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Review

An Overview of Machine Learning Applications on Plant Phenotyping, with a Focus on Sunflower

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Abstract: Machine learning is a widespread technology that plays a crucial role in digitalisation and aims to explore rules and patterns in large datasets to autonomously solve non-linear problems, taking advantage of multiple source data. Due to its versatility, machine learning can be applied to agriculture. Better crop management, plant health assessment, and early disease detection are some of the main challenges facing the agricultural sector. Plant phenotyping can play a key role in addressing these challenges, especially when combined with machine learning techniques. Therefore, this study reviews available scientific literature on the applications of machine learning algorithms in plant phenotyping with a specific focus on sunflowers. The most common algorithms in the agricultural field are described to emphasise possible uses. Subsequently, the overview highlights machine learning application on phenotyping in three primaries areas: crop management (i.e., yield prediction, biomass estimation, and growth stage monitoring), plant health (i.e., nutritional status and water stress), and disease detection. Finally, we focus on the adoption of machine learning techniques in sunflower phenotyping. The role of machine learning in plant phenotyping has been thoroughly investigated. Artificial neural networks and stacked models seems to be the best way to analyse data.

Keywords: artificial intelligence; precision agriculture; digital agriculture; neural networks; internet of things; data mining

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1. Introduction

Nowadays, the agricultural sector is constrained in meeting the demand for increased food production due to population growth [1]. Cook et al. [2] claim that "while there is general agreement on the increased global demand for food to be expected in the coming decades, there is uncertainty surrounding global agriculture's capacity to service this demand through an expansion in the food supply". Climate change makes the scenario even more alarming, affecting food availability and contributing to extreme and dangerous weather phenomena [3,4]. A strategy to counter these challenges is to adopt precision agriculture, which aims to achieve better efficiency, productivity, and sustainability of agri-food chains [5–8].

Sunflower (*Helianthus annuus* L.) is one of the most important oilseed crops belonging to the Asteraceae family. In the last 20 years, the total production has increased by 183% (from 20.6 to 58.2 Mt), and the yield has increased by 71% (from 1.15 t/ha to 1.97 t/ha) [9]. This growth is due to multiple factors, including plant breeding, to improve agronomic performance [10]. Sunflower cultivation has spread in Europe thanks to the advantages offered both by its cultivation (i.e., good productivity, enhancement of areas affected by summer drought, and extraction of high-quality oil) and for its nutritional value [11]. The growing interest in sunflower cultivation is primarily due to the current geopolitical situation involving the Russian–Ukrainian conflict that causes uncertainty in the sunflower oil global market [12–15] and the use of sunflower oil as a substitute for palm oil [16], as well as being a high-quality edible oil and food [17–19]. Global demand for vegetable oil is projected to increase by around 46% by 2050 [20]. To safeguard the global market and consumers, the first step is to boost phenotyping on sunflowers, improving experimental field management and leveraging advanced technology to select the best genotypes [21,22]. The goal is to intensify the development of high-oleic hybrids to satisfy edible oil demands [23], which can be achieved through precision agriculture.

Precision agriculture, also known as precision farming, is "doing the right thing, in the right place, at the right time" [24]. Farm management can also be viewed as a business based on on-field observations, data management, and site-specific actions deeply linked to crop needs [25,26]. Furthermore, it represents the starting point for developing advanced data analysis due to the use of multiple sensors, which allow the collection of large amounts of data. Subsequently, this led to the Internet of Things (IoT) era. This new paradigm enables communication between electronic devices and sensors through the internet to support decision making and automation in diverse fields [27]. IoT led to the possibility of creating models to evaluate crop development, soil resources, and water availability [28]. IoT is the key to transitioning from precision agriculture to agriculture 4.0, also known as the Digital Agricultural Revolution. By definition, it represents an evolution in agriculture by leveraging cutting-edge technologies to optimize farm management [29]. Agriculture 4.0 is characterized by data acquisition from sensors, which are transmitted to cloud servers via IoT technology for storage, processing, and analysis. Big Data and artificial intelligence-based techniques (i.e., machine learning) are helpful to convert data into valuable insights. Finally, a decision support system is needed to help make the information more accessible, with the aim of optimizing agricultural systems.

Plant phenotyping is one of the agricultural processes which can be enhanced through digitalization. Plant phenotyping represents the key to any breeding selection process [30] based on the quantification of quality, photosynthesis, development, architecture, growth, and biomass production of plants [31]. There are two steps of phenotyping. Plant breeding is the first one and aims to develop new cultivars based on better performance of genotypes in different environmental conditions through phenotype expression [31–33]. Then, in-field phenotyping aims to improve crop management, plant health assessment, and disease detection by collecting and analysing useful information through digital technologies [33–35]. Nowadays, digital plant phenotyping benefits from non-destructive high-throughput measurements that can be repeated over time [30]. However, there is still a bottleneck due to the delay in developing precise and accurate techniques [33]. The goal is to clarify the state of the art of digital plant phenotyping to provide perspectives for future research.

The aim of this paper is to provide an overview of the updated and relevant scientific literature on machine learning applied to plant phenotyping for digital agriculture. Specifically, this article focuses on the application of machine learning in sunflower phenotyping to boost the selection of new genotypes and improve field management. In this work, we also investigate the integration of machine learning and phenotyping for digital agriculture and identify knowledge gaps for future research.

This overview is organized as follows. Section 2 briefly explains machine learning and its application in agriculture. Section 3 deals with machine learning techniques for phenotyping and describes the most prevalent algorithms used in phenotyping. Section 4 details how machine learning can be useful for different phenotyping approaches in digital agriculture. Section 5 provides insights into sunflower phenotyping and discusses the integration of machine learning in sunflower phenotyping. Finally, in Section 6, we summarise the main findings of the overview and provide perspectives for future research.

2. Machine Learning and Agriculture

Machine Learning (ML) is a widespread technology for exploring rules and patterns in large datasets [36]. The term 'learning' is broad and refers to acquiring knowledge, skills, and understanding through instruction or experience [37]. ML involves a learning process based on experience, known as a "training dataset", to perform a specific task [38–40]. ML techniques can be classified based on learning type (supervised, unsupervised, semi-supervised, and reinforcement learning) and learning models (classification, regression, clustering, and dimensionality reduction). A summary is given in Table 1. In supervised learning, the input dataset x and the output labels y are known. The algorithm is trained to recognize the function f to link x and y. In unsupervised learning, the output labels are not provided, and the algorithm must find rules and patterns autonomously. Semi-supervised learning is a combination of the previous ones because there are labelled and non-labelled data. Lastly, reinforcement learning is used for real-time decision making based on the best actions that can lead to a more positive outcome [41,42].

