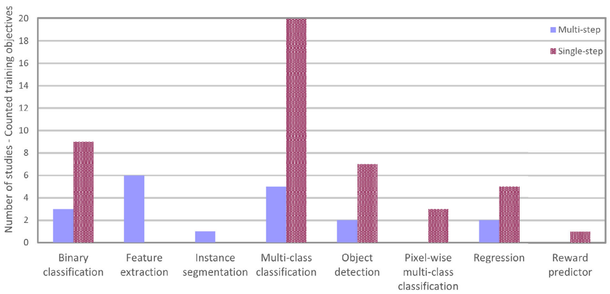


FIGURE 8. **Statistical analysis of the reported studies according to the type of architecture (pipeline) and training objectives.**

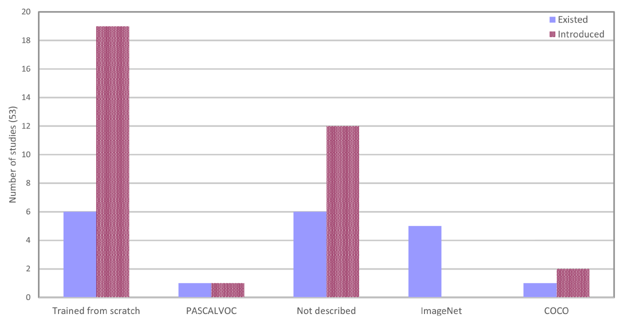


FIGURE 9. **Statistical analysis of the reported studies according to the pre-trained datasets and datasets used for fine-tuning.**

highlighting a promising area for further research. Due to the nature of the anomaly detection problem - which focuses on identifying a few anomalous samples within a large set of normal ones - annotated large-scale datasets could be highly imbalanced. Thus, unsupervised-based approaches trained to reconstruct normal data can be used during inference to identify anomalous data in the cases of reporting higher reconstruction errors.

Considering that the vast majority of such models rely explicitly on CNN types (30 compared to 11 that rely explicitly on other types), Fig. 8 illustrates the statistical analysis of the examined methods (64 in total) of the studies without reference to the types of DL networks and their supervision spectrum for simplicity.

The studies are firstly classified according to the type of architecture, with 10 studies (19 methods) deployed as multi-step architectures (purple) and the rest 42 studies (45 methods) as single-step (dark red). Because studies in the multi-step category consist of two training objectives (except [138]), the total number depicted in this category is 19. There are also three studies in the single-step category with two objectives, bringing the total number of single-step studies to 45.

According to Fig. 8, it is evident that the majority of training objectives (40) are related to classification problems, including binary (12), multi-class (25), and pixel-wise (3) classification tasks. This predominance is likely related to the supervision spectrum, as most studies (39 out of 40) utilize supervised learning, which is typically associated with classification tasks.

D. DATASETS AND EVALUATION

Fig. 9 depicts the studies that use either a self-proposed (introduced, dark red) dataset or an existing (widely used, purple) dataset. As showcased, the majority of the studies (34) were trained and evaluated using self-proposed datasets, whereas only 18 models utilized existing datasets to leverage a common benchmarking framework.

In addition, the datasets used in the pre-trained models are well-known datasets in the computer vision domain, such as ImageNet [160], COCO [159], and PASCALVOC [161]. This practice is commonly followed by proposed architectures to utilize already trained weights from large-scale datasets and perform fine-tuning on the target domain by updating all or part of the network's weights. A special case is noted for study [110], which uses two datasets in the pre-trained models and hence the depicted datasets are in total 53.

Moreover, many studies that do not rely on a pre-trained model and are trained from scratch amount to 25 in both the existing (6) and introduced (19) categories. Finally, it is noted that a significant number of studies (18 studies) do not provide detailed information and are depicted as "Not described". This includes studies that rely on pre-trained models without specifying the details of the weights used; in three studies [115], [116], [125], the authors do not provide sufficient details of the datasets used for training, as also noted in the study [126] that is trained from scratch.

E. ANALYSIS

In this subsection, the key attributes of the proposed taxonomy are summarized and presented to capture the overall conclusions of the categorization. Additionally, a comprehensive overview of the computational resources required for each DL approach is provided. For the overall discussion, we have considered the most significant categorization attributes extracted from three of the four sub-taxonomies, i.e. a) agriculture categories and their relevance with anomalies, b) data modalities and their types, and c) training objectives and their deployed architectures, as depicted in Fig. 3.

