Algorithms for Plant Monitoring Applications: A Comprehensive Review

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Review

Algorithms for Plant Monitoring Applications: A Comprehensive Review

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Abstract: Many sciences exploit algorithms in a large variety of applications. In agronomy, large amounts of agricultural data are handled by adopting procedures for optimization, clustering, or automatic learning. In this particular field, the number of scientific papers has significantly increased in recent years, triggered by scientists using artificial intelligence, comprising deep learning and machine learning methods or bots, to process field, crop, plant, or leaf images. Moreover, many other examples can be found, with different algorithms applied to plant diseases and phenology. This paper reviews the publications which have appeared in the past three years, analyzing the algorithms used and classifying the agronomic aims and the crops to which the methods are applied. Starting from a broad selection of 6060 papers, we subsequently refined the search, reducing the number to 358 research articles and 30 comprehensive reviews. By summarizing the advantages of applying algorithms to agronomic analyses, we propose a guide to farming practitioners, agronomists, researchers, and policymakers regarding best practices, challenges, and visions to counteract the effects of climate change, promoting a transition towards more sustainable, productive, and cost-effective farming and encouraging the introduction of smart technologies.

Keywords: algorithms; agriculture; smart agriculture; artificial intelligence; clustering; deep learning; machine learning; optimization; transformer; transfer learning; disease identification; mycotoxins; phenology; plant disease; computer vision; image detection; proximal monitoring; remote monitoring

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1. Introduction

In recent years, huge amounts of data have been made available for a large variety of agronomical applications. In remote sensing, pictures taken from satellites offer soil and crop RGB and hyper-spectral images [1]. When higher precision is required, one can use an Unmanned Aerial Vehicle (UAV). In proximal sensing, the introduction of new wireless technologies like LoRa, SigFox and Nb-IoT allows data collection from miniaturized sensors with low energy consumption, making it possible to increase deployment density and acquisition frequency. Moreover, new trends have emerged recently, with picture collection in fields performed with smartphones [2] or multimedia proximal sensors and cameras [3]. In this scenario, artificial intelligence, through machine learning and deep learning algorithms, can process these streams of data in real time, enabling the dynamic monitoring and early detection of potential threats, opening new avenues for predictive modeling and proximal disease management, and leading to smarter and more resilient farming practices [4].

The listed sources primarily offer images with different spatial resolutions. Among satellites, Landsat 8 provides data with a spatial resolution of 30 m, Sentinel-2 offers data with a resolution down to 10 m, Airbus Spot 6 down to to 1.5 m, and Pléiades down to 50 cm. The frequency for Landsat 8 is every 16 days, for Sentinel-2 every 3/5 days (depending on the areas), and for Airbus Spot 6 and Pléiades, it varies upon specific demand. UAVs offer resolution down to 1 cm, with frequency decided by the end-user. Proximal cameras or smartphones are used to acquire punctual daily pictures. As a result, large images datasets can be constructed; this huge flow of images is typically processed by means of algorithms, but algorithms are also adopted to plan UAV flights [5] or to choose the deployment of proximal sensors [6].

Additional inputs are obtained by the application of data fusion to precision agriculture; this process integrates multiple data sources to improve accuracy and efficiency in plant monitoring applications. As an example, recent studies highlight its potential by combining spatial interpolation methods with UAV-based assessments to accelerate crop variability evaluation and enhance site-specific management [7].

Agriculture can benefit from the availability of this large amount of data, especially in two fields: to document plant phenology and to identify or detect plant diseases early. In both cases, data processing through algorithms represents an efficient means to extract indicators strongly supporting crop management, both from the perspective of phenology and that of plant diseases.

Phenology is the study of plant and animal life cycles, in particular, the time sequence originated by weather and climate changes [8]. Phenology is a key adaptive feature of organisms, tuning biotic interactions in response to the environment. Knowledge of the phenological phase sequence is crucial for changes across environments and ecosystems with the relevant impact of climate change [9]. Phenological phases can be analyzed through satellite and UAV images and many researchers apply algorithms for the fast and effective extraction of input, soil, and yield indicators.

Plant diseases are one of the greatest challenges faced by global agriculture, causing considerable crop losses, food insecurity, and economic hardships and challenging food safety. According to estimates, crop diseases account for 20–40 percent of global agricultural production losses annually, highlighting the need for effective plant disease management strategies [10]. Phytosanitary issues, such as disease outbreaks and the resulting harmful effects on plants, directly threaten crop productivity and represent significant challenges for food security. An accurate identification of diseases, combined with an understanding of crop phenology, is essential for timely interventions to mitigate plant damages and minimize yield losses. By linking diverse data sources, algorithms can help predict outbreaks, monitor disease progression, and inform comprehensive, integrated management strategies. In this way, they contribute to the protection of ecosystems while supporting agricultural productivity [11].

Phenology and plant diseases have a direct correlation with the plants' ability to develop mycotoxins. These toxic compounds, produced by certain fungal pathogens in the field, contaminate crops and commodities, posing serious risks to human and animal health. Managing mycotoxin contamination requires reliable detection and predictive tools, and algorithms provide strong support in finding valuable solutions [12].

In summary, the aim of this work is to highlight how algorithms effectively contribute to plant monitoring through phenology observation and disease detection, as a valuable support for crop management.

2. Materials and Methods

2.1. Search Strategy and Preliminary Search Outcomes

A comprehensive literature search was conducted to identify relevant studies, investigating the use of algorithms to classify plant phenology and plant diseases. This systematic review was carried out in accordance with the Preferred Reporting Items for Systematic Reviews [13].

Initially, the Web of Science (WoS) database was searched and several keywords were tested on the full journal texts, both from the agronomical and algorithmic points of view [14]. After comparing the results, we identified three agronomical keywords as relevant and complementary: "phenology", "plant disease", and "mycotoxin". From the perspective of the algorithms, the two algorithmic keywords that generated the majority of the results were represented by "machine learning" and "deep learning". Restricting the search from the full journal text to a set of three fields formed by title, abstract, and keywords, we did not experience limitations with the agronomical keywords, while we noticed that several papers using transfer learning methodology or transformer architecture were no longer selected by the query, as for those papers the set of the three search fields did not include any reference to the two algorithmic keywords. For this reason, we decided to add "transformer" and "transfer learning" to the set of algorithmic keywords. Moreover, we understood that one additional keyword should be added: "optimization". The optimization algorithm's goal is to maximize or minimize an objective function; hence, they are commonly used in machine learning and deep learning, but their usage is wider and alternate applications would have not be accounted for if "optimization" was not included in the algorithmic keywords. As a result, the following query was formulated as the basis of the search:

```
IN ( (title) OR (abstract) OR (keyword) )
SEARCH ("phenology" OR plant disease* OR "mycotoxin") AND
("machine learning" OR "deep learning" OR
"transfer learning" OR "transformer" OR "optimization")
```

The search on WoS was initially conducted in August 2024 and regularly updated during the preparation of this paper, until the end of November 2024. Consequently, we report here some generic statistical analyses covering the period between 1 January 2000 and 30 November 2024.

The yearly publication count since 2000 is shown in Figure 1. It can be noticed that the number of published papers has significantly increased, starting in 2015, since when it has become stably higher than 100 per year. Starting in 2022, the increasing rate has been lowering and the number has progressively stabilized.

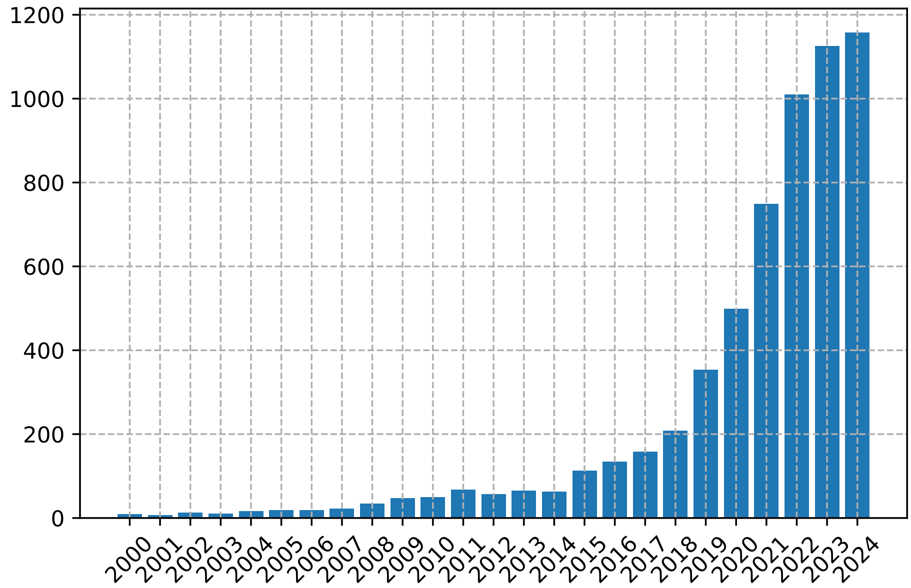

Figure 1. Web of Science (WoS) search outcomes grouped per year, from 1 January 2000 to 30 November 2024.

Figure 2 shows the number of papers containing each of the three agronomic keywords appearing in the search query. As can be seen, the majority of authors concentrate on algorithm application to plant diseases and phenology, with a research trend that follows the general one. Mycotoxin studies are less present but more numerically constant over the past decade.

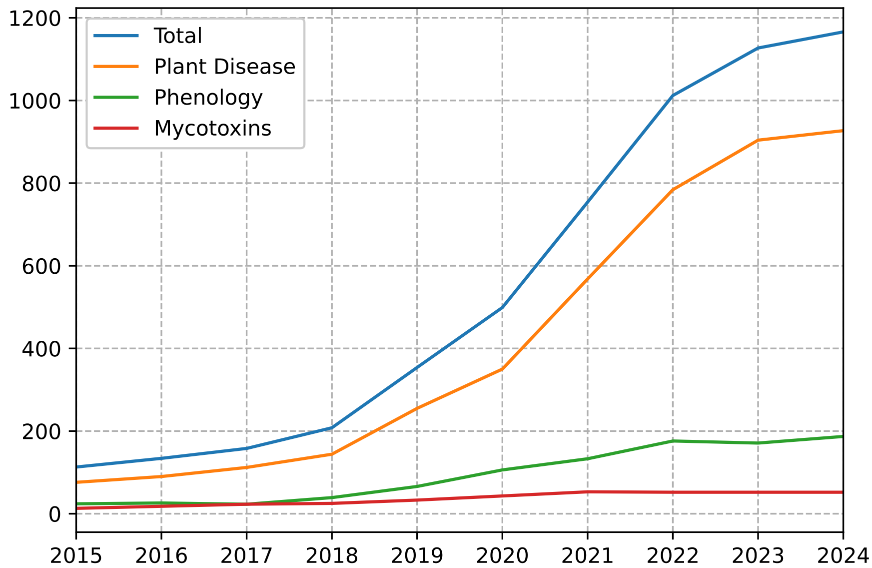

Figure 2. Recurrence of the agronomic keywords in the papers indexed in the Web of Science (WoS) during the period 2015–2024.

Concerning the different categories of algorithms, the situation is summarized in Figure 3. Deep learning has played the most important role during the past five years, with a constant and significant increase in papers, while machine learning was applied more frequently before 2019. The usage of all algorithms has increased over the years. Optimization employment has been more stable over the past ten years. The comparison between the optimization and machine learning curves shows how optimization examples can be found without a direct application in machine learning.