Table 1. For an immediate and intuitive understanding, each row of the table corresponds to a learning type, its possible use, and the algorithms available, adapted from [42,43]. Given the versatility of the use of ML techniques, the main algorithms used in agriculture have been reported.

Learning Type	Used for	Algorithms
Supervised Learning	Classification Regression Prediction	Bayesian networks Support Vector Machine Random Forest Neural networks Decision tree Hidden Markov model Naïve Bayes
Unsupervised Learning	Clustering Dimensionality reduction	k-means x-means Principal Component Analysis Independent Component Analysis Gaussian mixture models
Semi-supervised Learning	Hybrid	Self-training Transductive Support Vector Machine Generative models
Reinforcement Learning	Real-time decision making	Q-learning Markov decision process

One of the main advantages of ML techniques is the capability of autonomously solving large non-linear problems using datasets from multiple sources [36]. The overall advantages and disadvantages of ML are reported in Table 2. ML plays a crucial role in digitalizing and sharing big data technologies and high-performance computing. Thus, ML has found wide applications in many areas, including agriculture.

ML is a branch of artificial intelligence that has revolutionized crop management by improving crop mapping, quality monitoring, yield prediction, optimal irrigation scheduling, and pest and weed management [45]. Improved crop management allows productivity to be increased while meeting the demands of sustainability and natural resource conservation [46]. Figure 1 shows an example of the workflow for applying supervised ML techniques in agriculture. The initial step is data acquisition from multiple sources (e.g., sensors for surveying and assessing vegetation and soil characteristics, meteorological stations, and tracking and harvesting devices) that allow the construction of a comprehensive dataset. Then, the dataset is divided into a training set and a testing set, 70% and 30%, respectively. The former is used for algorithm training to group data by specific rules, while the latter is used to evaluate the algorithm's performance. Therefore, a robust ML model capable of making classifications or predictions can be applied to different agriculture domains.

Table 2. The advantages and disadvantages of machine learning in agriculture are described below, adapted from Chhaya and Sarode [44].

Advantages	Disadvantages
Ability to identify trends and patterns that are invisible to humans.	Algorithms require huge unbiased datasets for training.
Automation due to the ability of algorithms to self-learn and improve.	Requires a lot of time and resources.
Continuous improvement in accuracy and efficiency.	Specific skills are required to achieve good interpretation of results.
Possibility to handle multi-dimensional and multi-sources data.	High error-susceptibility, especially when the algorithm is trained on insufficient datasets that generate bias.
Wide applications (engineering, medicine, agriculture, etc.).	

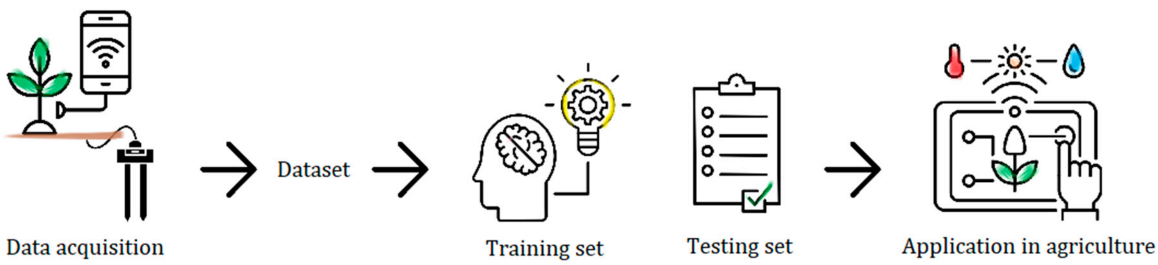

Figure 1. Decision support systems involves data acquisition from multiple sources as input for machine learning algorithms. Then, a supervised learning model splits the dataset into a training set and a testing set. When high accuracy is achieved, the model is ready to predict or classify based on experience and can be used by farmers.

The application of ML techniques has become widespread in the last decade, as highlighted in Figure 2. The graph highlights the results of the search for the following combinations of keywords on Scopus: "machine AND learning" (black line), "machine AND learning AND agriculture" (red line), "machine AND learning AND precision AND agriculture" (green line), "machine AND learning AND digital AND agriculture" (yellow line), and "machine AND learning AND phenotyping" (blue line). The graph represents the trend of publications from 1995, year of the first scientific paper published about agriculture and ML [37], until January 2024 (last accessed on 30 January 2024). It is crucial to note the order of thousands of articles referenced: tens of thousands for the keywords "machine AND learning" (left vertical axis) and thousands for others (right vertical axis). Nevertheless, the exponential increase in published articles occurred after 2014, and interest in the topic keeps growing.

The integration of ML in agriculture dates back to the early 2000s as an application in dairy farming. It was first used to detect oestrus [47] and interpret parity–group average lactation curves [48] in dairy cows. At the same time, in crop production, it was first applied in the classification of bruised apples for commercial purposes [49] and was later introduced for hyperspectral data processing [50].

Several examples of applications of machine learning in precision agriculture [51] are reported, i.e., soil properties detection [52–54], crop yield predictions [55–59], disease [60–63] and weed detection [64–66], site-specific irrigation [67–69], and livestock production and management [70–72]. One of the most in-depth topics is the analysis of plant health with hyperspectral data [73]. The hyperspectral reflection of the leaf is the sample, and the health state of the plant can be considered the output label [74]. An interesting application of ML concerns vegetable cultivation in the absence of freshwater and soil by using a self-sustaining platform. ML was used to predict water consumption and rationalize its use [75]. The analysis of vegetation indices, essential to crop management, is another example of ML application in precision agriculture [76–78]. A recent study investigated the possibility of estimating the NDVI (Normalized Difference Vegetation Index) through an artificial intelligence approach from RGB images, a revolution for small-sized farms due to the low-cost cameras used [79]. In another study, the automation of agrochemical spraying based on two types of algorithms for foliage and grape detection was carried out to reduce the agrochemical distribution [80]. A new area of interest is agrophotovoltaic systems, which have recently been integrated because of European Union policy. Photovoltaic systems can potentially mitigate climate change and their effects. ML can be used to optimize solar installations and evaluate solar energy generation and crop production performance of agrophotovoltaic systems [81,82]. Object-Based Image Analysis and ML have also been combined to classify agrophotovoltaic parks [83]. Considering the wide literature available on the integration between agriculture and machine learning, this work deepens plant phenotyping for digital agriculture because it can be the starting point for agriculture.