The agriculture categories, shown on the left of Fig. 3, are extracted from the 52 studies analysed in this document. More than half of these studies either address or could be adapted to address corresponding problems as anomaly detection issues. A strong correlation to anomalies is illustrated in the categories of plant pest/disease recognition and crop monitoring. In the first category, the studies are related to anomalies, such as detecting diseases and pests. In the second category, the studies are related to monitoring, which can be justified by the fact that crop monitoring studies are mainly focused on data collection and recommendations rather than the detection of anomalies within the data.

Moreover, the studies are mapped to related types of anomalies. For non-anomaly-related studies, further categorization is not necessary until the training objectives are considered. For the rest, a dominant assignment to point anomalies is depicted. This can be explained by viewing the subsequent steps (RGB/Non-RGB, Single-modal/Multi-modal), where the majority of the studies rely only on the RGB modality. Given that these studies process still images, the detection of point anomalies is strongly related to identifying outliers within the data.

In addition, the type of architecture reveals that studies are implemented using either a single-step or multi-step approach, without a particular focus on anomaly-related studies. In contrast, studies irrelevant to anomaly detection are strongly correlated with single-step architectures, indicating that these studies are more focused on solving specific domain problems, such as crop size and mass estimation.

Furthermore, all studies are analysed and mapped according to their training objectives. Taking into account that many studies address multiple methods, the total number of training objectives is 64. There is a clear association of single-step methods with classification tasks, either binary or multi-class. Notably, multi-step approaches typically involve learning features in one step and using them in the next.

Finally, We have reviewed the 52 studies for extracting their hardware dependencies, particularly Graphical Process Unit (GPU) usage as a vital part of DL approaches. It is worth noting that computational demands such as disk space, Random Access Memory (RAM), and Central Process Unit (CPU) are usually not reported by the authors however we can briefly state that the studies rely on Intel i5 and i7 CPUs and use 16GB RAM with few of them to use 64GB or more. Regarding GPU usage, from the 52 studies only 22 provide comprehensive implementation details; with three of them using only CPU for training or inference and the rest (19) using NVIDIA GPUs. There is a variety of virtual RAM for the GPU ranging from 2GB to 128GB depending on the training process and the network architecture. Regarding DL network types, from the 22 studies 18 employ CNN architectures, two RNNs, and two both CNN and RNN, leading to a strong correlation of GPU needs with CNN approaches.

VI. CONCLUSION

In this literature review, we identify, filter and analyze DL-based methods related to precision agriculture and their correlation to the anomaly detection problem. Following the PRISMA methodology, the records were collected and filtered, then further reviewed and categorized into a taxonomy that provides insights for researchers in related domains. A detailed summary covering four aspects of the reported studies is illustrated: a) agriculture categories and their relevance with anomalies, b) data modalities and their types, c) training objectives and their deployed architectures, and d) datasets and evaluation. The meta-analysis is presented in four tables and through a graphical view for easy extraction of tangible outcomes.

The analysis outcomes reveal several key trends, including an increase in the publication of studies in the precision agriculture domain in recent years, a correlation between plant disease and pest recognition and the anomaly detection problem, a preference for using single data modalities with a focus on visual analysis, the widespread use of domain-specific datasets, a lack of large-scale datasets applicable for multiple objectives, and the careful selection of DL methods for addressing classification problems.

Future work includes the analysis of domain-specific datasets for further usage and improvements, aiming to apply them to various agriculture-related tasks focused on detecting and identifying possible anomalies in the field. This can be further investigated through crowdsourced data collection, synthetic dataset generation, or dataset consolidation.

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KONSTANTINOS GKOUNTAKOS received the degree from the Department of Computer Science, University of Ioannina, in 2013, and the M.Sc. degree in web intelligence from the International Hellenic University of Thessaloniki, in 2016. He is currently pursuing the Ph.D. degree with the Department of Agricultural Economics and Rural Development, Agricultural University of Athens.

He is currently a Senior Research Associate with the Centre for Research and Technology Hellas (CERTH), Information Technologies Institute (ITI). He has participated in several projects funded via the H2020 and Horizon Europe programs, including PERIVALLON, CREST, PREVISION, CONNEXIONs, and DANTE, and also in the FOF research project HR-Recycler. His scientific work has been published in prestigious peer-reviewed international conferences. His research interests include DL, image analysis, and anomaly detection.

