

Review

Hyperspectral Image Analysis and Machine Learning Techniques for Crop Disease Detection and Identification: A Review

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Abstract: Originally, the use of hyperspectral images was for military applications, but their use has been extended to precision agriculture. In particular, they are used for activities related to crop classification or disease detection, combining these hyperspectral images with machine learning techniques and algorithms. The study of hyperspectral images has a wide range of wavelengths for observation. These wavelengths allow for monitoring agricultural crops such as cereals, oilseeds, vegetables, and fruits, and other applications. In the ranges of these wavelengths, crop conditions such as maturity index and nutrient status, or the early detection of some diseases that cause losses in crops, can be studied and diagnosed. Therefore, this article proposes a technical review of the main applications of hyperspectral images in agricultural crops and perspectives and challenges that combine artificial intelligence algorithms such as machine learning and deep learning in the classification and detection of diseases of crops such as cereals, oilseeds, fruits, and vegetables. A systematic review of the scientific literature was carried out using a 10-year observation window to determine the evolution of the integration of these technological tools that support sustainable agriculture; among the findings, information on the most documented crops is highlighted, among which are some cereals and citrus fruits due to their high demand and large cultivation areas, as well as information on the main fruits and vegetables that are integrating these technologies. Also, the main artificial intelligence algorithms that are being worked on are summarized and classified, as well as the wavelength ranges for the prediction, disease detection, and analysis of other tasks of physiological characteristics used for sustainable production. This review can be useful as a reference for future research, based mainly on detection, classification, and other tasks in agricultural crops and decision making, to implement the most appropriate artificial intelligence algorithms.

Keywords: hyperspectral; crops; plant diseases; machine learning; deep learning



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1. Introduction

The world population has experienced a dizzying increase in recent decades. According to the United Nations (UN), it will reach at least 9.1 billion inhabitants by 2050 [1]. With this, it is expected that the demand for food will increase significantly in the coming decades, especially in developing countries, where food security will become a problem. Climate change imposes important challenges because it may affect agricultural production. Indeed, prolonged droughts, floods, and changes in temperatures and rainfall patterns have significant impacts on agriculture. Prolonged droughts, characterized by a prolonged period of abnormally low rainfall, can lead to water stress in crops, hindering their growth and reducing yields. Insufficient water supply can also result in soil degradation and desertification, making it challenging for agriculture to thrive in affected regions [2]. In this sense, the use of new technologies in agriculture is especially important for optimizing crops and enhancing their production efficiency in controlled environments. Among these

technologies, there is a growing trend in utilizing artificial intelligence and image analysis supported by hyperspectral cameras [3,4]. Therefore, this work will review the most relevant aspects of combining these tools.

The electromagnetic spectrum is composed of several bands that represent different types of light energy (Figure 1). The human eye has a capacity of 400 to 700 nm [5], but hyperspectral sensors typically collect more than 200 spectral bands, ranging from the ultraviolet (UV) to longwave infrared (LWIR) range. Hyperspectral cameras are an innovative technology that has revolutionized the agricultural sector in recent years. They are capable of capturing high-resolution images and multiple wavelength bands that provide sufficient information about crops, allowing farmers to detect problems in plant health and take preventive measures before they become a bigger problem [6,7].

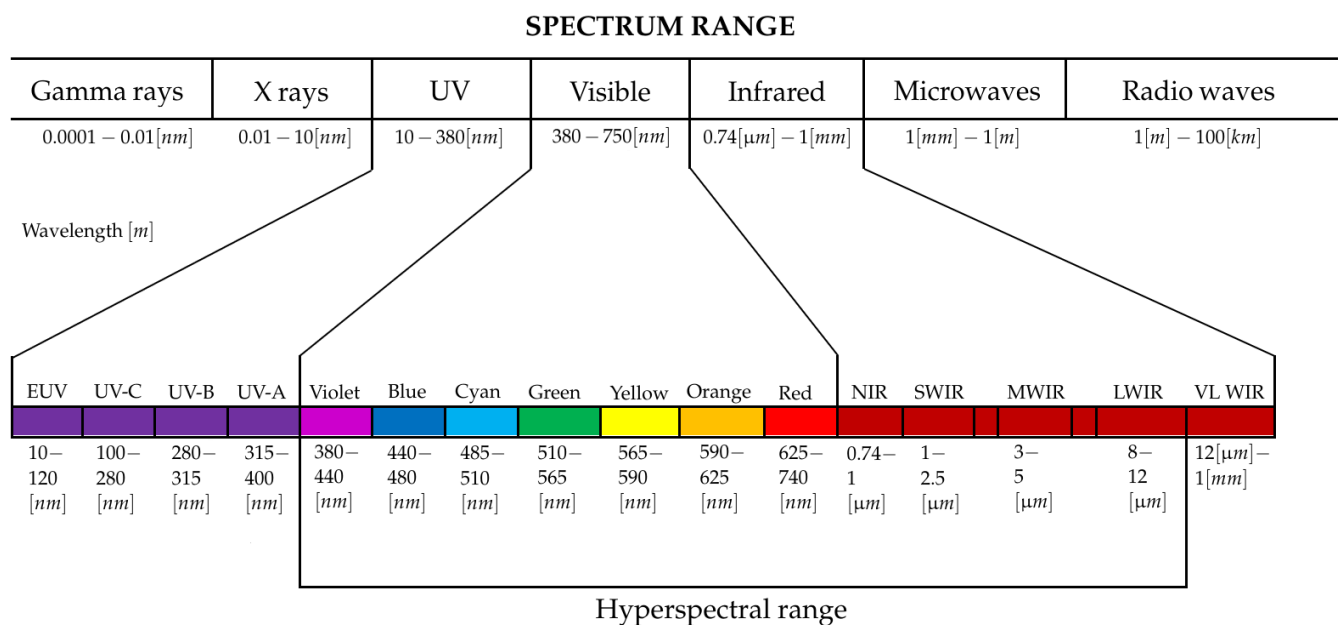


Figure 1. Hyperspectral range in the electromagnetic spectrum (source: authors).

For years, expert researchers have been carrying out work to identify diseases in crops using multispectral images (images that have 3 to 20 bands, and the bands are not contiguous with each other) [8], and they have obtained new findings by processing these images with techniques based on machine learning and deep learning, thus achieving more efficient analysis methods and saving time when the crops are large [9]. However, in recent years, the use of hyperspectral images (images with a greater number of bands, and the bands are contiguous with each other) has emerged as an alternative to multispectral images, allowing the analysis to be extended to a wider variety of chemical and biological traits of the plants and soils by analysing reflective properties in the narrowest spectral bands and combining them with artificial intelligence, computer vision, and machine learning methods [3].

There are several research studies whose purpose is to improve the management of agricultural crops; these focus mainly on non-invasive techniques, especially for the identification of diseases in agricultural crops, and their novelty is remote sensing using hyperspectral cameras [10,11].

There are also works that carry out applications for nutrient prediction, such as in wheat crops [12]. Hyperspectral imaging is also used for crop classification, variety identification, and plant phenotyping, analysing the anatomy, physiology, and biochemistry of plants, measuring these traits in a wide range of contiguous bands and allowing for a more detailed characterization of the plant performance and interactions with the environment [13]. There are also some articles based on the detection of diseases in agricultural crops that use remote sensing techniques [14–16]. Other studies also investigate the use of

techniques that combine robotics with hyperspectral image processing, and authors such as [17] propose a robotic system that replaces a human operator to take hyperspectral images in the field at the level of the plant leaf using a low-cost portable device.

On the other hand, machine learning emerges as a tool of artificial intelligence that has multiple applications and, combined with the information obtained from hyperspectral images, allows us to perform tasks such as identifying unwanted plants or weeds in some types of agricultural crops [18], allowing farmers to apply herbicides to selected areas instead of the entire field, reducing harmful effects on the environment. Likewise, hyperspectral images in combination with machine learning can evaluate the health of the soil and crops individually, limiting the application of pesticides only to plants that present some type of disease [8]. Machine learning can also be used in tasks such as the detection and classification of diseases in agricultural crops, or related activities such as estimating the level of nutrients, classifying varieties of some type of crop, or plant phenotyping [19–21].

Based on the above, this review article's purpose is to analyze the use of hyperspectral images in agricultural crops, identifying the main algorithms based on machine learning and deep learning for detection and classification, as well as the spectral ranges mainly used in crops such as cereals, oilseeds, and some fruits.