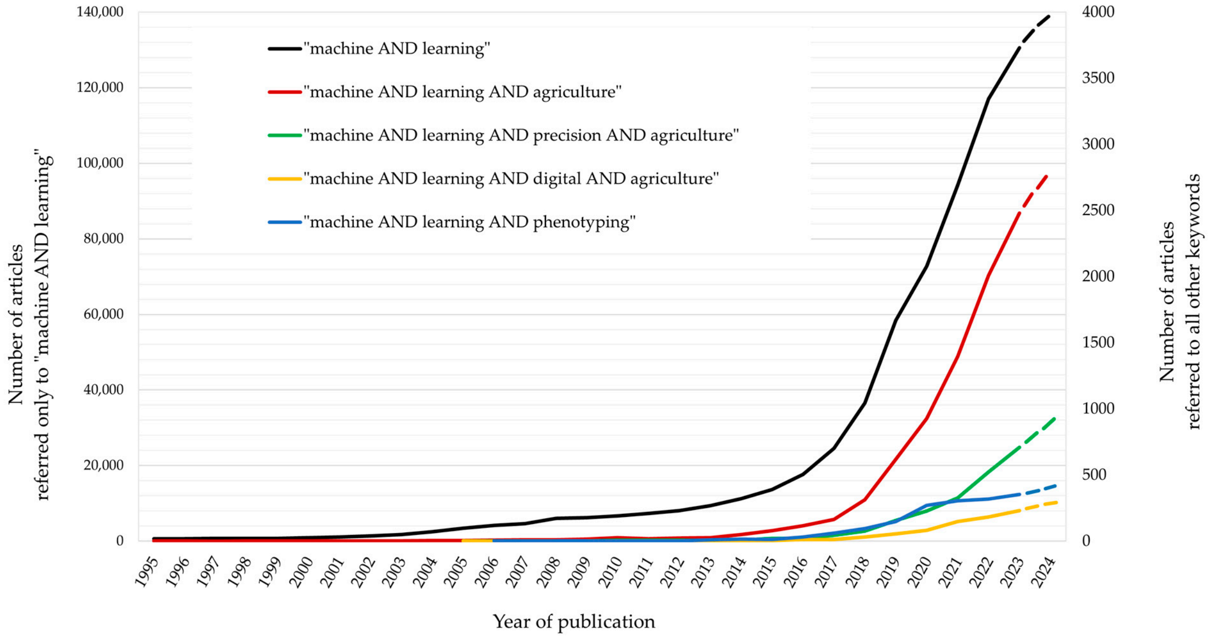

Figure 2. Publications found by searching for scientific papers published on machine learning (black line) and its integration in agriculture (red line), precision agriculture (green line), digital agriculture (yellow line), and phenotyping (blue line). The graph represents the trends of publications from 1995 to 2024, last accessed on 30 January 2024.

3. Machine Learning Techniques for Phenotyping

As highlighted in Figure 3, four main families of algorithms account for over 70% of the total found in 126 published scientific papers by searching for "machine AND learning AND phenotyping AND agriculture" keywords in Scopus. The pie chart shows that artificial neural networks, support vector machines, and decision trees are the most used algorithms in plant phenotyping, followed by k-Nearest Neighbors. The other algorithms are much lower ranked.

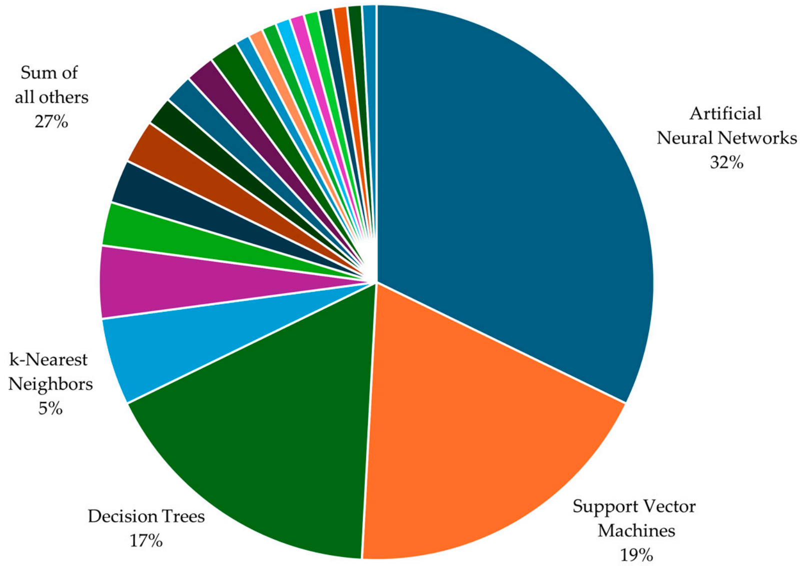

Figure 3. The pie chart identifies the most used machine learning algorithms in phenotyping activities in agriculture. The findings are limited to scientific articles and conference proceedings.

3.1. Artificial Neural Networks

Artificial Neural Networks (ANNs) are ML systems inspired by the biological network of neurons that make up the human brain [84,85] and are used in countless fields, including medicine, agriculture, and energy. Like the human brain, ANNs consist of a network of computational neurons that can receive and process inputs and return outputs [86,87]. The structure and mathematical functioning of a neural network are complex, and since this section aims to give a concise explanation of the main ML models used in agriculture, a brief description of its structure is reported.

ANNs consists of three or more layers: an input layer, one or more hidden layers, and an output layer (Figure 4a) [88,89]. The input layer receives data and passes it to the neurons in the hidden layer. The neurons then process the data, generating an output that can, in turn, serve as input to the next layer of neurons or can be delivered as the final results of the calculations [90]. Thus, the fundamental elements of ANNs are neuron mathematical functions, which take data as input, process it, and produce an output [91,92]. During the processing phase, each input data received by a neuron is multiplied by a coefficient (defined as weight) and added with a bias. After calculating the weighted sum of the inputs, the neuron fits an activation function to the result and generates an output [84,85,93].

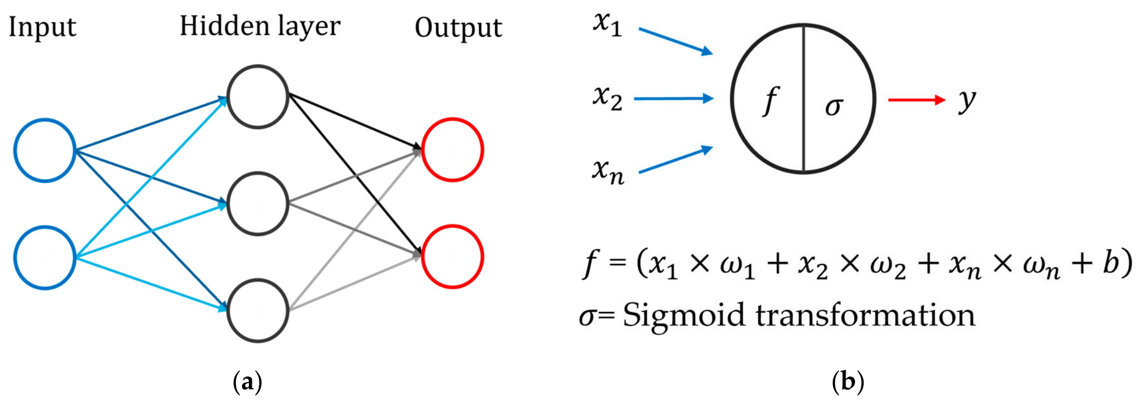

Figure 4. (**a**) Shows the basic structure of an ANN, with differing colours indicating different layers. (**b**) Illustrates the basic functioning of an artificial neuron, with colours retaining the same meaning of (**a**). Specifically, blue represents data input, black represents the processing phase, and red represents output generation.