KONSTANTINOS IOANNIDIS received the Diploma and Ph.D. degrees from the Department of Electrical and Computer Engineering, Democritus University of Thrace, Greece, in 2006 and 2013, respectively.

Currently, he is a Postdoctoral Research Fellow with the Centre for Research and Technology Hellas (CERTH), Information Technology Institute (ITI). He is involved in various EU and national funded projects, including H2020-SEC-ROBORDER, HORIZON-INFRA-TESTUDO, EDF-FaRADAI, H2020-BES-03-NESTOR as the Deputy Coordinator and the Deputy Scientific Technical Manager, H2020-LC-EEB-08-2020 ASHVIN as a Work Package Leader, H2020-DT-ICT-02-2018 DIH$\hat{2}$ as a Task Leader, and EPAnEK2014-2020-CoFly as Work-Package Leader. He has authored and co-authored more than ten journals, 25 conferences and workshops, and five book chapters. His research interests include mainly the areas of path planning and collective behavior in swarm robotics and computer vision models and ML/DL approaches focused on robotics, such as 3D representations, multi-object recognition and tracking, image enhancement, and aerial imagery.

KONSTANTINOS DEMESTICHAS received the Diploma and Ph.D. degrees in telecommunications from the School of Electrical and Computer Engineering, National Technical University of Athens (NTUA), in 2005 and 2009, respectively, the M.B.A. degree in techno-economic systems through the joint postgraduates' program from NTUA and the University of Piraeus, in 2012, and the M.Sc. degree in quality assurance from Hellenic Open University, in 2015.

In 2021, he joined the Department of Agricultural Economics and Rural Development, Agricultural University of Athens, as an Assistant Professor. He is a member of the Informatics Laboratory. Before joining the Agricultural University of Athens, he was a Lecturer with NTUA, University of Western Macedonia, University of West Attica, and Hellenic Open University. Since 2005, he has been actively involved in several European and national research projects. He was the concept initiator and primary proposal author of several EU-funded projects. He has served as a scientific or project coordinator in EU-funded projects dealing with AI and ML technologies. He has authored more than 160 publications. He has participated in the technical program committees of international conferences. He has assisted as a reviewer and an editor in top-ranked scientific journals. He has also served as a Technical Expert for the European Commission.

STEFANOS VROCHIDIS (Member, IEEE) received the Diploma degree in electrical engineering from the Aristotle University of Thessaloniki, Greece, the M.Sc. degree in radio frequency communication systems from the University of Southampton, and the Ph.D. degree in electronic engineering from the Queen Mary University of London, U.K.

He is currently a Senior Researcher (Grade B) with the Information Technologies Institute of the Centre for Research and Technology Hellas (ITI-CERTH) and the Head of the Multimodal Data Fusion and Analytics (M4D) Group, Multimedia Knowledge and Social Media Analytics Laboratory. He has participated in more than 80 European and national projects and has been a member of the organization team of several conferences and workshops. He has edited three books and authored more than 300 related scientific journals, conferences, and book chapter publications. His research interests include multimedia analysis and retrieval, multimodal fusion, computer vision, multimodal analytics, artificial intelligence, industrial, media and arts, environmental, and security applications. He has served as a reviewer in several international journals and as a technical program committee in well reputed conferences and workshops.

IOANNIS KOMPATSIARIS (Senior Member, IEEE) was born in Thessaloniki, in 1973. He received the B.S. degree in electrical and computer engineering and the Ph.D. degree from the Aristotle University of Thessaloniki, in 1996 and 2001, respectively.

He is currently the Director of the Information Technologies Institute and the Head of the Multimedia Knowledge and Social Media Analytics Laboratory. He is the co-author of 178 journal articles, more than 560 conference papers, and 59 book chapters. He holds eight patents. His research interests include image and video analysis, big data and social media analytics, semantics, human–computer interfaces (AR and BCI), eHealth, and security applications. He is a Senior Member of ACM. He has organized conferences, workshops, and summer schools. He is a member of the National Ethics and Technoethics Committee and an Elected Member of IEEE Image, Video, and Multidimensional Signal Processing—Technical Committee (IVMSP—TC). He is an Associate Editor of IEEE TRANSACTIONS ON IMAGE PROCESSING.

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