This work is organized as follows: this section provides an introduction to the technique based on hyperspectral images and its applications in agriculture. The second section shows the research strategy used for this review. Section three analyses the technology based on hyperspectral images and the results found in this review based primarily on artificial intelligence techniques such as machine learning and deep learning. The fourth and fifth sections continue with a discussion and conclusions of the findings and perspectives, and challenges are given.

2. Methodology

To carry out the analysis and discrimination of the bibliographic references addressed in this article, three stages of work described in Figure 2 were implemented.

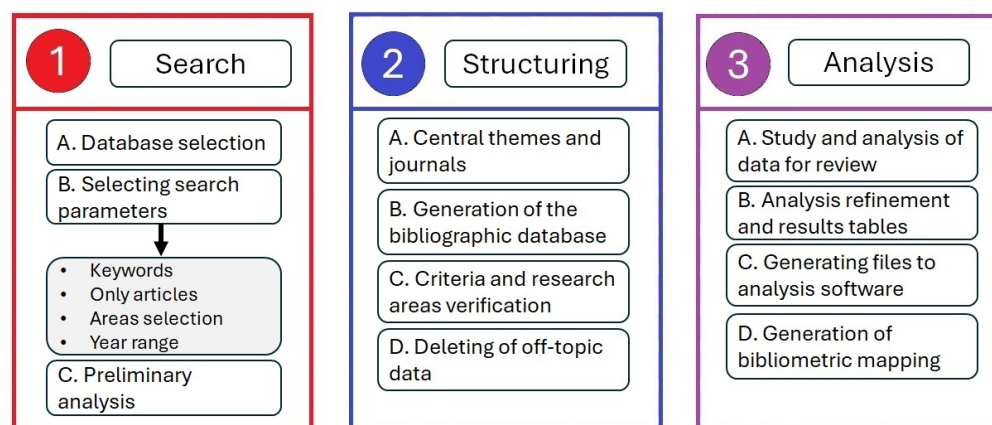


Figure 2. Stages implemented in the review analysis process (source: authors).

2.1. Stage 1: Search Strategy

Below is the methodological process used for the first stage of the search.

Database selection

A comprehensive search was conducted across several academic databases, including the following:

- ScienceDirect;
- Web of Science;
- Scopus;
- MDPI;

- Frontiers in Science;
- Google Scholar (for complementary grey literature).

Keywords

The following keywords and their combinations were used in the search strings:

- “Hyperspectral imaging” OR “HSI”;
- “Machine learning” OR “ML”;
- “Crop disease detection”;
- “Crop disease identification”;
- “Precision agriculture”.

Inclusion Criteria

- Peer-reviewed research articles published in English within the last 10 years (2013–2023).
- Studies focusing on the application of HSI and ML for crop disease detection and identification.
- Studies exploring various machine learning algorithms used for HSI data analysis in the context of crop disease detection and classification.
- Studies discussing the advantages and challenges associated with this approach.

Exclusion Criteria

- Studies solely focused on the development or engineering aspects of HSI technology without addressing its application in disease detection or classification.
- Conference proceedings, editorials, and opinion pieces were excluded unless they offered substantial data or reviews.
- Studies published in languages other than English.

Selection Process

- Initial search results were exported to a reference management software (e.g., Mendeley Desktop v1.19.8, EndNote 21) for duplicate removal.
- Titles and abstracts were screened based on the inclusion and exclusion criteria.
- Remaining articles were reviewed in detail based on the full text to ensure that they met the research question’s scope.

Synthesis Process

- A narrative synthesis approach was used to analyze and interpret the findings from the selected studies.
- Key themes and evidence were extracted regarding the application of HSI and various machine learning techniques for crop disease detection and identification.
- The review focused on advantages like early disease detection, non-invasiveness, and species differentiation potential.
- Challenges associated with data volume, cost, and variable field conditions were also discussed.
- Finally, the review explored future directions for research and development in this area.

Regarding the found data, initially, it was possible to determine that hyperspectral cameras are very useful for developing agricultural tasks such as the early detection of diseases or pests, optimization of irrigation and fertilizer application, and quality evaluation, and for applications such as determining the crop maturity. In the last 10 years, there have been more publications that relate agricultural crops with hyperspectral images. In a preliminary search, the keywords were the type of crop and the term “hyperspectral”, and a large number of publications were found, which are shown in Figure 3.

In this search process, it was found that the crops where hyperspectral images are used most frequently are cereals, mainly wheat, rice, and corn, whose numbers of publications in 2022 were 346, 346, and 291, respectively; among fruit trees, the most notable are citrus fruits such as oranges, with 413 publications, and apples, with 199. Legumes also stand out, like soybeans, with 211 publications, and beans, with 112. Throughout the year 2023, the number of publications amounts to 3297, exceeding the year 2022, which had a total of 2942 publications.

A large number of published works correspond to the detection of diseases using hyperspectral images [14,22–24], which is presented as a very novel technique as it is non-invasive and can be combined with tools such as neural networks to perform disease identification and classification tasks [25].

In this preliminary analysis, two focus groups of research were found: one focused on the identification of diseases in agricultural crops, and another large number of articles focused on the use of hyperspectral images for multiple tasks in agricultural crops: identification of nutrients, classification of vegetable varieties, leaf level identification, maturity indices, crop phenotyping, and others.

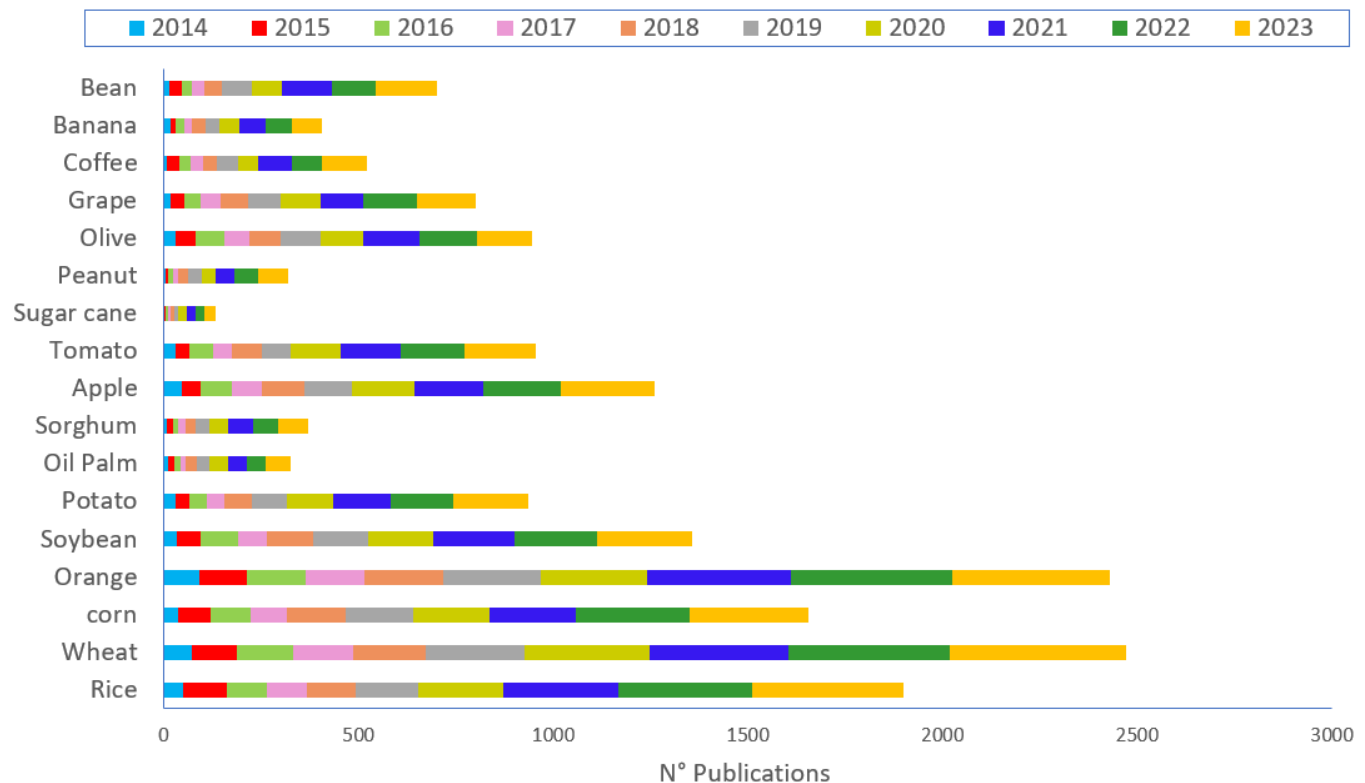


Figure 3. Number of publications per year containing the terms crops and hyperspectral images (source: authors).