The activation function introduces non-linearity to the data. Without this function, an ANN would consist of a multitude of linear transformations of the input, limiting the ability to adapt to multivariate data with complex patterns [94,95]. The sigmoid function is one of the most commonly used activation functions that scales data ($-\infty$, $+\infty$) to a range of 0 to 1 [94], and an example of how it works is reported in Figure 4b. The power of ANNs lies in their ability to learn from examples, in particular by recognizing patterns and adapting to new data [91,96]. The learning process is made possible by the back propagation algorithm. Thus, the back propagation utilises the error function to adjust the weight of each input to neurons in order to gradually reduce the error, which is the difference between the actual ANN's and the sought output [97,98].

Neural networks can have different structures. For instance, Convolutional Neural Networks (CNNs) are commonly used in image processing and differ from ANNs in the structure and functioning of the neurons [99]. Whereas neurons in conventional ANNs are arranged in fully connected layers, neurons in CNNs are organized in groups of neighbor neurons (convolutional layers), which are associated with only a limited number of inputs [100]. Thus, the image is divided between groups of neurons, allowing certain image features to be captured (e.g., edges or textures) and making the analysis efficient and localized [101].

3.2. Support Vector Machines

In the early 1990s, Cortes and Vapnik introduced a new algorithm called a Support Vector Network (SVN), designed as a binary classification method [102]. In later years, the SVN was renamed to SVM (Support Vector Machine) [103].

Presently, SVMs are referred to as the set of supervised learning methods applied in classification (Support Vector Classification, SVC) and regression (Support Vector Regression, SVR) problems [104]. SVRs are used for continuous values and non-linear data, in order to find a function that best approximates the relationship between the input data and the target variable. SVCs are used for separating a dataset into classes, producing a discrete output (class label). SVCs are widely used for both linear and non-linear data and are considered easily applicable to unseen datasets [105]. Although SVMs have some limitations, such as the inability to identify more than two classes at a time, or the difficulty of applying them to large datasets [106,107], they are still some of the most widely used classification algorithms in a few fields such as image classification and object detection in the field of remote sensing [107,108].

To comprehend the functioning of SVMs, it is essential to introduce the concepts of hyperplane and kernel function. A hyperplane can be defined as a decision boundary that separates the datapoints (or vectors) into two classes [109]. In a 2-dimensional space with linearly separable vectors, a hyperplane can be represented by a straight line that separates vectors (Figure 5a) [106,109]. When vectors are not linearly separable, the kernel function allows for the creation of a higher dimensional space, seeking to maximize the distances between vectors, and ultimately allows the identification of a hyperplane which linearly separates vectors into classes (Figure 5b) [103,104,110]. Although the SVM's classification process may appear simple, selecting the optimal hyperplane is not. There is no single hyperplane that can separate vectors into two classes. Instead, there are infinite possibilities (Figure 5c). Thus, the concept of a margin can be applied to select the best hyperplane. Figure 5d illustrates how the SVM algorithm constructs two additional hyperplanes parallel to the main one and tangent to the first two vectors (called support vectors) closest to the main hyperplane to select the optimal classification hyperplane. The support vectors thus define the distance (also called a "margin") between the two additional hyperplanes. Then, the SVM algorithm selects the classification hyperplane with an orientation that maximizes the margin, ensuring a more accurate classification [102,105,106,110].

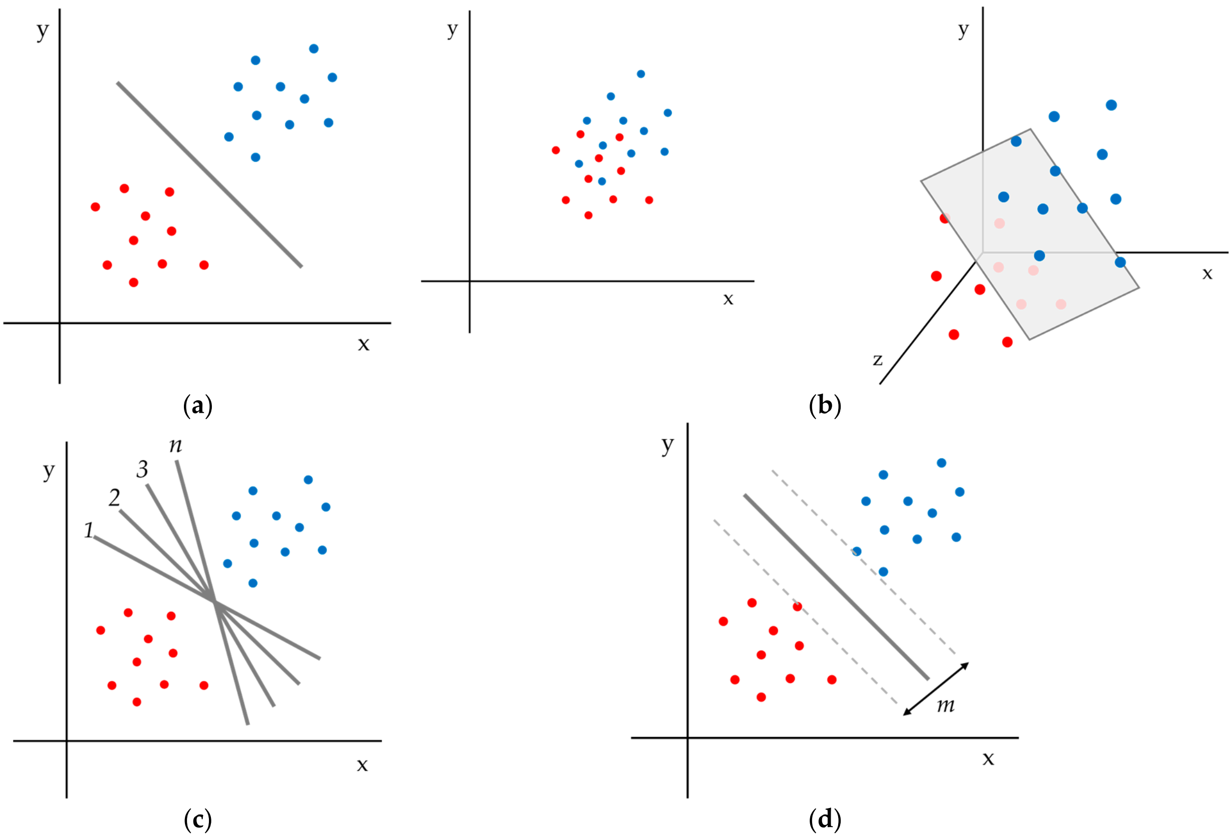

Figure 5. (**a**) Demonstrates how a bivariate dataset (red and blue dots) can be separated by a straight line, while (**b**) shows the transition to a higher dimensional space to fit a hyperplane that separates the dataset. (**c**) Displays the numerous possibilities of lines or hyperplanes (1, 2, 3. . .n) that can be chosen to separate the dataset. (**d**) Illustrates the concept of a margin (m), which enables the selection of the best hyperplane.