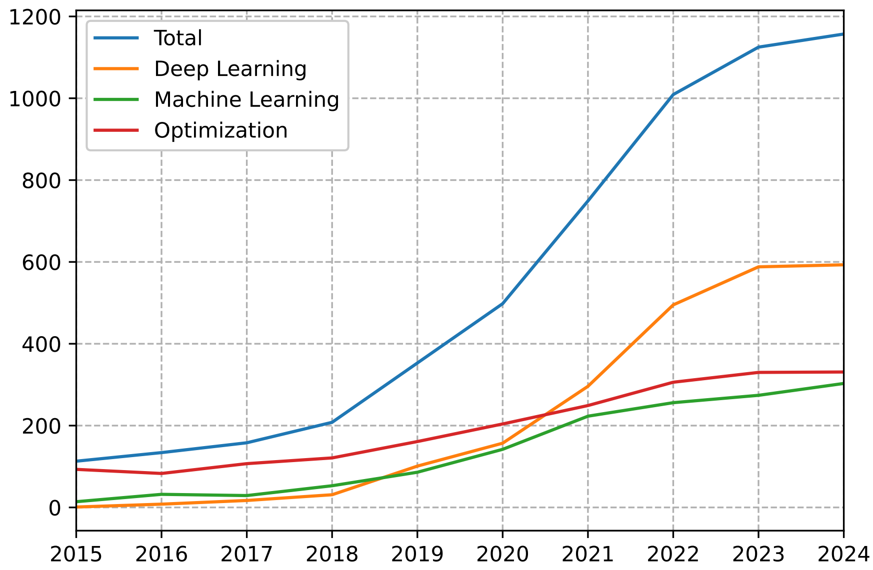

Figure 3. Recurrence of the algorithms in the papers indexed in the Web of Science (WoS) during the period 2015–2024.

We also classified the distribution of papers per country of application, summarizing results in Figure 4. China and India are the countries with more than 1000 published papers in the past 10 years. Studies conducted in Asia are more than 4150, in Europe more than 1750, in the Americas almost 1200, 500 in Africa, and 200 in Oceania. In Europe, the country with the largest number of studies is Italy (more than 200), followed by Spain.

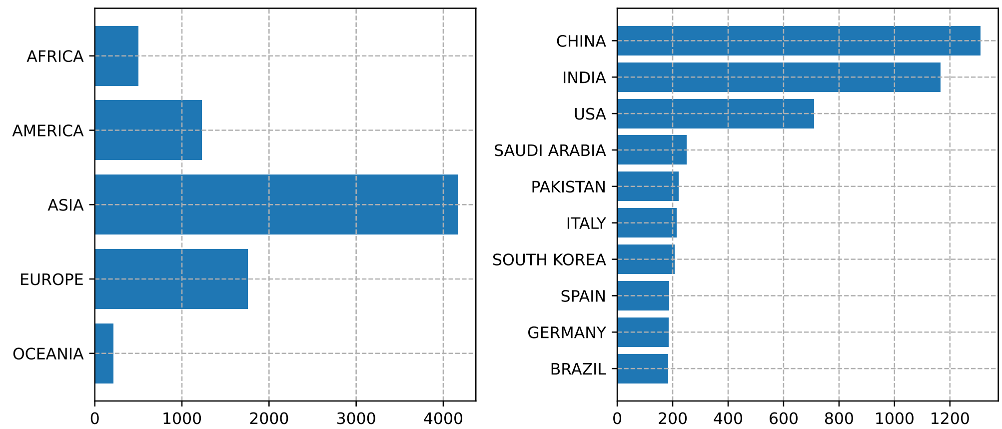

Figure 4. Histograms showing the geographical distribution of papers indexed in the Web of Science (WoS) by country of application during the period 2015–2024. Left: summary per continent. Right: the top 10 countries in the list.

We also classified publications versus publishers. Elsevier is the one with the highest record count, with 1230 papers (20.3%). Then, there is MDPI with 14.9%, Springer Nature with 13.1%, and IEEE with 8.1%. Wiley, Frontiers MediaSa, and Taylor & Francis follow, as shown in Table 1.

Table 1. Publication count in the Web of Science (WoS) per publisher in the period 2015–2024, showing the top 10 publishers in the list.

Publisher	Count
Elsevier	1230
MDPI	904
Springer Nature	793
IEEE	488
Wiley	293
Frontiers Media Sa	274
Taylor & Francis	151
Nature Portfolio	84
Oxford Univ Press	63
Amer Chemical Soc	61

The search results illustrate the distribution of record counts across different publication titles. The journals *Remote Sensing* and *Frontiers in Plant Science* have the highest record count, with 196 papers each (3.2%). Following closely are *Computers and Electronics in Agriculture* with 2.8% and *Multimedia Tools and Applications* with 1.8%. Other prominent titles include *IEEE Access*, *Agronomy Basel*, *Plants Basel*, *Scientific Reports*, *Agriculture Basel*, and *Sensors*, as shown in Table 2.

Table 2. Publication count in the Web of Science (WoS) per journal in the period 2015–2024, showing the top 10 titles in the list.

Publication Title	Count
Frontiers in Plant Science	196
Remote Sensing	196
Computers and Electronics in Agriculture	167
Multimedia Tools and Applications	112
IEEE Access	102
Agronomy Basel	83
Plants Basel	72
Scientific Reports	72
Agriculture Basel	67
Sensors	63

The data can also provide an overview of the distribution of records across different Sustainable Development Goals (SDGs), of which “03 Good Health and Well Being” stands out as the most prevalent goal, representing 43.3% of all records, followed by “13 Climate Action” with 23.1%, “15 Life on Land” with 18.2%, and “02 Zero Hunger” with 13.1%. These high percentages indicate a significant focus on health, environmental, and climate-related themes in the dataset. Other SDGs contribute to the dataset, albeit to a lesser extent (Figure 5).

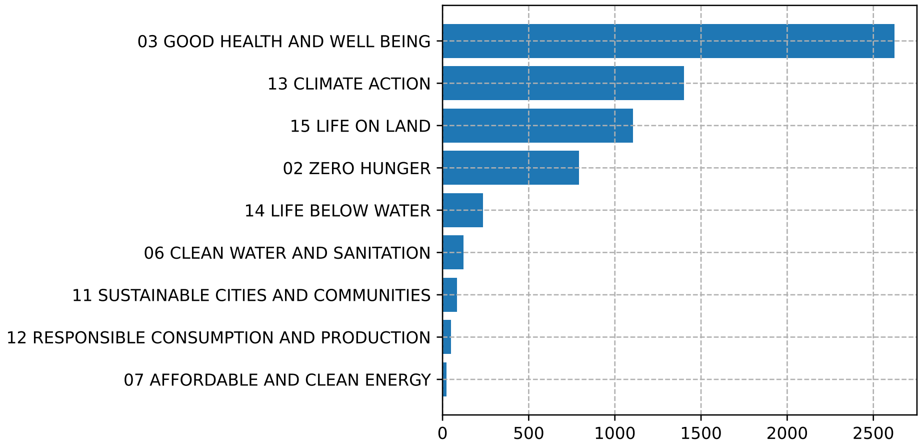

Figure 5. Histogram showing the annual publications of papers indexed in the Web of Science (WoS) by Sustainable Development Goal during the period 2015–2024.

2.2. Search Refinement and Paper Selection

The flow diagram applied to the paper selection is shown in Figure 6. The first paper selection was performed by running on the WoS search engine the query reported in Section 2.1. The results were filtered to the period between 1 January 2000 and 30 November 2024, obtaining 6060 papers. On a subset of this preliminary selection, all preliminary generic statistical analyses were carried out by applying a 10-year filter from 1 January 2015 to 30 November 2024, obtaining 5504 papers; the results are reported and discussed in Section 2.1. As is shown in Figure 1, the majority of the papers are concentrated in the past 3 years, so a more selective date filter was applied, between 1 January 2022 and 30 November 2024, obtaining 3291 papers. To refine the search, the query was run on two additional search engines, CAB Abstract and IEEE Xplore, and then filtered to the same period. The two searches yielded 433 and 260 papers, respectively.

Afterwards, to classify the algorithms and their usage, we selected papers present in at least two of the three search outcomes, reducing the total number to 693. Titles and abstracts were then read, analyzed, and classified for all papers belonging to this subset. As a result, 194 papers (174 research articles and 20 comprehensive reviews) were discarded as non-pertinent or not available in English, and 491 papers were advanced to the next phase, during which the whole article text was read and analyzed. During this last analysis, 103 papers were additionally discarded as redundant (98 research articles and 5 comprehensive reviews), obtaining 30 comprehensive reviews and 358 research articles that were classified on the basis of the agronomic aim, the crop, and the algorithm chosen.

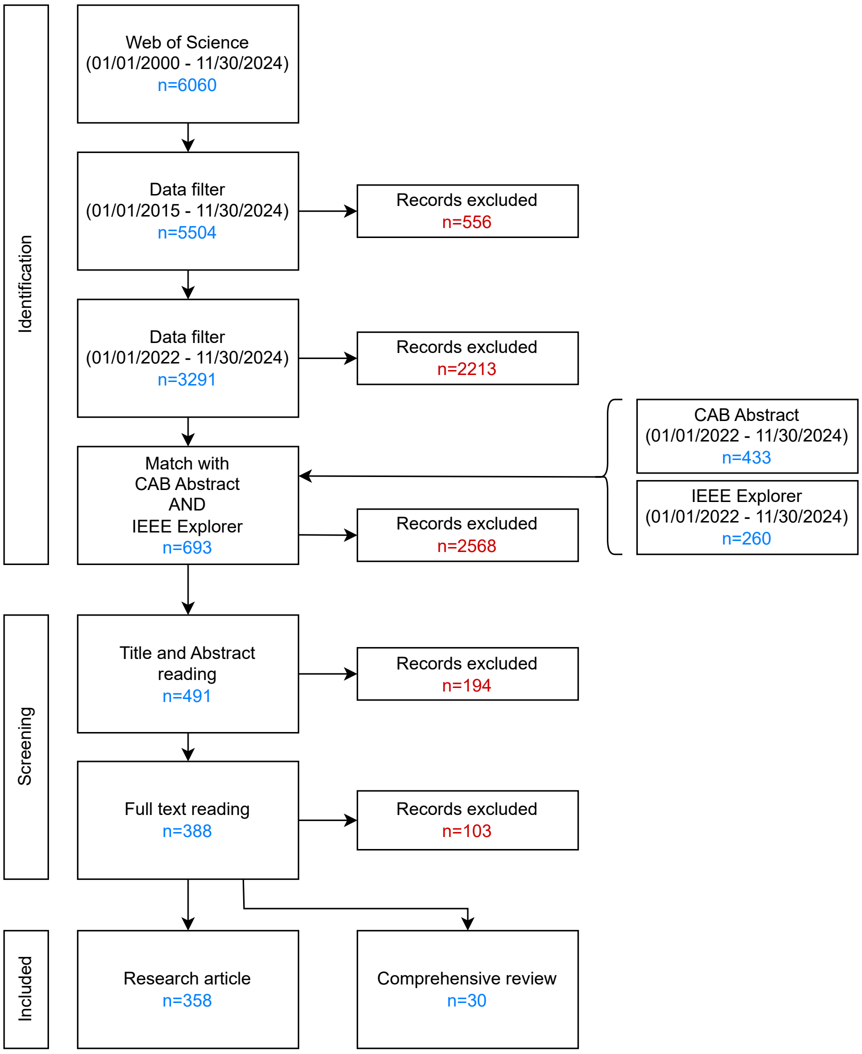

Figure 6. Flow diagram applied to paper selection. The numbers show the outcomes of each refinement. (blue): number of papers advanced to the next phase; (red): number of papers discarded.