2.2. Stage 2: Structuring

In this second stage, first, the central themes and journals were determined, taking into account the preliminary analysis presented in Figure 3. The relevant data are presented in Table 1, which summarizes some of the most important journals used in this review work.

Second, the bibliographic database was organized, and document management was conducted in order to check each selected article. Third, a verification of the criteria and research areas in each article was conducted to ensure that the information was relevant to the study. Fourth, all off-topic articles that did not contribute to the study were deleted.

Table 1. Summary of journals reviewed. SJR: SCImago Journal Rank, JCR: Journal Citation Report); ND: number of documents (source: authors).

Journal	Cite Score	SJR	H-Index	JCR	ISSN	ND
Computers and Electronics in Agriculture	13.6	1.59	149	8.3	0168-1699	19
Remote sensing	7.9	1.14	168	5.0	2072-4292	7
Infrared Physics and Technology	5.6	0.6	78	3.3	1350-4495	6
Food Chemistry	14.9	1.62	302	8.8	1873-7072	6
Sensors	6.8	0.76	219	3.9	1424-8220	5
Agronomy	5.2	0.66	67	3.7	2073-4395	4
Biosystems Engineering	10.1	1.06	125	5.1	1537-5129	3
Journal of Cereal Science	6.8	0.74	131	3.8	1095-9963	3
Journal of Food Composition and Analysis	5.5	0.65	130	4.3	1096-0481	2
Journal of Integrative Agriculture	7.2	0.94	69	4.8	2095-3119	2
Sensors and Actuators B: Chemical	14.6	0.64	145	8.4	0925-4005	2
Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy	7.9		0.64	145	1386-1425	2
ISPRS Journal of Photogrammetry and Remote Sensing	19.2	3.31	174	12.7	0924-2716	2
International Journal of Applied Earth Observation and Geoinformation	10.2	1.63	120	7.5	1872-826X	2
Plant Methods	5.1	1.12	86	5.1	1746-4811	2
Ecological Informatics	6.1	0.92	66	5.1	1574-9541	2
IEEE Computer Science Computer Science (miscellaneous)	3.5	0.93	204	3.9	2169-3536	2
International Journal of Remote Sensing	7	0.73	195	3.4	1366-5901	1
Frontiers of Plant Sciences	7.1	1.23	187	5.6	1664-462X	1

2.3. Stage 3: Analysis

In this final stage, the data analysis was realized. First, each article was revised and the relevant information was extracted. Second, the extracted information from each article was classified and placed in the results tables. Third and fourth, in order to generate a bibliometric analysis, the files to be imported into a bibliometric mapping software were generated; in this case, the VOSviewer [26] (open access software for scientific bibliometry) tool was used for constructing and visualizing bibliometric networks.

3. Results

3.1. Technology Based on Hyperspectral Images

Hyperspectral imaging sensors typically have high spectral resolution and low spatial resolution. The spatial and spectral characteristics of the acquired hyperspectral data are characterized by their pixels. Each pixel is a vector of values specifying the intensities at a location (x, y) in z different bands. The vector is known as the pixel spectrum and defines the spectral signature of the pixel located at (x, y). Figure 4 represents a three-dimensional structure that contains hyperspectral information captured by a sensor or camera.

The results shown in this review article confirm that, between years 2020 and 2023, the use of hyperspectral images in agriculture has increased exponentially, and it was also identified that they help in detecting plant stress (factors such as drought, nutrient deficiencies, or pest infestations), in diseases (before visible symptoms appear), in early nutrient deficiencies classification (analyzing the spectral reflectance of crops), in soil (evaluating the properties and composition of the soil), in weed detection (differentiating between crops and weeds based on their spectral signatures), in pest monitoring (detecting spectral changes in plants), in variety classification (analyzing crop varieties, even if they appear similar to the naked eye), and in optimal harvest time (monitoring crop maturity through spectral analysis). Based on the above, it can be summarized that researchers and agricultural producers can use hyperspectral data to optimize fertilization, pesticide application, and irrigation of water precisely where needed, and, also, that this allows for timely interventions to mitigate stress and predict crop yields more accurately, better soil management practices, targeted pest control measures, and for determining the best time to harvest for maximum yield and quality, optimizing resource use and reducing costs.

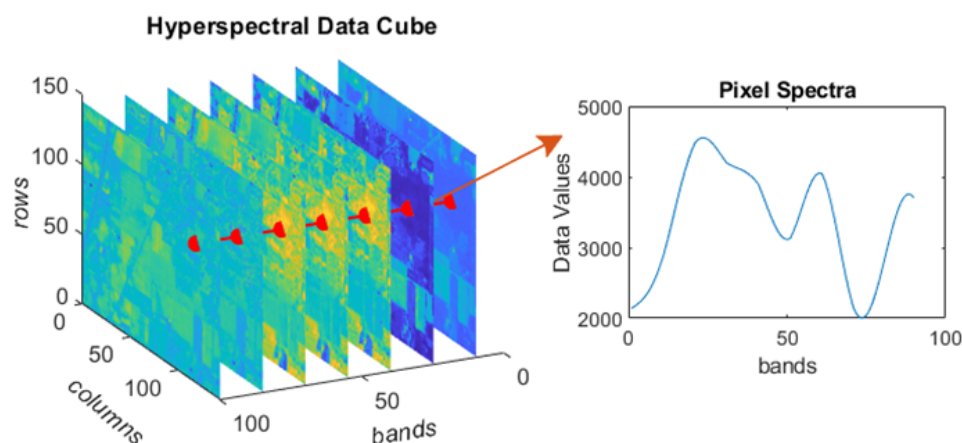


Figure 4. Hyperespectral data cube (Source: Mathworks®, Natick, Massachusetts (USA)).

Real Case Studies

Some of the case studies where hyperspectral imaging combined with machine learning has been successfully implemented are mentioned, for example, in viticulture, the cultivation of grapevines, which are highly susceptible to diseases such as powdery mildew and downy mildew, which can cause significant crop losses. Traditional methods of disease detection rely on visual inspection, which is labor-intensive and often not timely enough to prevent widespread infection. A study conducted in a vineyard in Napa Valley, California, utilized hyperspectral imaging combined with machine learning to detect and classify grapevine diseases at an early stage [27]. The hyperspectral images were captured using a drone-mounted hyperspectral camera that covered a spectral range from 400 nm to 1000 nm. These images provided detailed spectral information for each pixel, allowing for the identification of subtle differences in reflectance associated with diseased and healthy grapevines. The data collected from the hyperspectral images were fed into a machine learning model specifically designed for classification tasks. The model used was a random forest classifier, which is known for its robustness and accuracy in handling high-dimensional data. The training dataset consisted of labeled samples of healthy and diseased grapevines, which were used to teach the model to distinguish between different disease states based on their spectral signatures. The implementation resulted in a highly accurate detection system with an accuracy rate of over 90%. The system was able to identify the early onset of diseases such as powdery mildew before they became visible to the naked eye. This early detection capability allowed vineyard managers to apply targeted treatments only where needed, reducing the use of pesticides and lowering costs while improving the overall health of the vineyard. Another important research is [28], which focuses on classifying three major world crops: corn, soybean, and winter wheat. These crops are commonly grown in the US, particularly in the Midwest region, where Ponca City, Oklahoma is located. The study highlights the effectiveness of using cloud platforms like Google Earth Engine (GEE) for analyzing large hyperspectral datasets. This approach allows for the efficient processing of vast amounts of information, which is crucial for large-scale crop classification tasks. The research paves the way for the further development of cloud-based machine learning pipelines specifically designed for hyperspectral data analysis in agriculture. The results demonstrated high accuracy in crop classification, with CNNs showing superior performance due to their ability to capture complex spectral patterns. DESIS data generally provided higher accuracy compared to Hyperion due to better spatial resolution. Cloud computing facilitated the efficient processing of large datasets, significantly reducing computation time. The study concluded that integrating hyperspectral imaging with machine learning on cloud platforms is a powerful tool for precision agriculture, enabling better crop management and higher yields through accurate and scalable crop classification.