3.3. Decision Trees

Decision Trees (DTs) are a set of algorithms that fall under non-parametric supervised ML techniques and are used for both classification (Classification Decision Tree, CDT) and regression problems (Regression Decision Tree, RDT). They owe their name to the process of selecting variables (or features) which better characterize the dataset and its binary splitting, thereby producing a structure that can be schematized as a tree stem ('parent' dataset) that develops its nodes or branches (groups) and leaves (final sub-groups), as represented in Figure 6a. Whilst CDTs are used to label and predict categorical data, RDTs are used to predict numerical data, fitting models to each node. Thus, the entire dataset lies at the top of the tree and is repeatedly split, maximizing similarity within groups and differences between groups [111]. How does the algorithm decide how and up to what point the data should be split up? Splitting stops if the decrease in impurity is below a predetermined threshold [112]. CDT commonly uses two impurity metrics to assess whether the dataset is properly split: specifically, the Gini and Entropy indices. The former calculates the probability of misclassification of an element randomly extracted from the dataset with respect to the distribution of classes in the node [112–114]. The latter is used to measure the purity of a node by assessing the amount of disorder with respect to the target classes. Mathematically, it is calculated by summing the probabilities of the different class outcomes and multiplying them by the logarithm of these probabilities [112–114]. Meanwhile, the most common impurity metric of RDT is the well-known Sum of Squared Error, computed as the sum of the squares of the differences between each data point and the mean [113,115].

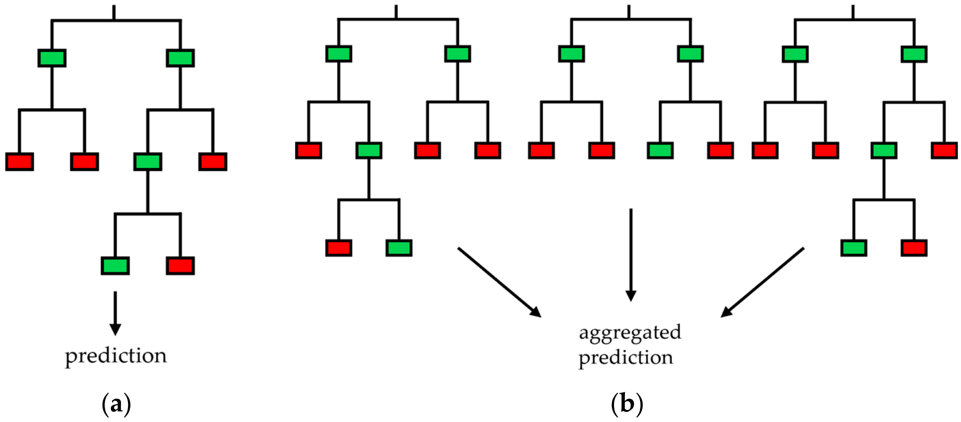

Figure 6. (**a**) Illustrates the workflow of a classic Decision Tree and (**b**) represents how Random Forests generate an aggregated prediction. In both cases, the algorithm votes for a class label. The class with the highest number of votes is the final predicted one (green box), while the other is discarded (red box).

In the 2000s, Breiman proposed a new algorithm based on the combination of multiple DTs and bootstrap aggregation (or bagging), trademarking the term Random Forest (RF) [116]. An example of how an RF works is depicted in Figure 6b. Thus, being a combination of multiple models, the RF falls within the category of ensemble ML techniques [108,113,116,117]. Bagging entails training each DT in the forest on a randomly selected portion of the training dataset. Through bootstrap sampling, a subset of the initial training data is randomly sampled from the dataset. The random selection of data ensures diversity among DTs, as each one is trained on a slightly varied subset of the original dataset [113,118,119]. Furthermore, to increase generalization and reduce overfitting, the RF adds an additional degree of randomization. Rather than seeking the most important feature for node splitting, the RF selects the optimal feature from a randomly selected subset of features [113,118]. Once the RF has been trained, each DT in the RF independently predicts an outcome. Following the individual predictions made by each DT, the next step is to aggregate the predictions. In classification problems, this typically entails a "voting" process, where each DT "votes" for a class label, and the class with the highest number of votes is selected as the final predicted label. Conversely, in regression tasks, the predictions from all trees are combined by averaging them to produce the final prediction [108,116,118].

3.4. k-Nearest Neighbors

The k-Nearest Neighbor (kNN) is a relatively simple supervised ML algorithm for regression and classification. In the case of classification, once the algorithm has been given a dataset consisting of samples belonging to known classes (hereafter referred to as "seen"), it will classify unknown samples (hereafter referred to as "unseen") based on their proximity to the seen samples (Figure 7). Specifically, once the unseen samples are passed to the kNN algorithm, it computes the distance between the unseen and seen samples [120]. The most used distance metric is the Euclidean distance. At this point, the unseen samples are classified into the class to which the K closest seen samples belong, where K is a predefined number of samples determined by the user. In regression problems, on the other hand, the predicted data for the unseen samples are the average of the target values of the K nearest neighbors. As can be expected, the key element for the success of a kNN model lies in the correct choice of K. If K is too low, this can lead to overfitting of the algorithm, while conversely, if K is too high, this can lead to underfitting [121,122]. One of the main techniques to assess the quality of the chosen K is cross-validation, a process that allows the systematic variation of K and fitting of the algorithm, whilst monitoring its performance [123].

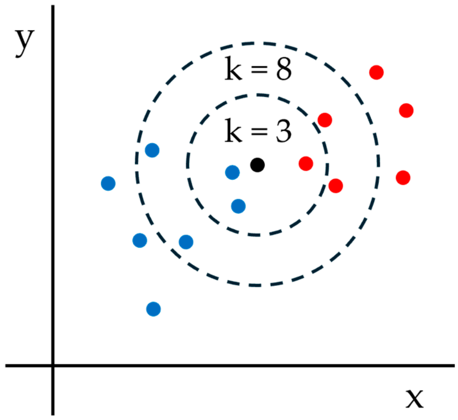

Figure 7. Unseen data (black dot) plotted with seen data belonging to two different classes (blue and red dots). The dotted circumference illustrates how different K values can lead to a different classification of unseen data.