2.3. Algorithm Classification

Since different typologies of algorithms were taken into consideration, in this section, we list the macro groups that we identified for their classification:

- Machine learning;
- Clustering;
- Deep learning;
- Optimization.

In the "machine learning" group, we classified all models and meta models (ensembles) that implement supervised and semi-supervised algorithms. Models, once trained on a given labeled dataset, can be used to solve classification or regression problems. Because of the huge amount of predictors, to limit acronym pollution, we considered algorithms with different model specializations as a single one; e.g., the K-Nearest Neighbors Regressor and the k-Nearest Neighbors Classifier are reported as the same algorithm. In the same way, variants based on different kernels or likelihood distributions were grouped under the same label. Meta models are estimators that combine the prediction of several base models, trained in different ways, to produce a more robust and accurate prediction output, such as voting, bagging, boosting, and stacking.

The “clustering” group is usually considered as part of the unsupervised learning methods. Therefore, it is generically included in the generic term “machine learning”. However, given its historical importance in the context of agriculture, we have chosen to dedicate an appropriate section to discuss papers using these algorithms. These methods are used to gather together unlabeled data, whose similarity is estimated as the distance between samples of a given dataset. Many methods and metrics are proposed in the literature to estimate this distance, especially when classic Euclidean distance cannot be calculated, as in the case of non-flat manifolds. This group is often used in hyper-spectral image analysis or as an alternative to pixel-based threshold algorithms [15].

The “deep learning” group is less simple to define, as it sometimes overlaps with classic machine learning. A good starting point is to include neural networks with a fair amount of hidden layers, trained with the back-propagation algorithm [16]. Occasionally, among the inspected papers, the network architecture details are not clearly stated; this is especially true for Multi-Layer Perceptron (MLP). Indeed, this particular algorithm is alternatively referred as machine learning or deep learning, depending on the number of hidden layers. To avoid confusion, in this review, MLP was always considered as part of the deep learning group. From the implementation side, some authors define their own architecture, while others prefer predefined ones, especially in the computer vision field using Convolutional Neural Network (CNN). A classic example is given by Yolo [17]. These models are convenient, since they are relatively easy to deploy and test, without the need to redefine from scratch the whole network architecture, an operation that can be quite challenging. Furthermore, a modern trend is to exploit transfer learning techniques on models pretrained on a correlated task, especially when the available dataset is not big enough to provide sufficient generalization. These methods usually freeze part of the network, allowing for a more efficient training on smaller and/or more specific datasets. Finally, attention was given to modern architectures such as transformer [18].

The “optimization” group includes algorithms used to solve a constrained optimization problem. Among these, we include heuristics and meta-heuristics, such as Genetic Algorithm (GA), used to find a suboptimal solution, usually employed when the exhaustive search of the solution space is infeasible. These methods are often used as backbone for higher level algorithms. For example, Stochastic Gradient Descent (SGD), with its several variants, is widely used in the back-propagation method [16]. Another example is the usage of Successive Projection Algorithm (SPA) in the context of feature selection, reduced to a combinatorial optimization problem [19]. However, it is important to highlight that these algorithms can be used not only in combination with machine learning and deep learning, but also to solve generic optimization problems; examples are reported in this review.

Algorithms used for dimensionality reduction, feature extraction, feature selection, and data processing in general can be classified as feature engineering. They were not classified separately, as the majority of the recurrences are related to their application as a sub-component of the machine learning framework.

In Figure 7, the usage count of papers by group is reported, confirming that machine learning and deep learning are very hot topics among researchers. On the contrary, the usage of optimization algorithms is limited, with the exception of their application as the backbone of other methods.

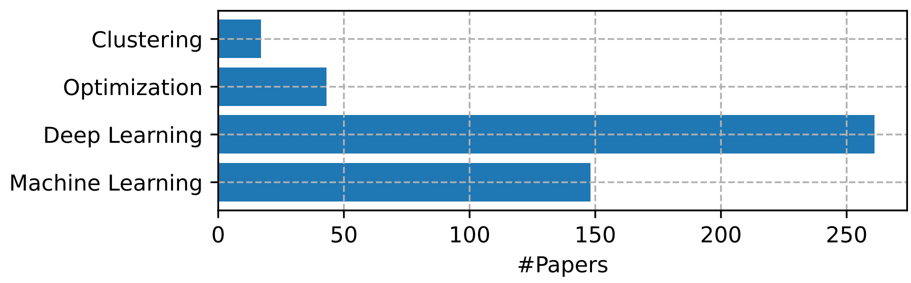

Figure 7. Histogram showing the usage of the algorithm typology in the analyzed studies.

2.4. Agronomic Aim and Crop Classification

We conducted a systematic analysis to classify the agronomic aim, and the analyzed crop systems. Based on the scope of each study, a post hoc categorization was performed, assigning studies to one of ten application areas:

- Crop mapping;
- Crop phenology prediction;
- Disease control;
- Disease identification;
- Disease prediction;
- Disease resistance assessment;
- Early disease detection;
- Plant health monitoring;
- Yield prediction;
- Generic.

The same approach was applied to categorize the crops in which the algorithms are used. Specifically, 16 categories were established as follows:

- Apple;
- Citrus;
- Coffee/tea;
- Forest trees;
- Fruits;
- Grapes;
- Maize;
- Nuts;
- Oil trees;
- Oil seeds;
- Rice;
- Small grains;
- Tomato/potato;
- Tropical;
- Vegetables;
- Generic.

Studies with a broad or nonspecific focus were grouped under the "Generic" category for both application and crop type.

Figure 8 shows the combinations of crops and agronomic aims that were found in the analyzed articles. The interest towards disease identification is dominant, while few papers treat other agronomic aims. Regarding the combination with crops, the group tomato/potato has the highest number of papers, 27, on disease identification, with a further 8 papers where the focus is on early disease detection. Maize (22), rice (18), and small grains (16) follow in the disease identification category, confirming the relevance of cereal studies. It should be noticed that 54 papers concentrate on disease identification without focusing on a specific crop, opening the method applicability to a wide range of cultures.

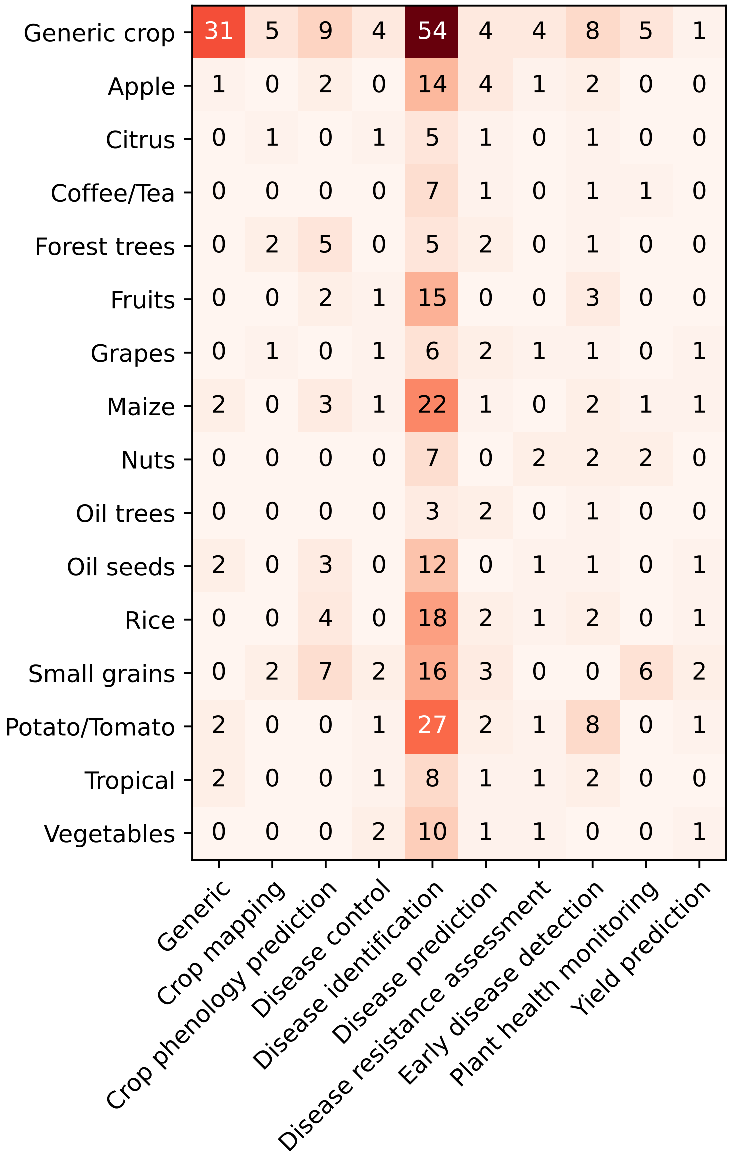

Figure 8. Heat map showing the intersection between agronomic aims and crops in the selected papers; the first column refers to studies applied to generic agronomic aims; the first row refers to studies applied to generic crops.

3. Literature Analysis

In this section, we analyze the 358 research articles and 30 comprehensive reviews selected in Section 2.2. Since the majority of the analyzed reviews focuses on a specific crop, an algorithm typology, or an agronomic aim, in the present study, we tried to provide an overview of algorithm application to plant monitoring for an inclusive variety of crops and agronomic aims. For this purpose, we grouped algorithms by category, reporting them in appropriate subsections, with different examples of application.

3.1. Comprehensive Reviews

Algorithms represent useful tools for scientists looking for solutions to enhance agronomic analyses. Some comprehensive reviews include a detailed description of the principle and methods of hyper-spectral sensing of plant diseases [15], with algorithms belonging to the categories of artificial intelligence [20], machine learning [21], and deep learning [22,23]. Major efforts are devoted to rice crops, with six papers discussing remote sensing, image analysis, and algorithm applications for disease detection [24–29]. Other reviewed crops are fresh and horticultural products [30,31]. Moreover, causal agents of diseases, like *Ganoderma* [32] and *Pseudomonas syringae* [33], or plant stress conditions [34,35] are studied. Comparative evaluations assess the performance of algorithms applied to important crops distributed worldwide, like apple, cassava, cotton, and potato. The added value in supporting crop chain management with a holistic view is confirmed, including variables related to host crops and diseases, environmental data, and management strategies [36]. A focus on hyper-spectral images combined with algorithms confirms the high potential to benefit agriculture and forest challenges, including those related to climate change [37]. The transition from Agriculture 4.0 to Agriculture 5.0, crucial in plant disease management, is discussed in [38]. Innovation and keen solutions to increase the level of automation are recommended and they should include the support of different areas, like hardware, telecommunications, and robotics. Automatized decision-making processes, with limited human intervention, are mandatory, therefore needing powerful algorithms and advanced robotics.

Agriculture mapping significantly aids decision-making. Artificial intelligence applied to diverse data sources, primarily images, can help land management, identifying cultivated soil, crop distribution, crop phenology, and health status, all of which are relevant aspects for sustainable agriculture [39]. The application of algorithms to plant phenotyping supports crop management to improve plant health. The analysis of spectral and hyper-spectral images by means of algorithms delivers information regarding plant stress, nutritional status, and disease occurrence [40]. UAVs equipped with sensors contribute to plant phenotyping, especially by collecting biophysical, physiological, and biochemical plant characters at a narrow scale. Challenges are documented, mainly related to data validation, but the combination with algorithms results in unquestionable advantages for many applications, including plant breeding [41].