3.2. Identification of Plant Diseases Using Hyperspectral Images

There is great interest in the use of hyperspectral images to monitor and forecast agri-food production through the study of components and detection of biological microbial contaminants in the process of identifying diseases in agricultural crops. Hyperspectral images, when used with specialized sensors, can measure the radiation reflected or emitted by plants in multiple spectral bands, which allows for obtaining detailed information about the state of the plants, like traits of their leaves, stems, and soil nutrient level, as well as for early diagnosis to determine anomalies or diseases [16,29].

Crops that use hyperspectral images are cereals such as wheat and rice [30] and, in these applications, these images are used to detect the water level of the plant or to determine nitrogen concentrations [31]. In the case of wheat leaf rust, which is one of the most frequent diseases that affect this cereal in the world, authors such as ref. [32] propose a tool based on deep learning for the detection of this disease, achieving about an 84.1% prediction accuracy.

Authors such as ref. [33] discuss how chlorophyll fluorescence together with hyperspectral images can help in the identification of common diseases such as wheat head blight, which is caused by fusarium. These works are performed in the laboratory, as well as in the field, and are based on a methodology that uses chlorophyll fluorescence (CFI), which is useful during the initial inspection phase, while hyperspectral imaging involves using several wavelengths in the analysis of images and therefore helps to monitor the disease.

3.3. Machine Learning

Machine learning is an application of artificial intelligence dedicated to simulating or implementing human learning behaviors, reorganizing existing knowledge structures, and continually improving their performance to be used in the prediction and classification of unknown data. In the context of detecting diseases in crops, machine learning is positioned as a very effective tool when it comes to analyzing hyperspectral images of crops because they can handle a large amount of information [3,34].

Authors such as ref. [35] applied algorithms of machine learning based on SVM and LDA techniques to detect the severity levels of the Verticillium wilt disease in olive crops on a large scale using a sweep of 300 hectares, reaching general precision levels of 59% with the LDA algorithm and 79.2% using the SVM.

In other works, algorithms based on machine learning were used to estimate chlorophyll in crops such as potatoes [36]; for example, in this work, a comparison and analysis of the models for estimating the content of chlorophyll were carried out. For chlorophyll in potato crops at different stages of growth, a model based on support vector machines (SVMs) was proposed, and greater precision was obtained in the estimation of chlorophyll content.

Algorithms based on machine learning are: SVMs, random forests, and gradient boosting; these are very powerful tools for analyzing vegetation indices or reflectance spectra in agricultural crops [37]. Some types of the most used algorithms are presented in the following subsection.

3.3.1. Supervised Machine Learning

Supervised machine learning is an approach in which an algorithm is taught to make predictions based on previously labeled examples. It is one of the most common techniques in the field of machine learning and is used for a wide range of analysis and prediction tasks; for example, in crops, supervised machine learning models rely on labeled datasets containing images, sensor data, or other relevant information to learn the patterns associated with different crop characteristics, diseases, or quality factors [38].

Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are increasingly used in agriculture for a variety of tasks, including disease and pest detection, yield monitoring, and crop quality assess-

ment. Hyperspectral images provide a wealth of information about crops, making them ideal for use with ANNs. Particularly in cereals such as wheat, they are used for the detection of some diseases caused by fungi, damage caused by cold, and estimation of grain hardness [39,40]. This algorithm is one of the most common methods for training artificial neural networks, especially in the context of supervised learning, that are based on classifiers that are widely used in different applications due to their high classification accuracy, simplicity, robustness, sensitivity, and automation [25,41].

Support Vector Machine (SVM)

SVMs are primarily used for classification problems, where the goal is to assign objects to one or more categories based on features or attributes. The fundamental principle behind SVMs is to find the optimal separation hyperplane that maximizes the margin between data classes. SVM-based machine learning techniques have been mainly used in the classification of different food products, agricultural crops, and disease detection [41,42]. In another study, an approach using objects and pixels was used to extract hyperspectral images for the classification of infected corn kernels. It was observed that the pixel approach improved the classification accuracy of the SVM to 100% [43]; the information obtained in this case, by pixels, is much more exhaustive and complete than that obtained from objects.

K-Nearest Neighbor (K-NN)

The k-nearest neighbors (K-NNs) algorithm is a machine learning method used for both classification and regression. It is an instance-based algorithm, which means that it does not explicitly learn a model during training but instead stores the training examples in memory and uses these examples to make predictions based on the similarity between the data [44].

Classification and Decision Tree (CART)

Decision trees are a versatile and interpretable machine learning method used for classification tasks. When applied to hyperspectral imaging in agriculture, decision trees can classify different crop types, detect stress or disease, and monitor crop health. Decision trees work by recursively partitioning the data space based on feature values, which makes them well suited for handling the high-dimensional data from hyperspectral images [45].

Logistic Regression (LR)

Logistic regression belongs to the class of supervised learning and is used in classification problems. It is basically based on the concept of probability and is a predictive analysis algorithm. In ref. [46], it is used to predict the threshold and classify healthy apples from those that have bitter pit disease. Logistic regression evaluates the relationship between the independent variable (characteristics) and the dependent variable. The difference between linear regression and logistic regression lies in the fact that the result of logistic regression is discrete while linear regression produces a continuous value.

Linear Regression

Hyperspectral imaging captures data across a wide range of wavelengths, providing a detailed picture of the chemical composition of plants. Linear regression attempts to establish a linear relationship between one or more independent variables (spectral bands in this case) and a dependent variable (e.g., crop yield, chlorophyll content, or presence/absence of disease) [47].

Multivariate Linear Regression (MLR)

Multivariate linear regression (MLR) is a statistical technique used to model the relationship between multiple dependent variables and one or more independent variables. It is an extension of simple linear regression, which deals with only one dependent variable. In the context of hyperspectral imaging for crops, MLR can be used to predict various

agronomic variables, such as biomass, chlorophyll content, moisture levels, yield, and other quantitative traits based on the spectral information captured by hyperspectral sensors [29,48].

Deep Forest

This is a relatively newer machine learning model that has shown promising results in various domains, including image classification and remote sensing applications such as hyperspectral imaging in agriculture. Unlike traditional models like neural networks, deep forests rely on an ensemble learning approach inspired by decision trees but with a hierarchical structure that enables efficient feature learning and representation. Deep forests can classify different crop types based on their spectral signatures extracted from hyperspectral images [49].

Backpropagation Neural Networks (BPNNs)

In combination with genetic algorithms (GAs), they are powerful computational tools that can be combined to enhance hyperspectral imaging analysis in agriculture. The integration of these two techniques leverages the strengths of neural networks in learning complex patterns and genetic algorithms in optimizing model parameters. Their ability to learn complex relationships and extract relevant features makes them valuable for precision agriculture applications. However, the computational cost, data requirements, and interpretability limitations require careful consideration when choosing the right model for one's specific needs [25].

Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA) is a statistical and machine learning technique used in multivariate analysis and supervised classification. Its main goal is to find a linear combination of features that can effectively separate multiple classes or groups in a data set. Due to the robustness of LDA, it has been widely applied for the classification of agricultural products or techniques for the discrimination of weeds in crops such as wheat or rice using hyperspectral images [35,50,51].

Naïve Bayes Algorithm

Naïve Bayes is a powerful yet simple generative machine learning classifier that uses the concept of conditional probability (Bayes' theorem) to describe the outcome probabilities of related events. It is used for the classification of agricultural crops [52,53]. Other authors used this technique to detect lesions or bruises on apples [45], in which the detection system included hyperspectral cameras equipped with sensors that operate in the visible range and in the near-infrared (NIR) (400 to 1000 nm) and short-wavelength infrared (SWIR) range (1000 to 2500 nm).

This tool is also used in classification techniques to understand the development of crops such as rice [47]. In this work, the estimation of nitrogen characteristics is based mainly on the use of remote sensors in the relationship between them and chlorophyll through the use of the visible and near-infrared (VNIR) range.

Modified Partial Least Squares Regression (MPLSR)

MPLSR, or modified partial least squares regression, is a statistical technique used for building predictive models, particularly beneficial when dealing with datasets that have certain characteristics. Hyperspectral images can have hundreds of spectral bands, leading to high-dimensional data. MPLSR is effective in reducing the dimensionality of these data while retaining the most relevant information for crop analysis. It achieves this by identifying latent variables that capture the most variance in the predictors (spectral bands) and the response variables (crop properties) [54,55].