4. Digital Plant Phenotyping

Digital plant phenotyping is focused on two priority areas, crop management and plant health. ML algorithms can enhance phenotyping due to their ability to find rules and patterns in large datasets.

4.1. Crop Management

Crop management is based on field data, such as biochemical and biophysical parameters, as well as structural and spatial parameters for plant recognition.

Biochemical and biophysical parameters are crucial for site-specific management due to their correlation with plant status. Various information can be extracted from different images in combination with ML algorithms to estimate and predict various biochemical and biophysical parameters, such as above-ground biomass, yield, structural information (plant height and canopy coverage), and textural information. Aerial images such as RGB, multispectral, hyperspectral, and thermal images can be useful in extracting information on these parameters by analysing them with different ML algorithms. Image-based analysis can help farmers properly manage their fields by explaining how crops respond to biotic and abiotic factors. For instance, an RF was also used to predict tomatoes' biomass and crop yield after the weekly acquisition of RGB, and multispectral images were analysed until harvest [124]. However, this requires following a standard procedure for data acquisition through drones and ground measurement. In other studies, an Extreme Learning Regression model was used to predict phenotypes based on vegetation indices, which were calculated using multispectral images. The model showed better performance than widely used partial least square regression and SVR models [125–127]. Impollonia et al. [128] also estimated the leaf area index and chlorophyll content using an RF and gaussian process regression, respectively. RGB, multispectral, and thermal images can also be merged for feature extraction of canopy structures and vegetation indices calculation [129]. The Deep Neural Network (DNN), a more robust and sophisticated model, was used to analyse RGB, multispectral, and thermal images to predict soybean yield [126]. Hyperspectral imaging combined with ML was also applied to classify and predict plants traits, such as salt stress [130], crop yield [131–136], and biomass quantity [137–140]. However, powerful data mining techniques are required. Crop management can also use CNNs trained to find patterns starting with sample images. A 3D CNN was used to predict soybean yield via analysing multitemporal images [141].

More recently, stacked regression has been gaining popularity, allowing the simultaneous use of multiple algorithms to analyse the same images. A recent study compared five basic learners, i.e., kNN, SVM, RF, ridge regression, elastic net, and stacked application, to predict faba bean above-ground biomass and yield. Stacked regression showed a higher accuracy of estimation than individual ones [142]. Another study focused on predicting the photosynthetic capacities of tobacco using high spectral images in combination with regression models for individual and stacked applications, i.e., ANN, partial least square regression, SVM, RF, least absolute shrinkage and selection operator, and gaussian process regression [143]. Promising results were found, where each model uses information from specific spectral regions with stacked regression showing the best performance. Phenotyping also benefits from non-destructive surveys to classify grapevine varieties with SVM, kNN, and DT models using near infrared spectra [144,145].

Automatised plant recognition is another important application of digital phenotyping in crop management [32,146]. Variety recognition and counting, as well as spike counting, enables farmers to adapt cultivation practices and harvesting based on real field conditions. ML applied to plant recognition makes it more efficient, rapid, and cost-effective in evaluating crop phenotypes [147–149]. Plant recognition benefits from automated learning on multiple data layers, and it can reach a high performance using CNN algorithms. For example, CNNs are powerful algorithms applied to counting plants, leaves, and flowers [150–153]. Wheat spike counting is crucial to increase crop yield [154–156], along with lettuce headcount and quality prediction for commercial purposes [157,158]. Another interesting application is sorghum panicle counting, where Mbaye and Audebert [159] reported no significant difference in the results of SVM and ANN (99% versus 98% accuracy). When few samples per class are available, it is better to use a pre-trained CNN and apply the few-shot learning algorithm [160]. The last advancement is to improve spike counting by embedding automatic object level augmentation and a CNN [161]. This approach can be extended to the analysis of phenological stages over time. A pre-trained CNN model was tested for autonomous feature extraction with a positive outcome [162]. High-throughput phenotyping [163], as well as ANN applied to satellite images [164], led to benefits of unsupervised models to predict plant heights. To improve harvesting management, it is useful to know lodged areas, and plant phenotyping can identify management zones. As shown in Figure 8, an automated ML was employed for binary classification "lodged" or "non-lodged" (image classification) and prediction of lodging score (image regression) [165,166]. CNN performance far exceeds that of traditional ML approaches, e.g., SVM, and it was demonstrated, for example, in rice seedling growth stage recognition [167].

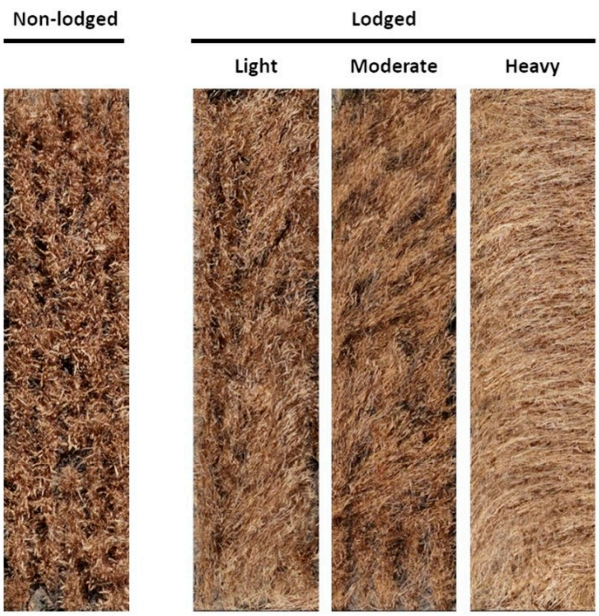

Figure 8. Highlight on-field condition of durum wheat by using a binary classification of "non-lodged" and "lodged". Image regression is useful for defining three levels of lodging intensity (light, moderate, and heavy). The illustration was taken from Koh et al., 2021 [165].