An example regarding sunflower shows the potential improvement of this crop, thanks to the combination of phenotyping and machine learning [40]. An issue regards the dimension of datasets that should include enough data for a fruitful application of algorithms, only partially solved by proximal and remote sensing. The interest in facing this challenge stimulates researchers to develop label-efficient machine learning/deep learning methods, tailored for agricultural applications. Several challenges are still unsolved but the remarkable potential to noticeably reduce the efforts requested for data collection is strongly confirmed [42]. Advantages and challenges are also discussed in a paper focused on soil sensing technology and data management [43].

In terms of projection towards the future, machine learning and deep learning help in deciphering omics data that are generated in plant pathology. In this case, a large amount of data are delivered and algorithm-assisted omics techniques are crucial in data analysis and interpretation, allowing a step forward in understanding plant–pathogen interaction [44]. Moving from crops to food, mycotoxin detection in the food chain is approached with the support of machine learning and deep learning, to manage analytical data. Remarkable progress in food safety is obtained with considerable advantages for human and animal health challenges [45].

3.2. Algorithms

3.2.1. Optimization

Optimization algorithms comprise many examples that can be used for several applications. Figure 9 shows the usage of such methods. Among them, the optimization of hyper parameters in machine learning [46] and deep learning models is frequently found. Nevertheless, Ariza-Sentis et al. in [47] use Ant Colony Optimization (ACO) to improve UAV path planning for collecting images in vineyards: the optimization is applied to different variables, such as the viewing angles when capturing crop images. Wang et al. in [48] show that SGD can be successfully used to optimize the parameters of different existing neural network architectures to improve accuracy, recall, and F1 score. A comparison with the Adam optimizer is reported, showing that SGD within the Swim Transformer (ST) scores best than others. Furthermore, Refs. [49,50] report the usage of both SGD and Gravitational Search Algorithm (GSA) to optimize neural networks also in the context of transfer learning methods, while Raohui et al. in [51] report the result of different algorithms optimizing a CNN. One of the main concerns when searching optimal solutions remains the presence of local minima. To avoid falling in this condition, cosine annealing is used in [52]. This method consists in tuning the learning rate, according to a cosine function, moving continuously from lower to higher values. Furthermore, in this study, the authors enhance the cosine function by changing its period during the learning phase, according to different conditions and criteria.

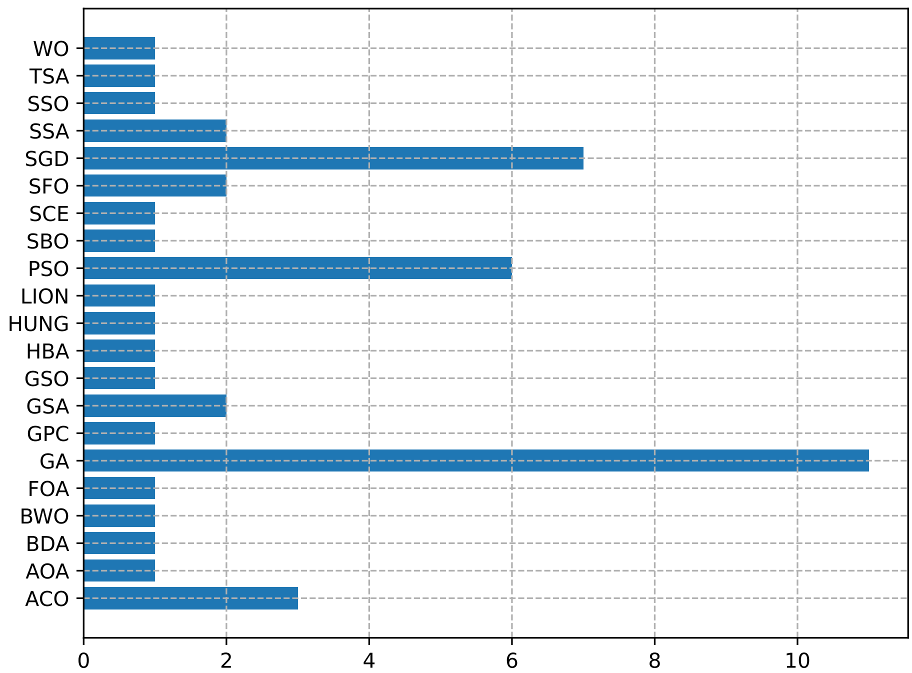

Figure 9. Histogram showing the recurrence of optimization algorithms among those used in the reviewed studies.

Optimization algorithms could be used also in Extreme Learning Machine (ELM), which does not rely on the back-propagation method during the training. For instance, in [53], Particle Swarm Optimization (PSO) is applied, instead of randomly initializing the weights of the hidden layers as defined by the original algorithm. Also GA, one of the most well-known meta-heuristics, is used for the same purpose [54]. Moreover Wang et al. in [55] report a comparison between PSO and GA. An interesting application of GA is reported in [56], which uses it for feature selection in a dataset composed by hyper-spectral and textural data. In general, meta-heuristics inspired by nature are very commonly used. For example, Ref. [57] uses Salp Swarm Algorithm (SSA) to perform feature selection in image-based disease detection. In [58], an enhanced version of Shuffled Shepherd Optimization (SSO) is used to improve convergence during the training of a CNN. In [59], Sun Flower Optimization (SFO) is used to optimize image segmentation methods. ACO is used in [60] to optimize the characteristic wavelength variables of spectral data.

Other combinatorial methods, such as the Hungarian algorithm (HUNG), are also used with complex transformer-based architectures, such as in [61], where predicted bounding boxes and ground truth are matched together to measure the similarity of the two sets.

3.2.2. Clustering

The use of clustering methods is reported in Figure 10. These algorithms are often used as part of more general frameworks to solve plant disease and phenology problems. For this reason, their usage is not always specifically reported.

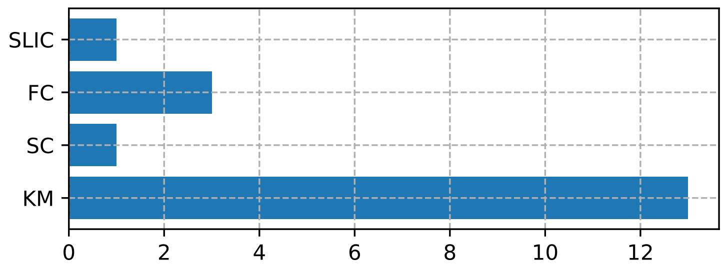

Figure 10. Histogram showing the recurrence of clustering algorithms among those used in the reviewed studies.

As an example, Ju et al. in [62] use both GA and K-Means (KM) to extract vegetation indexes from a dataset of multispectral images of wheat canopy. The authors use RelieF to find the initial centroid for KM to cluster the vegetation indexes: from the highest to the lowest weight, only vegetation indexes with positive precision are retained (feature selection). Instead, Aurangzeb et al. in [63] combine the Otsu algorithm, a famous threshold method, used to remove the background from leaf images, with KM that performs clustering on the remaining pixels, with the goal to detect disease evidence by checking the colors of the clusters. Javidan et al. in [64] use KM to isolate a portion of images featuring disease symptoms from healthy ones; therefore, they improve the resulting accuracy by performing a segmentation of the area of interest and allowing subsequent algorithms to focus only on that part. KM is also used as a one-class predictor in [65] to forecast the risk of potato late blight. Other algorithms such as Spectral Clustering (SC) are successfully used to select diseased plants on hyper-spectral images: Poblete et al. in [66] report successful results in detecting unusual shapes, while in [67], Murugan et al. use Fuzzy Clustering (FC) to discriminate a target crop from others present in the area. Recently, in addition to image processing, as is shown in [68], Bayesian Clustering (BC) was used to detect genetic structures in data sampled from forest trees in the center of Europe, as part of a genetic association study to investigate the response of trees in the presence of environmental stresses.

3.2.3. Machine Learning

Among the classic machine learning predictors, as shown in Figure 11, the most used ones are Random Forest (RF) and Support Vector Machine (SVM), two of the most popular algorithms in the field [69].

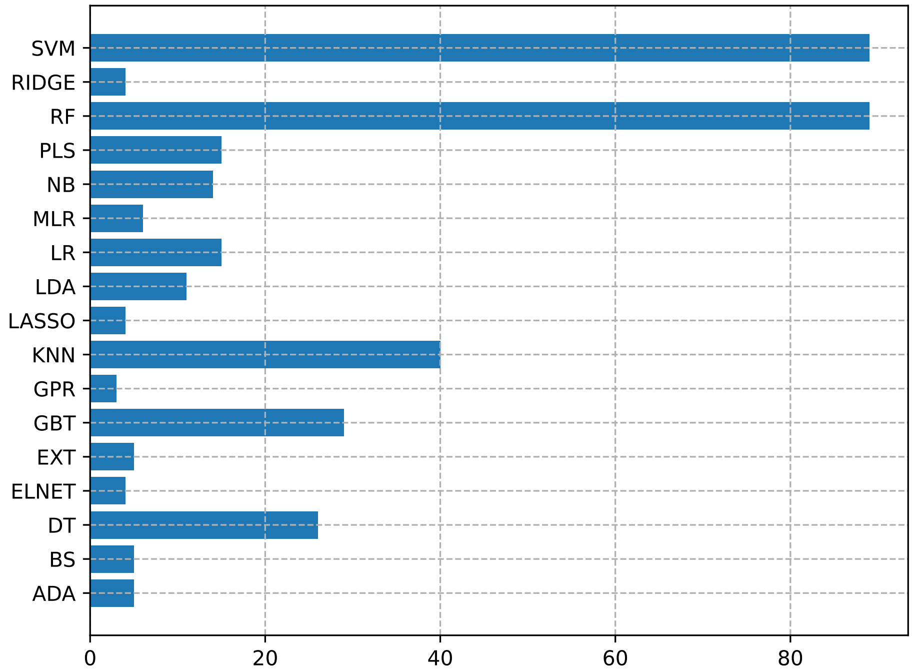

Figure 11. Histogram showing the recurrence of machine learning algorithms among those used in the reviewed studies.

Machine learning algorithms are versatile enough to be used in different scenarios; for example, the authors in [70–76] use proximal sensed data, acquired in different ways, to feed models that predict conditions in which various diseases may occur. Proximal monitoring is considered fundamental to help farmers in decision making. Besides sensors, meteorological data can be used [77–82]; as an example, the NASA Power platform provides up-to-date meteorological datasets, used by Torsoni et al. in [83]. High-resolution data are very important in this context, as reported in [84], where K-Nearest Neighbor (KNN) is used to evaluate *Alternaria* leaf spot on apple. Similarly, Meno et al. in [85] use RF to forecast the aerobiological risk level of *Phytophthora* on potato, while Bian et al. in [86] apply Decision Tree (DT) to predict grape downy mildew. Another available option, which provides interesting insights into phenology and disease analysis, is provided by in-field measurements and observations. In [87–92], ad hoc generated datasets are used as features for machine learning models, sometimes integrating sensors and meteorological data. Nevertheless, laboratory analyses supply valuable data to discriminate plant status that can be used to train models [93–97].