Light Gradient Boosting Machine (LightGBM)

This is a powerful open-source framework for gradient boosting decision trees. It is known for its efficiency, scalability, and accuracy in various machine learning tasks, particularly ranking, classification, and regression problems. LightGBM can be a valuable tool for analyzing hyperspectral imagery of crops, particularly for tasks like classification and regression [56,57].

3.3.2. Unsupervised Machine Learning

Unsupervised machine learning is a branch of machine learning that focuses on the exploration of hidden patterns and structures in data without the guidance of labels or predefined responses. This makes it useful in situations where labels are not available or where the objective is to discover hidden information in the data. In recent years, unsupervised learning algorithms have become an interesting alternative to traditional methods used for feature extraction and have made significant progress in the classification of remote sensing images [58].

K-Means Clustering

The k-means algorithm involves organizing data into groups with the goal of achieving high group similarity and low group similarity. Ref. [59] used a k-means-based approach with the mean color values in each super pixel region and finally categorized an image into the ears of a wheat crop. The excellent segmentation provided by k-means is used by authors such as ref. [60] to improve the classification accuracy of PLDA models in determining potato quality.

Hierarchical Clustering

This is a data mining technique that groups data points into a tree-like structure, called a dendrogram. The clusters are formed by iteratively merging or splitting groups based on their similarity or distance measures. Hierarchical clustering algorithms are often used to visualize relationships within data and to identify natural groupings of data points. Hierarchical cluster analysis is a valuable tool in the analysis of hyperspectral images for crop monitoring. It helps in uncovering patterns and relationships in spectral data, facilitating a better understanding and management of agricultural fields. By integrating hierarchical cluster analysis with hyperspectral imaging, researchers and agronomists can enhance their ability to monitor crop health, classify crop types, and detect issues early, leading to improved agricultural outcomes [25,61].

WEKAXMeans (WXM)

WEKAXMeans, an implementation of the X-means clustering algorithm within the Weka machine learning software suite, extends the traditional k-means clustering algorithm by automatically determining the optimal number of clusters based on data. This can be particularly useful in hyperspectral imaging for crops, where the goal is often to classify or segment different regions based on spectral signatures without predefined class labels. WEKAXMeans takes the complex hyperspectral data and groups pixels with similar spectral signatures into clusters. These clusters could represent healthy plants, stressed plants, or areas with different soil types. [62].

Iterative Self-Organizing Data Analysis Technique (ISODATA)

This is a clustering algorithm that iteratively partitions a dataset into clusters based on their similarity. It is a non-parametric method, meaning that it does not make any assumptions about the underlying distribution of the data. Hyperspectral imaging captures data across a wide range of wavelengths, providing a detailed picture of the chemical composition of plants within a field. Unsupervised learning techniques like ISODATA can be used to analyze these data without requiring pre-labeled information about the crops or their health status [63,64].

Dimensionality Reduction

Dimensionality reduction is a fundamental technique in data analysis and machine learning that involves reducing the number of features (dimensions) in a data set while preserving the most important information. High-dimensional data sets can be difficult to work with and can suffer from the curse of dimensionality, which can lead to increased computational complexity and overfitting [65].

Principal Component Analysis (PCA)

PCA is a multivariate analysis technique used to reduce the dimensionality of a data set while preserving as much of its variability as possible. The analysis consists of creating a new set of uncorrelated variables from a set of possibly correlated variables. This technique is used for a wide variety of disease detection and classification uses in cereals such as rice [43,66].

Singular Value Decomposition (SVD)

This is a versatile and powerful tool in the processing and analysis of hyperspectral images for agriculture. By reducing dimensionality, minimizing noise, and extracting key features, SVD enhances the ability to monitor crop health, classify crop types, and predict important crop properties. This results in more efficient and accurate agricultural management, ultimately leading to better crop yield and quality [37,67].

Partial Least Squares Regression (PLSR)

Partial least squares regression (PLSR) is a statistical method used to model the relationship between a set of predictor variables (independent variables or X variables) and a set of response variables (dependent variables or Y variables) [68]. In cereals such as wheat, it is used to determine micronutrients such as Ca, Mg, Mo, and Zn, which were predicted with high credibility by combining PLSR modeling and hyperspectral images [12]. PLSR is used in multivariate regression analysis and dimensionality reduction. It is particularly useful when dealing with high-dimensional and multicollinearity data sets (strong correlations between predictor variables) [69]. PLSR combines elements of principal component analysis (PCA). The difference between linear regression and logistic regression lies in the fact that the result of logistic regression is discrete while linear regression produces a continuous value [70].

3.3.3. Deep Learning

Deep learning involves a representation learning method using a deep ANN composed of multiple layers of neurons. The application of deep learning in agricultural crops is relatively new; in many cases, it is used for image classification in crops [71,72]. In vegetables such as tomato, this tool is used to determine the firmness level of the plant [73]. Deep learning can effectively extract high-level abstract features and demonstrates an excellent classification capacity superior to the traditional techniques already adopted by machine learning. In the case of deep learning, it is also used in tasks such as detecting weeds in crops such as soybeans. Authors such as ref. [39] used tools based on deep learning using convolutional neural networks. The most sensitive wavelengths used by the classification model are in the near-infrared (NIR) region; this spectral range is commonly used to determine the health of a plant. In the article [4], nearly 400 images and a 5-layer convolutional neural network were used, which obtained results of a 97.7% detection accuracy.

Convolutional Neural Network (CNN)

This is a powerful and versatile tool for analyzing hyperspectral imagery of crops. Their ability to automatically extract features, handle non-linear relationships, and preserve spatial information makes them valuable for various applications in precision agriculture. However, the computational cost, data requirements, and “black box” nature require

careful consideration. CNNs are designed to preserve spatial information through their convolutional layers, which analyze local patterns and relationships between neighboring pixels. This spatial context is essential in identifying spatially distributed crop issues. It is one of the most used in cereals like rice [74–77].

Recurrent Neural Networks (RNNs)

These are a type of neural network particularly suited for sequential data, making them applicable to time-series analysis and sequences of data points, including hyperspectral imaging in agriculture. While RNNs are commonly associated with tasks like natural language processing and speech recognition, their application to hyperspectral imaging allows for the analysis of spatial and temporal patterns in crop data captured over multiple spectral bands [11].

Long Short-Term Memory (LSTM)

This is a type of recurrent neural network (RNN) that is particularly well suited for sequential data and time-series analysis. When applied to the hyperspectral imaging of crops, LSTM can leverage the sequential nature of spectral bands or temporal changes in crop conditions. LSTM can analyze hyperspectral data to monitor crop health by identifying stress factors such as diseases, pests, and nutrient deficiencies. By learning the temporal patterns of crop health indicators, it can provide early warnings and actionable insights. By analyzing temporal hyperspectral data, LSTM can predict crop yields more accurately. It can incorporate changes in spectral signatures over the growing season to make informed yield predictions [3].

Stacked Denoising Autoencoder (SDAE)

This features multiple layers of denoising autoencoders stacked on top of each other. Each layer of the SDAE takes the output of the previous layer as input and learns increasingly abstract representations of the input data. SDAEs are a powerful deep learning technique used for feature extraction in hyperspectral data analysis, particularly for applications in crop health monitoring and classification [32].

Residual Attention Convolutional Neural Networks (RACNNs)

They have been increasingly used in agriculture for tasks such as crop disease detection, weed identification, and yield prediction, and have a neural network architecture that integrates wavelet analysis, attention mechanisms, and convolutional layers. This architecture is designed to extract features from data, particularly in tasks involving signal processing or image analysis, by leveraging the benefits of wavelet transforms, attention mechanisms, and convolutional operations [78,79].

Wavelet Attention Convolutional Neural Networks (WACNNs)

They combine wavelet transforms with attention mechanisms to enhance feature extraction and improve model performance. In agriculture, WACNNs can be particularly useful for tasks such as crop disease detection, soil moisture estimation, and plant classification [80,81].

One-Dimensional Convolutional Neural Network (1D CNN)

This is a type of neural network architecture that is specifically designed for processing one-dimensional sequential data, such as time series data or text data. While traditional convolutional neural networks (CNNs) are commonly used for two-dimensional data like images, 1D CNNs are tailored for one-dimensional input [73].