4.2. Plant Health

Plant health is one of the hottest topics for digital agriculture and involves stress detection, e.g., nutritional status analysis, water stress, and disease detection. The importance of plant health lies in the possibility of producing higher yields by rationalizing agrochemicals and fertilizers. For example, in 2018, a group of researchers built a Deep Convolutional Neural Network (DCNN) that can detect soybean stress caused by bacterial blight, Septoria brown spot, frogeye leaf spot, herbicide injury, potassium deficiency, iron deficiency chlorosis, bacterial pustule, and sudden death syndrome [168]. The DCNN architecture and explanation phases are shown in Figure 9 to help understand the complexity of this subject. Hyperspectral imaging leads to a non-invasive, precise, and high-throughput plant phenotyping. For example, nutritional status detection can be performed with a VIS/SWIR sensor (visible to short wave infrared bands), and a good outcome was carried out with a Radial Basis Function Network based on an SVM [169]. The SVM classifier is an effective algorithm for detecting and classifying leaves affected by chlorosis in lettuce with 100% accuracy [170]. In-field phenotyping is often carried out with RGB images that can express great potential through pretrained CNN combined with a long–short term memory network [171]. Okyere et al. [172] also assessed nitrogen and phosphorus content in cowpea and quinoa at different growth stages using hybrid CNN to analyse hyperspectral images. In another study to determine nitrogen content using RF regression, prediction models constructed on multispectral images achieved better performance than RGB images due to the increased number of bands [173].

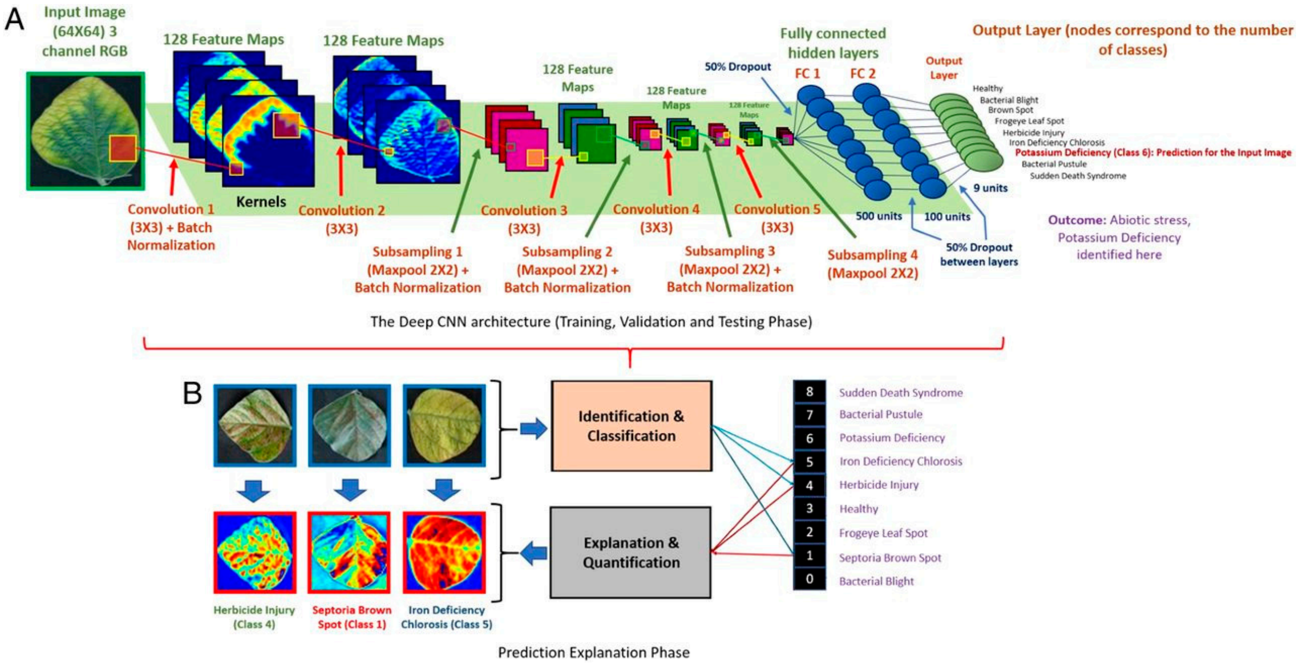

Figure 9. Overall diagram of the DCNN architecture (**A**) and the prediction explanation phases (**B**) to distinguish the eight different stresses from the healthy leaf of soybean. The illustration was taken from Ghosal et al., 2018 [168].

Water plays a critical role in agriculture. Therefore, finding innovative solutions for proper management is paramount. Drought stress can be explained as a lack of soil moisture during plant growth and causes severe damage to crop quality and quantity. High-throughput phenotyping allows farmers to detect drought stress early. For instance, multi-colour and chlorophyll fluorescence imaging techniques can detect water stress through an SVM model [174]. Hyperspectral imaging fits well with ML for water stress detection. SVMs and RF classifiers can be useful with selected bands (692, 714–716, 763–769, 774–882, 870, and 949 nm) to identify two water stress levels [175]. RFs can be useful in classifying different varieties' drought tolerance, such as in potatoes [176]. Recently, deep learning algorithms have also been introduced to detect water stress. Three types of DCNN were applied to maize, okra, and soybean to classify "non-stressed" and "stressed" crops by using colour-based feature extraction [177]. A study using a CNN model based on Gabor feature extraction showed promising results for a real-time application to detect water stress on field conditions [178]. Information about water stress can also be derived from temperature and stomatal conductance measured with optical and thermal infrared imaging cameras [179]. The RF model performed well in predicting temperature and stomatal conductance, giving an idea of the potential on-field drought stress of maize. Another innovative methodology for detecting water stress involves terahertz time-domain spectroscopy technology integrated with ML algorithms. Although it is a more promising approach due to its sensitivity and non-destructive nature, its application is limited by the high cost of the camera. Zahid et al. [180] integrated ML and terahertz waves for species identification and plants' stress detection at the cellular level in the frequency range of 0.75 and 1.1 THz. Feature extraction and selection were followed by applying SVM, RF, and kNN classifiers. All three models performed well for leaf detection, but RF achieved a higher accuracy of 99.42% for water stress detection.

Crops can be affected by several pathogens compromising the agri-food chain in terms of quality and quantity. Disease detection over time and space is crucial for farmers to act promptly. Therefore, agriculture needs to have an early, rapid, and non-destructive disease detection technique available. There are many examples of ML application for disease detection. For instance, Wahabzada et al. [181], developed metro maps of plant disease dynamics by collecting hyperspectral images on barley plants and processing them with Bayesian networks used for regression. Results confirmed that disease symptomatology and plant signature are deeply linked and can be used to make a helpful disease map. Another study used infrared, thermal, and autofluorescence images processed with logistic regression analysis and an ANN on zucchini [182]. Results highlight the positive potential of thermography and multicolour fluorescence imaging to distinguish healthy or infected areas inoculated with *Dickeya dadantii*. The data mining of this work was subsequently enriched first by evaluating the SVM model approach [183] and then expanding image acquisition to chlorophyll fluorescence [184].