Another very common and popular practice is the usage of vegetation indexes to predict the different conditions of the crops. Usually obtained by processing satellite or UAV images, these indexes provide a valuable and convenient way to train classifier and regressor models [98]. Some specific applications regard the detection of potato late blight [99], peanut disease defoliation, leaf spot and southern blight [100–102], *Fusarium* head blight and scab in wheat [103,104], generic wheat diseases [105], rice panicle blast [106], and *Xanthomonas* in broccoli [107]. This approach is also applied to describe the spatial variability of biotic and abiotic plant diseases [108–114], and in plant phenology and yield monitoring [81,115–118]. Methods such as RelieF and Pearson Correlation are commonly used in this context for feature selection [119]. Moreover, hyper-spectral images can also be directly processed, using different techniques, to extract different spectral bands. Many papers provide different benchmarks regarding model accuracy and propose different methodologies and workflows applied to different practical applications. The early detection of diseases is applied for *Phytophtora* in pepper [120], wheat rust [121], bacterial diseases and crown rot in tomato [121,122], late blight in potato [56,123], *Fusarium* head blight and powdery mildew in wheat [124,125] , Valsa canker in apple [126], *Pseudomonas* in kiwi [127], and leaf diseases in rubber trees, soya, and coffee [128–132]. Pathogen and plant field monitoring takes advantage of image processing [133–136], as does fruit sorting [137–139]. Working with these kinds of images poses high dimensionality issues, often solved with feature engineering methods, such as Principal Component Analysis (PCA) or SPA.

Classic RGB images are also valuable datasets in machine learning, despite the fact that in recent years, image processing has been mostly carried out by means of deep learning. The authors in [140–145] use leaf images to detect visual symptoms: for this purpose, different image vision feature descriptors, such as Gray Level Co-occurrence Matrix (GLCM) [146] or Histogram of Oriented Gradients (HOG) [147], are exploited. Classic dimensionality reduction techniques such as PCA are also used [148]. Additionally, RGB and hyper-spectral images are mixed together, as in [149], to estimate phenological dates.

An additional usage of machine learning models is represented by [150], where bioclimatic variables and habitat heterogeneity data are correlated to climate change. In [151], Oriama et al. use SVM to predict the protein sequences of candidate disease resistance genes for common beans. Meanwhile, Liu et al. in [152] demonstrate the applicability of different models to predict biomarkers which are useful for detecting a specific citrus disease (Huanglongbing) on a global scale. Finally, Zhang et al. in [153] use different machine learning-based numerical models to make predictions between the bioactivity and chemical properties of ligands.

Machine learning can be efficiently applied to data fused together from different sources, as in [154], where Reiana et al. exploit both RGB images and vegetation indexes as input to a multimodal fusion model.

3.2.4. Deep Learning

In this group, a relevant predominance of the CNN is observed; see Figure 12. One of the main methods in agronomical research is the application of computer vision technology to detect plant diseases. Although classic computer vision is still used [63], the convolutional operator in neural networks has become very popular, thanks to the ability of CNN in images processing. Occasionally, different models can be used in conjunction with CNN.

As in classic machine learning, hyper-spectral images are also widely used in deep learning: the authors in [155–161] propose different architectures, optimization methods, and loss functions. Hyper-spectral features can be used for disease detection on wheat [162], but also for crop mapping, thanks to the application of modern Encoder-Decoder (ED) architectures [163]. Nevertheless, many papers show the application of CNNs to classic RGB pictures captured by UAVs or directly on the field, exploiting both predefined network architectures and novel ones. Applications include plant height identification [164], flowering [165], disease detection [166–170], and mapping [171]. Crops involved in disease detection are maize [172,173], rice [174–176], wheat [177], tomato [178–180], beans [181], apple [182,183], stone fruits [184,185], grapes [186,187], banana [188,189], sugarcane [190], forest trees [191,192], tropical trees [193,194], and tea [195,196]. Nyarco et al. in [197] use Single Shot Detector (SSD) to detect tomato diseases while Egusquiza et al. in [198] exploit Siamese networks.

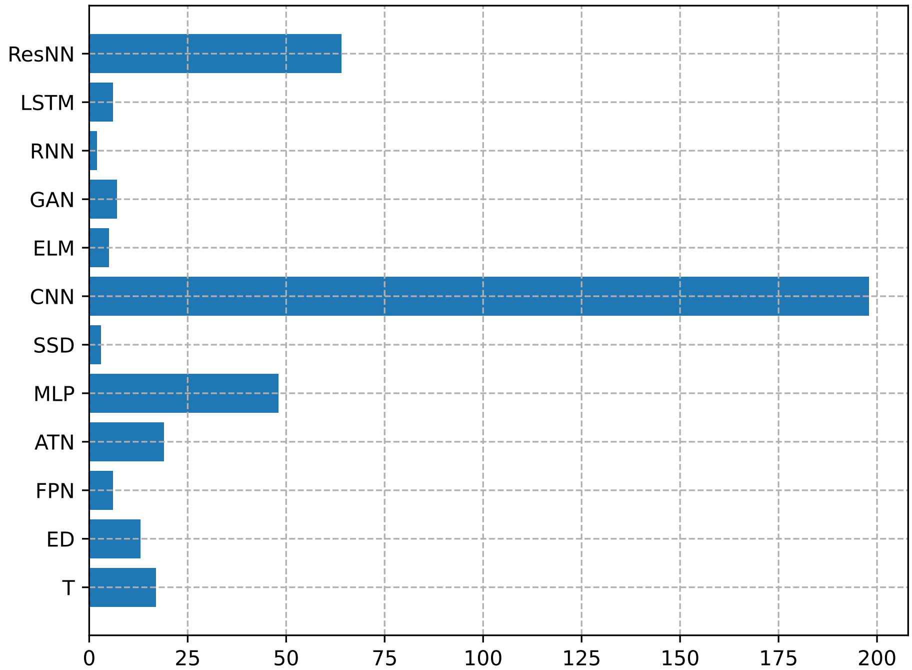

Figure 12. Histogram showing the recurrence of deep learning algorithms among those used in the reviewed studies.

An interesting characteristic of CNNs is its ability to automatically extract the most relevant features from an image. Nevertheless, in some cases, image preprocessing can be useful: Zhang et al. in [179] use the Asymptotic Non-Local Means algorithm for denoising the input samples.

Aside from classification, CNNs are used in image segmentation: Gonzalez et al. in [199] evaluate different network architectures for both purposes. CNNs can also be used for other goals; Kang et al. in [200] perform a simultaneous identification of tomato leaf diseases and fruit counting, while Xiong et al. in [201] count tobacco lesions in complex agricultural settings.

Li et al. in [202] focus on possible issues that arise while applying incremental learning to identify new diseases from unseen data. In general, the importance of having a well-crafted dataset is discussed in [203]. Occasionally, researchers face the problem of unbalanced data, especially when building custom ones. In these situations, the training phase may suffer from poor generalization or unbalanced label relevance underestimation. Divyanth et al. in [204] propose a comprehensive method to deal with this problem, by using Generative Adversarial Network (GAN) to increase the amount of unbalanced class samples. Indeed, this kind of neural network, trained on a target dataset, learns how to generate new data with the same statistical characteristics. In [205,206], GANs are used to expand a dataset of leaf images, avoiding the general struggle of dealing with unlabeled data. In general, dataset availability remains a common problem in machine learning and deep learning. Some studies exploit public ones like PlantVillage [207–210], whereas others combine different datasets in order to achieve more generalization [112,211]. Platforms like Kaggle are also employed [212], while Muthusamy et al. [213] make use of datasets extracted from the literature. Indeed, many authors build custom datasets, making them available for future use [214–227].

Multi-task deep learning is leveraged with multimodal data fusion for innovative applications like monitoring the growth of film-mulched winter wheat [228].

3.2.5. Transfer Learning Methodology

Among the possible methodologies, we decided to emphasize the transfer learning techniques, used to exploit a model already trained for a specific task to solve a different problem. Domain adaptation, often considered a subfield of transfer learning, is applied when using a model trained on one domain in a slightly different target domain.

The reviewed papers show a trend to use transfer learning in computer vision applications, often by means of predefined pretrained CNNs. The usage of these models is very convenient and it simplifies the adoption of the CNN models. Nevertheless, these pretrained models can be used as they are or in conjunction with transfer learning. A typical workflow in transfer learning consists in taking a pretrained network, excluding the top layers, defining some new fully connected layers that depend on the target application, and performing training with the new dataset and the base model frozen. Optionally, a final fine-tuning of the entire network with a small learning rate can be performed. Figure 13 shows the usage of predefined pretrained architectures across the inspected papers.

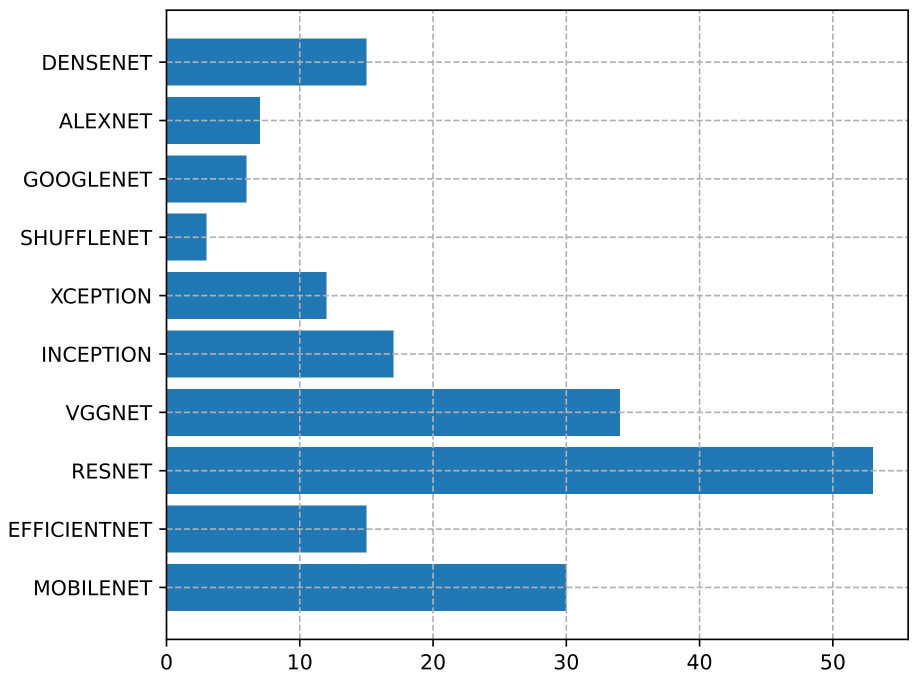

Figure 13. Histogram showing the usage of predefined CNN architectures across the inspected works; different versions of the same network are grouped under a generic label.

An interesting aspect of transfer learning usage in agriculture is that it helps to overcome situations with a scarcity of data for some specific crop diseases. As an example, in [229], Yin et al. exploit a crafted dataset of generic disease spots of different shapes and sizes on jujubes, to obtain parameters that can be imported inside the target network. In [230], Premkumar et al. propose VggNet, freezing the weights in the convolutional layers for feature extraction. In general, networks that are pretrained with huge public datasets are used to retain the learned weights. Transfer learning is applied by replacing or adding small parts of the network that are consequently retrained. This methodology can be used to train models used to support disease identification [231–237] on different kind of crops such as tomato [54,238,239], pepper [240], soybean [241], rice [242,243], groundnut [244], cotton [245], grapes [246], fruits [247,248], citrus [249], palm [250], and cordia [251]. Other applications include rust detection in different crops [252], tea stress detection [253], and grapevine digital ampelography [254]. However, when using these methods, choosing the right network architecture can also be challenging: in [255], a benchmark of 38 different models is provided, reporting the accuracy score for each one. Also, other works report similar benchmarks, each one with its own outcomes, based on the specific domain and dataset used [49,256–262]. In [263], comparisons are conducted using both ImageNet and a plant dataset for pretraining, in order to verify the effect on the final accuracy. Instead, Gadiraju et al. in [264] discuss the usability of a network initially trained in a different domain (domain shifting), and Yan et al. in [265] improve the correlation between the mixed domain images. Another application is presented in [266], where transfer learning is used to produce synthetic multi-spectral images from an RGB camera, while Zhu et al. in [267] discuss its usage along with pruning, a method that consists in removing unimportant parameters from the CNN, without a significant drop in accuracy.