Figure 5 summarizes the machine learning techniques used by the authors for the identification of diseases in agricultural crops or for classification. The classification methods in this review article were divided into those using traditional machine learning and those using deep learning. Unlike ordinary machine learning, which requires pre-design to extract classification features, deep learning methods can automatically extract optimal

classification features. Figure 5 summarizes the most frequently used machine learning and deep learning algorithms for detecting diseases in crops or for classifying some variable in an agricultural crop, such as nutrient level, crop type, maturity, chlorophyll index, weed detection, nitrogen level, and fruit maturity index, among others.

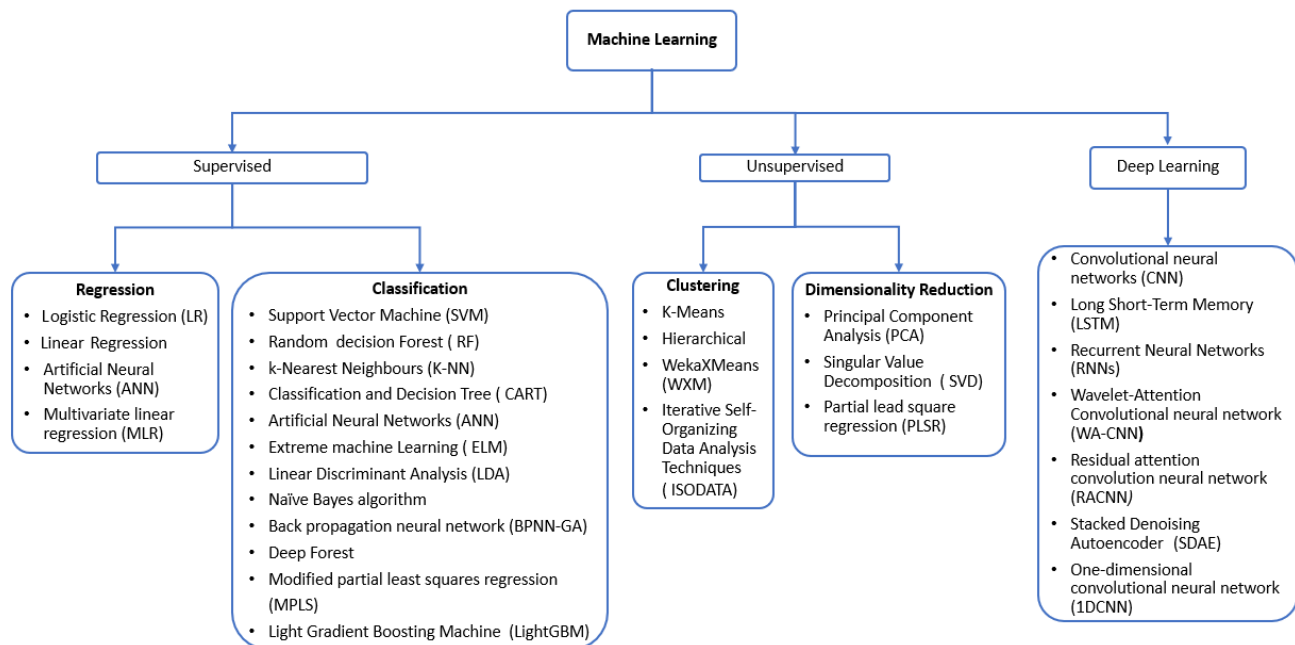


Figure 5. Machine learning algorithms used in crops (source: authors).

Hyperspectral imaging captures data across hundreds of continuous spectral bands, providing a comprehensive fingerprint for material identification and classification. However, extracting meaningful information from these complex data requires powerful tools. Machine learning models are well suited for this task, but choosing the right model depends on the application [19,82]. Table 2 summarizes some of the most used machine learning methods in the treatment of hyperspectral images. Support vector machines (SVMs) demonstrate robustness in classification tasks but require significant computational resources and parameter tuning. Convolutional neural networks (CNNs) excel in feature learning but demand large, labeled datasets and computational power. Backpropagation neural networks (BPNNs) offer flexibility and power but are computationally intensive and require extensive hyperparameter tuning. Random forests (RFs) provide insights into spectral importance but may suffer from interpretability issues and overfitting. Deep Forests show promise in handling high-dimensional data but present complexity and interpretation challenges. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks capture temporal patterns but face training complexity and computational load. K-nearest neighbors (k-NNs) are intuitive but computationally expensive and memory-intensive. Extreme learning machines (ELMs) offer fast training and generalization but lack interpretability and can be sensitive to initialization. Partial least squares regression (PLSR) effectively reduces dimensionality while preserving interpretability but may struggle with nonlinear relationships and overfitting. In summary, each model presents unique strengths and limitations in handling hyperspectral data, emphasizing the importance of selecting appropriate techniques based on specific requirements and constraints.

Table 2. Evaluation of machine learning algorithm performance (source: authors).

Model	Performance	Advantages	Drawbacks
Support Vector Machines (SVMs)	SVMs are widely used in hyperspectral imaging for classification tasks due to their effectiveness in high-dimensional spaces.	Robustness: SVMs are capable of handling non-linear data distributions with the use of kernel functions Generalization: They are less prone to overfitting, especially in scenarios with limited training data.	Computational Intensity: Training and testing can be slow, particularly with large datasets. Parameter Tuning: They require the careful selection of parameters, like the regularization parameter and kernel type, which can be computationally expensive.
Convolutional Neural Networks (CNNs)	CNNs excel in image processing, including hyperspectral imaging, by leveraging spatial and spectral correlations.	Feature Learning: They automatically learn hierarchical features from data, feature extraction, integration of spatial and spectral information, and robustness to noise. Spatial Context: They have improved classification accuracy, scalability, flexibility in network design, and the ability to leverage transfer learning.	Data Requirements: They require large amounts of labeled data for effective training. Computational Resources: Training CNNs is resource-intensive, often requiring GPUs.
Backpropagation Neural Networks (BPNNs)	BPNNs offer a flexible and powerful approach for analyzing hyperspectral imaging data, capable of addressing various tasks such as classification, regression, dimensionality reduction, and feature learning	Classification: BPNNs can be used for classification tasks in hyperspectral imaging, where the goal is to classify each pixel in an image into predefined classes or categories. By training on labeled hyperspectral data, BPNNs can learn to identify spectral signatures associated with different materials or land cover types. Feature Learning: BPNNs are capable of learning hierarchical representations of data, which can be beneficial for feature learning in hyperspectral imaging. Transfer Learning: BPNNs trained on large-scale datasets from other domains, such as natural images, can be fine-tuned for hyperspectral imaging tasks through transfer learning by leveraging pre-trained models and adapting them to hyperspectral data.	Training Time and Computational Resources: Training deep BPNNs on large hyperspectral datasets can be computationally intensive and time-consuming, especially when using complex architectures and optimization algorithms. Hyperparameter Tuning: BPNNs have several hyperparameters, including the number of layers, the number of neurons per layer, the learning rate, and the activation functions, which need to be carefully tuned to achieve optimal performance. Finding the right combination of hyperparameters can be challenging and may require extensive experimentation.
Random Forests (RFs)	RFs are effective for both classification and regression tasks in hyperspectral data processing, leveraging an ensemble of decision trees.	Non-linearity Handling: They are capable of modeling complex relationships. Feature Importance: They provide insights into the importance of different spectral bands. Scalability: They efficiently handle large datasets.	Interpretability: They are less interpretable than simpler models. Overfitting: There is a risk of overfitting if not properly validated, though typically less than other methods.
Deep Forest	Deep forests show promise for hyperspectral image analysis, particularly due to their strengths in handling complex, high-dimensional data.	Efficient Handling of High-Dimensional Data: Hyperspectral images consist of a large number of spectral bands, resulting in high-dimensional data. Deep forests, with their hierarchical feature learning approach, can effectively handle such high-dimensional data by learning hierarchical representations of the spectral information. Robustness to Noise: Hyperspectral images may contain noise due to various factors such as sensor limitations or atmospheric conditions. Deep forests have shown robustness to noise, which can be beneficial in real-world hyperspectral imaging applications where data quality may be variable.	Complexity: Deep forests involve multiple layers of decision forests, which can increase the complexity of the model. This complexity may lead to longer training times and increased computational resources required, especially for large-scale hyperspectral imaging datasets. Interpretability: Although deep forests provide hierarchical representations of the data, their overall structure can be complex, making them challenging to interpret compared to simpler models like decision trees. Understanding how the model arrives at its predictions may be more difficult, which can be a drawback in applications where interpretability is crucial.