The SVM classifier is also an effective algorithm for detecting and classifying leaves affected by disease in different crops. For example, potato was assessed through RGB images for late blight (*Phytophthora infestans*) and early blight (*Alternaria solani*) detection [185], winter wheat was assessed by using a spectroradiometer for Fusarium head blight (*Fusarium* spp.) detection [186], and sugarcane affected by orange rust (*Puccinia kuehnii*) and brown rust (*Puccinia melanocephala*) was assessed through multispectral data [187]. In 2021, a comparison between six ML algorithms, i.e., SVM, kNN, linear discrimination analysis, Naïve Bayes, CDT, and DNN, was carried out to develop a diagnostic method for rice [188]. The goal was to distinguish healthy leaves from leaves affected by leaf blast, bacterial leaf blight, and tungro. The authors reported that all ML classification models provided excellent classification performance. Another advanced application of ML is using the feature selection model for spot tagging leaf disease detection on corn with an estimated accuracy of 97% [189]. ML can also be useful for classifying disease severity and help farmers streamline the distribution of agrochemicals. For example, powdery mildew on melon can be detected and classified due to the combined use of pre-trained CNN and SVM [190].

It is worth noting that at the beginning of 2024 a powerful database called Plant Phenomics Analysis of Disease (PlantPAD) was developed to identify and analyse plant disease [191]. As explained by the authors, the database includes over 420,000 images for 63 crops and 310 disease phenotypes. PlantPAD can be used to diagnose the disease, as a teaching tool for students, and to identify the appropriate control strategy.

5. Overview of Digital Sunflower Phenotyping

Sunflower is one of the most important oilseed crops in the world, and it is reasonable to believe that researchers and farmers have a growing interest in it. As explained in the introduction, one of the priorities is to boost phenotyping on sunflowers through advanced technologies. Extensive scientific literature is available on major crops, such as wheat and maize. In contrast, a limited number of scientific articles are available on the application of ML on sunflower phenotyping.

From sowing to emergence and first growth stages, plant recognition could be crucial for the main phenotyping objectives of fast-growing plant selection and early weed detection. It is important to monitor fast-growing plants in the early stages to limit damage, for example, from wild fauna. Moreover, early weed detection helps farmers to act promptly to prevent weeds from stifling the growth of sunflower seedlings. To address these challenges, single or aerial images can be used. Single images captured by camera are subjected to a segmentation process and feature extraction [192]. The former is used to obtain binary images in which '0' stands for ground and '1' represents vegetation, and the latter is for image pattern recognition based on mathematical rules. Two neural networks were used for leaf selection and classification discriminating "sunflower" or "non-sunflower" [192]. Aerial images captured by drone require orthorectification and mosaicking processes. The obtained image can be used to calculate vegetation indices via mathematical computation of two or more wavelengths. Then, the Hough Transform can be used for crop row detection. The objective is to recognize weeds based on their position with respect to the crop row. Pérez-Ortiz et al. [193] used six classification models belonging to the three learning types (unsupervised, semi-supervised, and supervised learning) from drone imagery for weed mapping. Results showed the possibility of combining spectral information, vegetation indices, and Hough Transform as input features. Secondly, classification performance is better as the flight height of image acquisition decreases. Regarding the best combination of input features, the semi-supervised SVM outperformed other algorithms at 30 m and 60 m of flight height, while the repeated k-means performed better at 100 m of flight height.

During the growing season, crop yield prediction is one of the most widespread strategies to help farmers in site-specific management. SVMs, ANNs, and RFs have been deeply investigated as powerful ML algorithms for predicting sunflower yield based on multiyear data [194]. Furthermore, SVMs and RFs are used in comparison with multiple linear regression. Results show that the highest correlation was observed with vegetation indices obtained during the inflorescence emergence stage, and the RF model achieved better accuracy [78,195]. An interesting application of ML models is sunflower oil yield prediction, which allows breeders to select the most productive varieties. Cvejić et al. [23] tested four algorithms (ANN, RF regression, SVR, and kNN) on a two-year dataset of sunflower oil yield and found RF regression as the best regressor to predict oil yield.

The SVM is a robust classification algorithm that can be used to identify lodging disorders in sunflower cultivation. Furthermore, a deep learning approach may be applied to achieve better performance and highlight the severity [196].

Plant health is a determining factor in obtaining an optimal crop yield in terms of quality and quantity. Sunflower is one of the major oilseed crops, and therefore equally strong research on this topic is needed. The detection of disease and nutritional disorders drives the development of ML techniques with an adaptable, easy-to-use, and rapid methodology. Sunflower is affected by nutritional disorders caused by a holoparasite, a broomrape (*Orobanche cumana* Wallr.). Logistic regression enables the classification of infected and non-infected sunflowers [197]. An interesting study was conducted on sunflower leaves to classify leaf spots, rust, and powdering mildew with respect to healthy leaves [198]. Multinomial logistic regression was shown to be the best classifier with an average 92.6% accuracy, followed by SVM, kNN, and Naïve Bayes respectively, with an average accuracy of 92.2%, 89.3%, and 89.1%. Two years later, another study investigated the accuracy of the RF algorithm to classify four diseases in the light of leaf symptoms (black spot, powdery mildew, bacterial leaf spot, and downy mildew) [199]. Thanks to the development of CNN, pretrained algorithms (e.g., ResNet152) were found to be very accurate in identifying sunflower disease taking into account leaf colour, texture, and shape [200].

Lastly, an innovative approach was proposed. A transfer learning model was combined with CNNs to diagnose sunflower disease [201]. In more detail, a pretrained model was used for feature extraction followed by a single layered CNN to classify sunflower leaves affected by four different diseases (i.e., downy mildew, gray mold, leaf scars, and fresh leaf).

6. Conclusions and Perspectives

Digital plant phenotyping revolves around some key factors, i.e., crop management and plant health. Research must progress in this direction to help farmers to improve crop yield and to streamline the use of inputs, e.g., agrochemicals, fertilizers, and water.

The current overview highlights that the most used machine learning algorithms are ANNs, followed by SVMs, DTs, and kNN. The last three have been extensively studied and are consolidated algorithms for classification and regression, while ANNs are more complex to apply due to their relationship with neural connections similar to the human brain. We show in this review that each model exploits specific spectral regions to extract information and train the algorithm. This is why, in cases where it was studied, the best performance is ensured by stacked models. Future research must deepen ANNs, particularly DCNNs, and their application for agricultural purposes. Furthermore, the stacked approach should thoroughly exploit information from different input sources.

Machine learning algorithms enhance RGB, multispectral, and hyperspectral images. This review highlights that the better models are built on hyperspectral and multispectral images due to the increased number of bands. In addition, researchers agree on the need to use standard procedures for data surveys and processing to achieve better performances.

The integration between machine learning and digital plant phenotyping for sunflowers has not been fully harnessed. Considering the importance of sunflowers in the global market, future research must focus on this oilseed crop to improve its agronomic performance. More importantly, it is critical to enhance early sunflower disease detection and also manage nutritional and water deficiencies. Research on sunflower production should be expanded, given the potential offered by machine learning.

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