3.2.6. Transformer Architecture

Among the possible architectures used in deep learning, we decided to emphasize the transformer, a kind of sequence-to-sequence architecture usually composed by an encoder and a decoder. Initially proposed for natural language processing, it is currently also used in many other fields. The encoder maps internally the input sequence to a high-dimensional one that is subsequently processed by the decoder to produce the output. The transformer learns how to create this internal mapping thanks to dedicated training sequences. In this scenario, the attention mechanism plays a crucial role, assigning different weights to each value of the sequence, in order to capture relationships among them [18].

A subsequent exploitation of such a technology is proposed in [268], where transformer is used for end-to-end object detection, thanks to the DEtection TRansformer (DETR) model. The same model finds practical usage in agronomy, as reported in [61], where such a method is exploited to detect images of diseased rice leaves.

In general, using transformer in agronomy is not a trivial task, due to challenges emerging from language-to-vision adaptation. For this reason, ST [269] and Vision Transformer (ViT) [270] are proposed. Ma et al. in [271] show the usage of ST within the YOLO model, to identify common maize leaf spot, gray spot, and rust diseases. In [272], ST is used in an ensemble with Residual Neural Network (ResNN). The accuracy of this method is also proved by [273], testing it with pictures taken in a complex natural environment. In the same way, ViT is employed to detect leaf disease in conjunction with transfer learning in [274]. Finally, in [275], Remya et al. use ViT together with acoustic sensors in order to detect cotton pest insects.

3.3. Agronomic Aims and Data Sources

Agronomic practices are primarily based on visual observations. For example, diseases are traditionally identified with a visual diagnosis of symptoms, followed by laboratory analyses when observations are not sufficient. This traditional approach is time-consuming, it involves skilled personnel, sometimes it lacks objectivity, and it is not efficient for early disease detection [121]. Therefore, it represents a limiting factor in sustainable agriculture [276]. Visual observation is still relevant, but it is progressively substituted by image acquisition. Pictures can be used for a large variety of agronomic aims, with specific differences in terms of methods and algorithms. An example is provided by yield prediction and disease detection; the former leverages hyper-spectral images, eventually fused together with meteorological and phenological data [277,278], to compute vegetation indexes, and consequently it employs classic machine learning predictors. On the contrary, disease detection typically uses images taken in the visible spectrum; the region of interest on the leaf, where symptoms usually appear, is extracted using clustering or segmentation methods; in this way, noisy background is removed and classifiers can work only on leaf pixels.

In general, different combinations of data and algorithms are found, even if the agronomic aims are common. Hyper-spectral cameras are frequently used, mainly remotely but also proximally. Proximal data collection is reported in [37,121,279–281], and it is applied to *Colletotrichum gloeosporioides* in citrus fruits [279], tomato bacterial spot disease caused by *Xanthomonas perforans* [121], strawberry gray mold and anthracnose [280], and wheat stripe rust [281]. For the early detection of root rot in chili pepper, spectral variations should be analyzed several times by a spectrophotometer [282]. A similar approach allows the acquisition of images in situ for the non-destructive diagnosis of tomato bacterial speck caused by *Pseudomonas syringae* pv. *tomato*, and bacterial spot, caused by *Xanthomonas euvesicatoria*, on leaves [283], and for the early detection of wheat stripe rust. This study analyzes the minimum detection limit, a characteristic that determines the scope and the applicability of a measurement technique [134].

The near-infrared (nir) spectroscopy technique is used, instead, to quantify aflatoxin B1 (AFB1) in peanuts [284]. Visible/nir spectroscopy, supported by different algorithms, is successfully used in sugarcane for early disease detection [285] and in banana [286], to identify fruits infected with *Colletotrichum musae*; one-day resolution is obtained with an accuracy of around 95 percent.

Remote collection is primarily carried out with satellites and UAVs. Satellite data are useful for pre-harvest crop mapping, applied to soybean, sorghum, cotton, and sugarcane crops, to predict production [287] and to map invasive species [288], but also for coffee rust detection [132]. Nevertheless, cloud cover is still challenging and the most used approach is based on UAVs with multi-spectral or ultra-high-resolution cameras [287]. Multi-spectral resolution is usefully applied to quantify peanut defoliation due to fungal diseases [289], rubber tree powdery mildew [290], *Fusarium* wilt and banana blood disease, two significant diseases that infect banana trees, caused by *Fusarium oxysporum*, wheat resistance to *Fusarium* head blight [162], rise diseases [291], *Ralstonia syzygii* [100], and Basal Stem Rot disease caused by *Ganoderma boninense* [159]. Multi-spectral analysis is useful to monitor leaf rust in wheat and to screen disease resistance among different wheat varieties, as well as for virus resistance in sweet potato [292]. Applications are found in other crops, like rice [293], maize [294,295], grapes [47], peanuts [116], palm [194], and pine trees [191]. These studies predominantly focus on the qualitative identification of healthy and infected plants. Instead, pixel-level regression analysis for the quantification of the wheat stripe rust disease index is performed in [158]; the authors successfully obtain continuous phenotypes, including crop yield and plant height, and develop disease distribution maps for wheat stripe rust.

RGB cameras are also used, both in remote and proximal sensing. Advantages are highlighted by [98] with a dual-drone collaborative approach, one with multi-spectral cameras, the other with ultra-high-resolution ones; by integrating the vegetation indexes derived from the multi-spectral UAV and the texture index derived from the RGB camera, accuracy improvements are obtained for late blight monitoring in potato. Rice Bakanae disease infection rates are monitored using drones with RGB cameras [296]; the same cameras are used for maize plants, creating a database of pictures acquired in the field, showing healthy plants and those infected by common rust, gray-leaf spot, and blight [4]. Field photos, managed with algorithms, are also used for *Botrytis fabae* [297], tomato disease [179], habanero disease [298], and wheat rust identification [52]. Autonomous rovers, equipped with RGB cameras or smartphones, move in tomato [200] and citrus nurseries to detect diseases; additional equipment for automatic spray application is also proposed in [299].

The collection of plant disease images can be carried out with a smartphone, and Jiahui et al. in [300] document the effort to unify images from different sources (wheat stripe rust, wheat leaf rust, and wheat powdery mildew) to contribute to disease identification. Even though the source can impact on the identification, satisfactory results can be achieved applying proper algorithms.

Several papers aim to build open datasets. The authors in [214] collect high-resolution leaf images in sugarcane crops and construct an open dataset called "Sugarcane Leaf Dataset", with leaf images classified in eleven categories, including diseased, healthy, and dried leaves. Ref. [4] illustrates similar work for maize, introducing four categories: common rust, gray-leaf spot, blight, and healthy leaves. Open databases are very helpful for scientists without experimental settlements or with limited ones. PlantVillage is an example; it offers leaf pictures regarding diverse crops and diseases. It is used for algorithm application by several authors interested in different crops and diseases [146,207,210,230, 301–303]. NWRD is another open-source dataset for wheat diseases [226]. The MODIS dataset [304] is used by [305] to map croplands mixed with paddy fields and rice–crayfish fields over large areas, while [305] takes advantage of data published by the Pan European Phenological Project [306] to elaborate phenological data.

Photo collection in the field is crucial for disease identification, but inoculum source detection is equally important. The authors in [307] collect a huge amount of microscope images, both of single (8959) and mixed (1450) spores with the aim of quantifying pathogen inoculum thanks to the application of algorithms, stressing their relevance in the automatic detection of rice blast fungus spores. Similarly, the authors in [308] use a diffraction–polarization imaging system and the diffraction fingerprint images of fungal spores to classify airborne spores in greenhouses. Tomato gray mold, cucumber downy mold, and cucumber powdery mildew spores are correctly identified with around 96 percent correct identification, thanks to SVM. Other examples based on microscope image analysis for spore attribution to fungal species regard *Botrytis cinerea*, for its detection in cucumber [309] and *Lasiodiplodia* species associated to grapevines showing *Botryosphaeria* dieback, with four species included (*L. brasiliensis*, *L. crassispora*, *L. exigua*, and *L. gilanensis*) [187]. The two papers apply CNNs, with excellent accuracy performance in spore identification. A step forward is obtained by [310]: after training with microscope images, spore counting is directly obtained from air sampling in the field for *Alternaria* spp.

The application of algorithms to data fusion from different sources is used by Liu et al. in [152], working on huanglongbing on citrus. Working on phytobiomes to predict diseases, several different databases are considered and, thanks to the application of ten algorithms, a high prediction accuracy is obtained. The use of different data sources in agriculture is relevant because of the efforts needed to deliver sufficient data for algorithm application. An alternative is suggested in [48], which proposes a novel sliding segmentation method to face the issue of insufficient data volume in soybean disease diagnosis. Instead, working on kiwifruit trunk disease, ref. [311] suggests an image generative model able to create credible and varied samples.

4. Algorithm Usage

To provide a clear insight into how algorithms are applied to a specific agronomical aim or to a crop, in this section, we present some heat maps showing the number of papers among the 358 selected which introduce a specific algorithm to an agronomic aim or in a crop.

Papers introducing optimization and clustering algorithms represent a small portion of the identified set, where machine learning and deep learning play the major role. In Figure 14, the application of optimization algorithms to different crops is reported. GA, PSO, and SGD are the most used, but no pattern with crops emerges. ACO, Arithmetic Optimization Algorithm (AOA) [163], Binary Dragonfly Algorithm (BDA) [312], Forest Optimization Algorithm (FOA) [313], Giza Pyramids Construction (GPC) [314], GSA [314], Golden Search Optimization (GSO) [315], Honey Badger Optimization Algorithm (HBA) [316], HUNG, Evolved Sign Momentum (LION) [317], Satin Bowerbird Optimizer (SBO) [318], Shuffled Complex Evolution (SCE) [319], SFO, SSA, Tunicate Swarm Algorithm (TSA) [320], and Whale Optimization (WO) [263] appear in our search, with smaller numerical consistence. Potato and tomato, maize, and rice are the crops most investigated. Moreover, a good number of papers propose algorithm application to generic cultures.

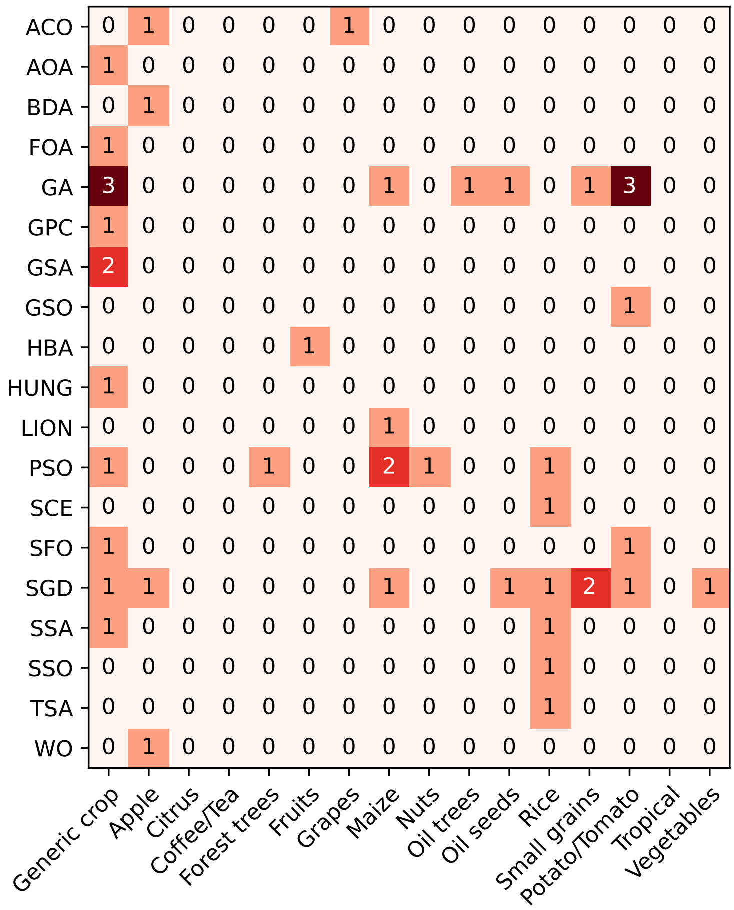

Figure 14. Heat map showing the number of papers using a specific optimization algorithm applied to a specific crop.