Table 2. Cont.

Model	Performance	Advantages	Drawbacks
Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks	RNNs and LSTM networks are suited for sequential data, making them adaptable to the spectral dimension in hyperspectral data.	Sequence Modeling: LSTM networks captures dependencies across spectral bands due to their memory capabilities. Temporal Patterns: They are effective at learning patterns across the spectral sequence.	Training: Complexity: They can be difficult to train due to issues like vanishing gradients. Computational Load: They have a high computational demand for training and inference
K-Nearest Neighbors (k-NNs)	K-nearest neighbors (k-NNs) are non-parametric machine learning algorithms widely used in hyperspectral image classification.	Intuitive Approach: k-NNs are straightforward and easy to understand. They classify a sample based on the majority label among its k-nearest neighbors. No Training Phase: Unlike other models that require an extensive training process, k-NN is a lazy learning algorithm. This means that it does not require a separate training phase, making implementation simpler and faster.	High Computational Cost: The algorithm requires computing distances between the test sample and all training samples, which can be computationally expensive, especially with large datasets typical in hyperspectral imaging. Memory Usage: Storing all training samples for distance computation can require significant memory resources.
Extreme Learning Machines (ELMs)	ELMs (extreme learning machines) can be a valuable tool for analyzing hyperspectral images, offering some advantages over traditional methods.	Fast Training: ELMs excel in training speed compared to traditional neural networks. This is particularly beneficial for hyperspectral data, which can be high-dimensional and computationally expensive to analyze. Good Generalization: ELMs can achieve good performance on unseen data, making them suitable for real-world applications where the model needs to handle variations not present in the training set. Less Prone to Overfitting: The random assignment of weights in ELMs helps to reduce the risk of overfitting the training data, which can be a common issue with hyperspectral image analysis due to the high dimensionality. Potentially Competitive Accuracy: ELMs can achieve a classification accuracy comparable to other methods like support vector machines (SVMs) with significantly faster training times.	Limited Interpretability: Like many other machine learning algorithms, ELMs are often considered as “black box” models, meaning that it can be challenging to interpret how the model arrives at its predictions. In hyperspectral imaging applications where interpretability is crucial for understanding the underlying physical phenomena, this lack of interpretability could be a drawback. Sensitivity to Initialization: ELMs rely on randomly generated input-to-hidden layer weights, which can make them sensitive to initialization. Although this randomness contributes to their fast training speed, it can also lead to variability in model performance and requires the careful tuning of hyperparameters.
Partial Least Squares Regression (PLSR)	Partial least squares regression (PLSR) is primarily used for dimensionality reduction and regression tasks, but it can also be applied to classification tasks in hyperspectral imaging.	Dimensionality Reduction: PLSR can effectively reduce the dimensionality of hyperspectral data while preserving relevant spectral information. Interpretability: PLSR models are relatively interpretable compared to some other machine learning techniques, such as deep learning models. The latent variables extracted by PLSR represent linear combinations of the original spectral bands, allowing researchers to understand how different spectral features contribute to the prediction of the target variable.	Linear Model Assumption: PLSR assumes a linear relationship between the spectral data and the target variable. If the underlying relationship is highly nonlinear, PLSR may not capture it accurately, leading to suboptimal predictions. Overfitting: Like any regression technique, PLSR is susceptible to overfitting, especially when the number of latent variables or components is not properly chosen. Overfitting can occur if the model captures noise in the training data rather than the underlying signal, resulting in poor generalization performance on unseen data. Interpretability Trade-off: While PLSR provides relatively interpretable models compared to some other machine learning techniques, such as deep learning models, the interpretation of latent variables and their contributions to the prediction may not always be straightforward, especially in high-dimensional datasets.

Table 2. Cont.

Model	Performance	Advantajes	Drawbacks
Naïve Bayes	The Naïve Bayes algorithm is used for classification problems.	Efficiency: Naive Bayes is computationally efficient, making it suitable for analyzing hyperspectral data, which often involves a large number of spectral bands. Simple Model: Its simplicity makes it easy to implement and understand, which can be advantageous for quick analysis and prototyping. Handling of High-Dimensional Data: Naive Bayes can handle high-dimensional data effectively, making it suitable for hyperspectral imaging, where each pixel in an image is represented by a large number of spectral bands. Probabilistic Predictions: Naive Bayes provides probabilistic predictions, allowing for the estimation of class probabilities. This can be useful for decision making and assessing the confidence of predictions.	Strong Independence Assumption: The “naive” assumption of independence between features may not hold true in hyperspectral data, where spectral bands are often correlated. This can lead to suboptimal performance when features are dependent. Limited Expressiveness: Naive Bayes may struggle to capture complex relationships and interactions between spectral bands in hyperspectral data. As a result, it may not perform as well as more complex models in scenarios where feature dependencies are significant.
Classification and Decision Tree (CART)	A decision tree is a supervised learning algorithm that is used for classification and regression modeling.	Interpretability: Decision trees are highly interpretable models, which makes them suitable for analyzing hyperspectral imaging data. They provide insights into the decision-making process by visualizing the hierarchical structure of the tree. Handling of High-Dimensional Data: Decision trees can handle high-dimensional data, such as hyperspectral images, effectively. They select the most informative spectral bands for classification, which can aid in feature selection and dimensionality reduction.	Overfitting: Decision trees are prone to overfitting, especially when the tree depth is not appropriately controlled. A deep tree may capture noise in the training data, leading to poor generalization performance on unseen data. High Variance: Decision trees have high variance, meaning that they can produce different trees for the same dataset due to small variations in the training data. This sensitivity to data changes can make decision trees less robust.

Table 3 summarizes the most relevant works related to the detection of diseases in agricultural crops (cereals and oilseeds) using hyperspectral images and machine learning. As mentioned in the previous section, there are a large number of articles dedicated to cereal crops such as wheat and rice. However, we cannot conclusively establish that there is a specific range of wavelengths to determine or detect any disease in any type of cereal. In the case of the Fusarium head blight (FHB) disease of wheat, we can say that this disease itself does not have a specific spectral signature, and certain changes in the development of the plant and the affected tissues can generate characteristic patterns in the hyperspectral images. However, some studies use certain ranges of wavelengths [59].

Table 3. Summary of techniques used to detect diseases (cereals and oilseeds) (source: authors).

Reference	Crops	Disease	Bandwidths (nm)	Algorithms
[83]	Wheat	Frost and drought stress	(280–500)	Partial least squares regression (PLSR)
[42]	Wheat	Fusarium head blight	(400–1000, 1000–2500)	Support vector machine (SVM)
[59]	Wheat	Fusarium head blight	(600–1100)	Support vector machine (SVM), artificial neural network (ANN), logistic regression (LR)
[59]	Wheat	Fusarium head blight	(400–750)	Combined convolutional neural network (CNN)
[84]	Wheat	Fusarium head blight	(450–950)	Random forest (RF) algorithm
[85]	Wheat	Fusarium head blight	(1100, 1197, 1308, 1394)	Partial least squares discriminant analysis (PLSDA)
[86]	Wheat	Fusarium head blight	(941, 876, 732)	Competitive adaptive reweighting algorithm (CAR5)
[79]	Wheat	Fusarium head blight	Variable	Residual attention convolution neural network (RACNN)
[87]	Wheat	Yellow rust	(400–1000)	Support vector machine (SVM)
[88]	Wheat	Rice weevil	(866.4–1701)	Linear discriminant analysis (LDA), support vector machine (SVM), principal component analysis (PCA)
[89]	Rice	Insect damage	Variable	Principal component analysis (PCA)
[90]	Rice	Sheath blight	(726–930)	Support vector machine (SVM)
[91]	Rice	Nitrogen deficiency	(550–690)	Long short-term memory (LSTM), multivariate linear regression (MLR)
[92]	Rice	Rice false smut	(874.41–1734.91)	Principal component analysis (PCA)
[93]	Corn	Glyphosate-resistant (GR)	(400–900)	K-nearest neighbor (k-NN), random forest (RF), support vector machine (SVM)
[94]	Corn	Cold damage	(395–885)	Convolutional neural network (CNN)
[95]	Corn	Aflatoxin contamination	Variable	Partial least squares discriminant analysis (PLSDA)

Table 4 presents the most important works on disease detection in legumes, where diseases such as drought stress in chickpea were studied, which can manifest in various ways in terms of spectral responses [96]. Drought stress causes changes in the way that plants absorb and reflect light at different wavelengths. While there is no single specific wavelength that universally indicates drought stress, there are certain spectral features and regions of interest that researchers typically focus on when analyzing hyperspectral data to detect drought stress in plants.