Figure 15 shows the application of optimization algorithms to different agronomic aims, where disease identification plays the most relevant role, with 33 papers.

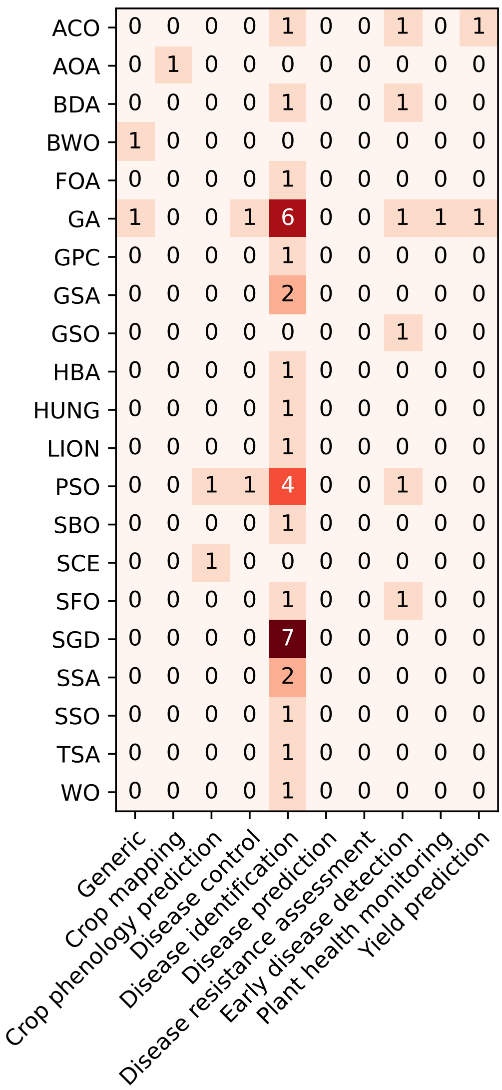

Figure 15. Heat map showing the number of papers using a specific optimization algorithm applied to a specific agronomic aim.

Regarding clustering, Figure 16 shows the application of this group to crops. Figure 17 reports their application to agronomic aims, with a clear preference for disease identification. KM is the most used, with general interest, independently on crop typology. FC follows, with SC and simple linear iterative clustering (SLIC) being rarely used.

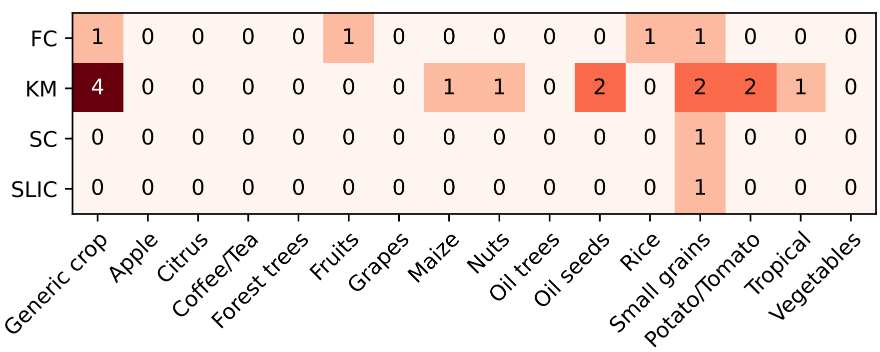

Figure 16. Heat map showing the number of papers using a specific clustering algorithm applied to a specific crop.

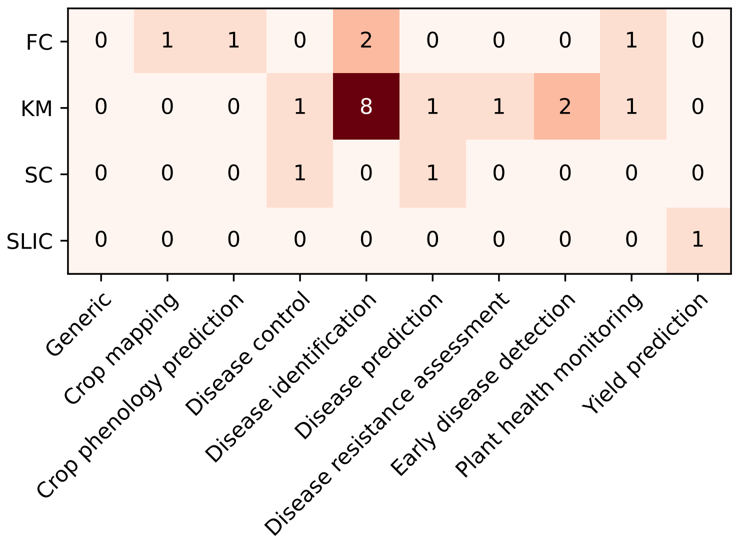

Figure 17. Heat map showing the number of papers using a specific clustering algorithm applied to a specific agronomic aim.

When crossing machine learning or deep learning algorithms with crops and agronomic aims, heat maps start to become denser. Figure 18 shows the correlation between machine learning and crops, and Figure 19 displays the correlation between machine learning and agronomic aims.

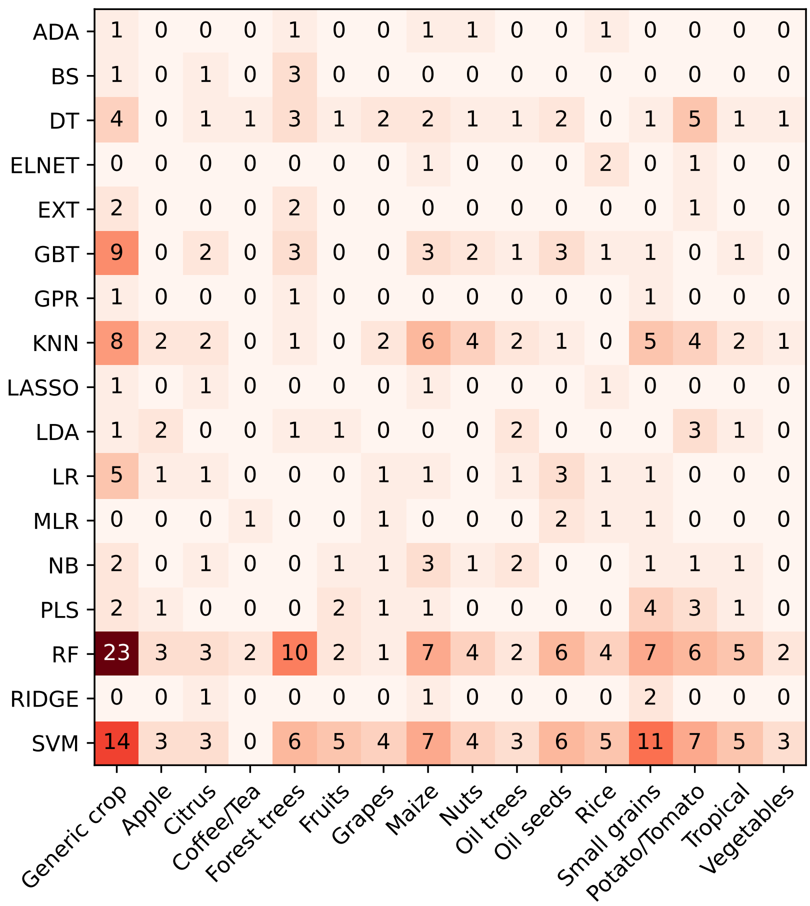

Figure 18. Heat map showing the number of papers using a specific machine learning algorithm applied to a specific crop.

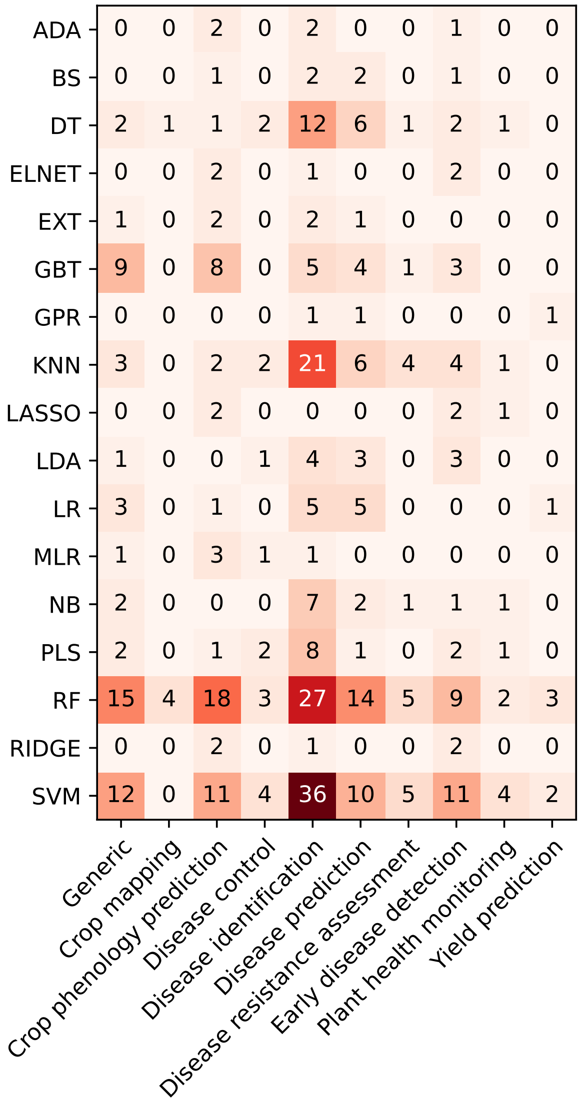

Figure 19. Heat map showing the number of papers using a specific machine learning algorithm applied to a specific agronomic aim.

The most used algorithms are RF [78,321–335] and SVM [336,337], followed by KNN [332,338] and other tree-based models such as DT [324,339] and Gradient Boosting Tree (GBT) [321–323,327,333,340–343]. Multiple Linear Regression (MLR), Naive Bayes (NB), AdaBoost (ADA), Bagging or Bootstrap Aggregating (BS) [344], Elastic-Net (ELNET), Extra Tree Classifier (EXT) [341], Gaussian Process Regression (GPR) [345], Least Absolute Shrinkage and Selection Operator (LASSO), Linear Discriminant Analysis (LDA) [332,338,346], Logistic Regression (LR) [78,347], Partial Least Square (PLS) [333,345,348], and Ridge Regression (RIDGE) [345] are found in papers, but less frequently. Instead, the most frequent crops are forest trees, maize, small grains, and potato/tomato. The generic crop category is the one to which models are most applied. Regarding agronomic aims, generic disease, crop phenology, disease identification, disease prediction, and early disease prediction are the most considered. However, disease identification shows the highest score and the greatest number of different algorithms exploited, while other agronomic aims mostly tend to use only RF and SVM.

Deep learning model usage is reported in Figure 20 in correlation to crops and Figure 21 in correlation to agronomic aims. The most studied crops in this context, for different diseases, are maize [349–351], rice [352,353], wheat [354–356], potato/tomato [357–359], berries [360–362], fruits [348,363,364], beans [365–369], peanuts [370,371], cotton [372,373], sugarcane [322], coffee [341], paprika and pepper [330,374], shallot [375], cassava [376], and camellia oleifera [377]. However, the majority of papers analyze generic crops, with many authors proposing the use of CNNs with public large datasets, including different crops, focusing on the whole plant [339,344,378–383] or specific leaf diseases [347,384,385]. Other applications are investigated: monitoring the crop characteristics and their abiotic stress factors [386–392], or supporting tools for smart agriculture [393–397]. Some other algorithms appear: ResNN [398] and MLP [323,330,331,341,346,356,385,399–402], alongside Attention Mechanism (ATN) [403–407], ED [348,355,395–397,408–411], ELM [333,412], Feature Pyramid Network (FPN) [413], GAN [366,414], Long Short-Term Memory (LSTM) [342,366,415,416], Radial Basis Function Neural Network (RBFNN), Recurrent Neural Network (RNN) [358], and SSD. Transformer (T) [348,356,362,367,376,385,396,417,418] appears in the very last part of the searched period, foreseeing promising implementations in the next months. Regarding agronomic aims, CNNs are widely used for disease identification and slightly less for other topics. All other models, with smaller numbers, follow the same trend.

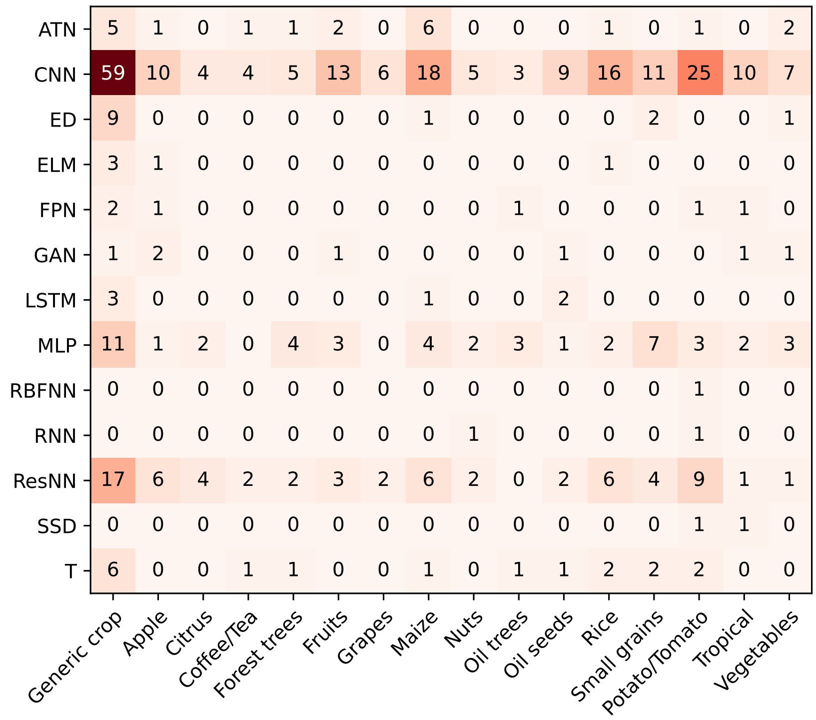

Figure 20. Heat map showing the number of papers using a specific deep learning algorithm applied to a specific crop.

In general, we can conclude that the papers that apply algorithms to agronomics are mainly focused on disease identification (264 for deep learning and 137 for machine learning), disease prediction (24 and 55, respectively), and early disease detection (25 and 43, respectively), sometimes combined. In addition, crop phenology is analyzed, with 21 papers for deep learning and 57 for machine learning. The most dominant deep learning algorithm used for plant disease is CNN (146 for disease identification, 24 for disease prediction, and 25 for early disease detection), followed by MLP (20, 7, and 5, respectively) and ResNN (48, 2, and 4, respectively). SVM (36, 10, and 11, respectively) and RF (27, 14, and 9, respectively) are the most used machine learning algorithms applied to the same agronomic aims. The same algorithm relevance is confirmed looking at crop phenology. Regarding crops, cereals attract the main interest, with 69 papers regarding maize and

60 small grains, including both deep and machine learning, but the group including potato and tomato also counts 75 papers.

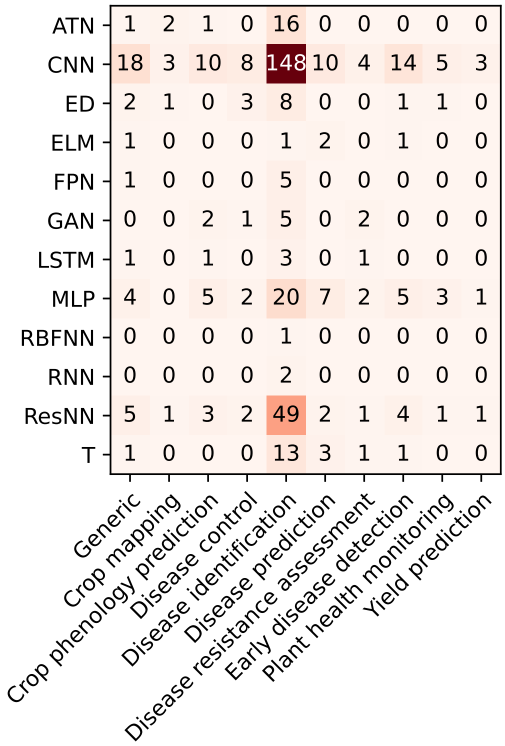

Figure 21. Heat map showing the number of papers using a specific deep learning algorithm applied to a specific agronomic aim.

Analyzing Figures 19 and 21, we can conclude that machine learning algorithms, compared to deep learning ones, are uniformly applied to a broader variety of agronomic aims, with a light preference for crop phenology prediction, thanks to the easy applicability of some methods like RF or GBT. On the contrary, deep learning algorithms are preferred for disease detection, thanks to their capability to use CNNs on heavy tasks like image analysis, in a simpler and more efficient way, compared to machine learning methods.

5. Challenges and Future Directions

Precision agriculture, enabled by the integration of intelligent sensors, next-generation wireless networks, and data analysis, has made significant advances for the enhancement of farming practices. However, today's path of transformation presents several challenges and constraints. A relevant limitation at the moment lies in the acquisition of data, especially those that can be detected with proximal sensors, where elements such as calibration, maintenance, sensor durability, and digital divide influence the reliability of the collected data. Among these, digital divide is particularly critical, as it affects primarily the countryside, particularly the uninhabited areas, where the application of smart sensors would be more profitable. Therefore, research efforts and investments should be dedicated to favoring the adoption of new energy-efficient, cost-effective, license-free Internet of Things (IoT) wireless standards.

On the contrary, satellite data are available from various sources, with the main limitation being represented by the resolution of images. The use of UAVs can offer much higher resolution, unfortunately with a significant increase in costs. On the contrary, algorithm techniques have significantly improved during the past 10 years, thanks to machine learning in the beginning and then deep learning. Because of the listed difficulties, many studies have been applied to existing datasets, and consequently transfer learning techniques have been increasingly introduced. The explosion of transformer use in recent months forecasts an imminent adoption of artificial intelligence techniques in the research fields investigated in this paper.

One of the challenges is represented by the lack of standardized image datasets. Plant monitoring is frequently conducted by means of image processing, where deep learning architectures play a crucial role. While many studies demonstrate the possibility to achieve high scores, the lack of standard image datasets reduces the possibility to compare or benchmark different models. Moreover, the adoption of these technologies outside research remains an issue, often because public datasets poorly generalize realistic use cases. The problem is partially overcome by the application of transfer learning, even if it does not eliminate the need of recognized public datasets captured in the field.

6. Conclusions

Field data collection has been a crucial agronomic task for a long time, but at present, sustainability issues, green deal rules, climate change challenges, and safe food expectations demand crop monitoring with enhanced requirements. On the other side, human efforts should be minimized and research has been looking for solutions to automate monitoring, maximizing outcome details. Proximal and remote sensing offer images with enhanced spatial resolution or almost continuous environmental data. This availability of large amounts of data is essential, but algorithms are fundamental methods to automatically extrapolate relevant results. On the contrary, when limited acquisitions are available, algorithms offer segmentation approaches or methods to rationally merge data from different sources. The synergy between sensing and algorithms is a relevant characteristic of IoT, repeatedly analyzed in this paper, and it represents the key factor to stimulate the evolution towards the next generation of intelligent farming.

This study shows the high interest of the research community in applying algorithms to a variety of different agronomic aims. The reliability of the analyzed technologies is proved by many papers, and the adoption of new architectures such as transformer is encouraged. Efforts should be dedicated to improving their generalization and usability in real scenarios, allowing stakeholders to concretely take advantage of the technological achievements.

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Abbreviations

The following abbreviations are used in this manuscript:

ACO	Ant Colony Optimization
ADA	AdaBoost
AOA	Arithmetic Optimization Algorithm
ATN	Attention Mechanism
BC	Bayesian Clustering
BDA	Binary Dragonfly Algorithm
BS	Bagging or Bootstrap Aggregating
CNN	Convolutional Neural Network
DETR	DEtection TRansformer
DP	Deep Learning
DT	Decision Tree
ED	Encoder-Decoder
ELM	Extreme Learning Machine
ELNET	Elastic-Net
EXT	Extra Tree Classifier
FC	Fuzzy Clustering
FOA	Forest Optimization Algorithm
FPN	Feature Pyramid Network
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GBT	Gradient Boosting Tree
GLCM	Gray Level Co-occurrence Matrix
GPC	Giza Pyramids Construction
GPR	Gaussian Process Regression
GSA	Gravitational Search Algorithm
GSO	Golden Search Optimization
HBA	Honey Badger Optimization Algorithm
HOG	Histogram of Oriented Gradients
HUNG	Hungarian algorithm
IoT	Internet of Things
KM	K-Means
KNN	K-Nearest Neighbor
LASSO	Least Absolute Shrinkage and Selection Operator
LDA	Linear Discriminant Analysis
LION	Evolved Sign Momentum
LR	Logistic Regression
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multi-Layer Perceptron
MLR	Multiple Linear Regression
NB	Naive Bayes
PCA	Principal Component Analysis
PLS	Partial Least Square
PSO	Particle Swarm Optimization
RBFNN	Radial Basis Function Neural Network
RF	Random Forest
RIDGE	Ridge Regression

RNN	Recurrent Neural Network
ResNN	Residual Neural Network
SBO	Satin Bowerbird Optimizer
SC	Spectral Clustering
SCE	Shuffled Complex Evolution
SFO	Sun Flower Optimization
SGD	Stochastic Gradient Descent
SLIC	Simple Linear Iterative Clustering
SPA	Successive Projection Algorithm
SPA	Successive Projection Algorithm
SSA	Salp Swarm Algorithm
SSD	Single Shot Detector
SSO	Shuffled Shepherd Optimization
ST	Swim Transformer
SVM	Support Vector Machine
T	Transformer
TSA	Tunicate Swarm Algorithm
UAV	Unmanned Aerial Vehicle
ViT	Vision Transformer
WO	Whale Optimization
WoS	Web of Science

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