In crops such as oil palm, the detection of diseases such as basal stem rot stands out, with authors such as ref. [97] placing it at near-infrared (NIR) lengths. In crops such as potatoes, diseases such as late blight [98] are detected, or the disease known as bacterial wilt in peanut plants, in which the sensitivities of the wavelengths in the NIR region were significantly different between the various stages of the disease [99].

In the detection of fruit quality in citrus fruits, authors such as [100,101] focus their studies on evaluating the quality of citrus fruits such as orange, where the wavelength ranges used were (400–1000 nm) for the first authors and (900–1700 nm) for the latter, whose strategy focused on optimal clustering for spatial data reduction to obtain quantitative maps of some quality attributes in healthy oranges.

Table 4. Summary of techniques used to detect diseases (other crops) (source: authors).

Reference	Crops	Disease	Bandwidths (nm)	Algorithms
[102]	Potato	Alternaria solani	(550–750)	Partial least squares discriminant analysis (PLS-DA), support vector machines (SVMs)
[98]	Potato	Late blight	(450–950)	3D convolutional neural network (3D-CNN)
[60]	Potato	Bruised	(450–1000)	Principal component analysis (PCA)
[103]	Strawberry	Leaves	(359–1020)	Extreme learning machine (ELM), support vector machine (SVM), k-nearest neighbor (k-NN)
[104]	Leek	White tip	(800–870)	Supervised machine learning (SVM)
[64]	Tea	Anthraco nose	(450–950)	Iterative self-organizing data analysis techniques (ISODATAs)
[105]	Chickpea	Ascochyta blight	(666–840)	Discriminant analysis (DA), support vector machine (SVM)
[99]	Peanut	Bacterial wilt	(730–900)	Analysis of variance (ANOVA), multilayer perceptron (MLP)
[106]	Cucumber	Powdery mildew	(400–900)	Support vector machine (SVM)
[107]	Tobacco	Spotted wilt virus	(400–1000)	Regression tree (CART)
[108]	Citrus	Fungal infection	(325–1100)	Principal component analysis (PCA)
[109]	Citrus	Diagnosis of citrus Huanglongbing	(450–1023)	Least squares–support vector machine (LS-SVM)
[66]	Green-peel citrus	Thrips defect	(523, 587, 700, 768)	Principal component analysis (PCA)
[110]	Tomato	Firmness estimation	(400–1000)	One-dimensional (1D) convolutional ResNet
[110]	Tomato	Early blight	(380–1023)	Extreme learning machine (ELM)
[35]	Olive	Verticillium wilt	(650–720 680–800 8000–15000)	Support vector machine (SVM), linear discriminant analysis (LDA)
[111]	Grape	Leafroll	(690, 715, 731, 1409, 1425, 1582)	Least squares–support vector machine (LS-SVM)
[44]	Apple	Marssonina blotch	(800–1100)	Orthogonal subspace projection (OSP)
[45]	Apple	Bruising	(400–1000) 1000–2500	Support vector machine (SVM), linear discriminant analysis (LDA)
[46]	Apple	Bitter pit detection	(550–1700)	Partial least square regression (PLSR)
[57]	Beet	Seed Germination	(1000–2500)	Support vector machine (SVM), random forest (RF), light gradient boosting machine (LightGBM)

Table 5 summarizes important studies dedicated to classification tasks of crops such as cereals and oilseeds, studies comprising the classification of the variety of crops [80,112], and others, in particular, crops such as wheat or rice varieties [75,76].

In studies and analyses on nitrogen content, there are works such as that of ref. [113] where nitrogen deficiency in rice crops is analyzed. Another task where hyperspectral images are used is the analysis of chlorophyll content [33].

In crops such as corn, techniques based on machine learning are used to estimate biomass content [51] or to determine the level of soil moisture [114]. In crops such as soybeans, there are works related to the identification of early mosaic virus [115,116].

Table 5. Summary of techniques used for multiple tasks (cereals and oilseeds) (source: authors).

Reference	Crops	Disease	Bandwidths (nm)	Algorithms
[28]	Various	Classification	(400–1000 400–2500)	Random forest (RF), support vector machine (SVM), naive Bayes (NB), WekaXMeans (WXM)
[80]	Various	Classification	(400–1000)	Wavelet attention convolutional neural network (WA-CNN)
[112]	Various	Classification	(400–700 700–1000 100–2500)	Convolutional neural network (CNN)
[50]	Wheat	Wheat and weed discrimination	(400–1000)	Partial least squares discriminant analysis (PLS-DA), support vector machine (SVM)
[40]	Wheat	Kernel presence	(990–1200)	Partial least squares discriminant analysis (PLS-DA)
[12]	Wheat	Predicting micronutrients	(375–1000)	Partial least squares regression (PLSR)
[30]	Wheat	Nitrogen and water status	(400–850 95–1750)	Analysis of variance, or ANOVA
[117]	Rice	Rice variety	(400–1000)	Principal component analysis network
[76]	Rice	Rice varieties	(400–950)	Convolutional neural network (CNN)
[118]	Rice	Rice vigor	(873–1374)	Convolutional neural network (CNN)
[119]	Rice	Chlorophyll content estimation	(450–950)	Partial least squares regression (PLSR), support vector machine (SVM), artificial neural network (ANN)
[75]	Rice	Rice classification	(450–950)	Convolutional neural network (CNN)
[113]	Rice	Nitrogen stress	Variable	Convolutional neural network (CNN)
[76]	Rice	Rice classification	(320–1100)	Convolutional neural network (CNN)
[47]	Rice	Nitrogen content	Variable	Partial least squares regression (PLSR), support vector machine (SVM), artificial neural network (ANN)
[120]	Rice	Rice flour intensity	(500–900)	Stepwise multiple linear regressions (SMLRs) and random forest (RF)
[121]	Rice	Rice seeds vigor	(874.41–1734.91)	Deep convolution neural network (DCNN), principal component analysis (PCA)
[91]	Rice	Nitrogen concentration	Variable	Multivariate linear regression (MLR), long short-term memory (LSTM)
[122]	Corn	Corn seedling recognition	(400–1000)	Convolutional neural network (CNN)
[51]	Maize	Biomass estimating	(450–950)	Random forest (RF)
[53]	Maize seed	Moisture content (MC)	(930–2548)	Partial least squares regression (PLSR), least squares–support vector machine (LS-SVM)
[123]	Maize	Hardness for maize	(399.75–1005.8)	Partial least squares regression (PLSR)
[114]	Corn Maize	Moisture detection	(968.05–2575.05)	Convolutional neural network (CNN), long short-term memory (LSTM)
[112]	Corn Soybean Wheat Alfalfa	Normalized difference vegetation index (NDVI), and modified normalized difference water index (MNDWI)	(400–700 700–1000 1000–2500)	Convolutional neural network (CNN)
[124]	Maize	Crop traits in maize	Variable	Partial least squares (PLS), successive projection algorithm (SPA) random forest (RF) algorithms, adaptive reweighted sampling (CARS)
[125]	Maize	Water and nitrogen status	(325–1075)	Analysis of variance (ANOVA)
[126]	Barley	Nutrient concentration	(1000–2500)	Partial least squares regression (PLS)
[127]	Barley	Phenology of barley	(395–793)	Support vector machines (SVMs)
[128]	Barley	Phenolic compounds	(950–1760)	principal component analysis (PCA), support vector machines (SVMs)
[129]	Sorghum	Sorghum purity	(935–1720)	Principal component analysis (PCA)
[115]	Soybean	Soybean crop variables	(350–2500)	Partial least squares (PLS)
[130]	Soybean	Identification of soybean seed varieties	(874–1734)	Convolutional neural networks (CNNs)
[131]	Oil Palm	Weight and ripeness	(560, 680, 740, 910)	Multilinear regression (MLR)
[132]	Oil Palm	Fruit grading	(750–910)	Artificial neural network (ANN)
[133]	Peanut	Peanut maturity	(400–1000)	Linear mixture model (LMM)

There is a significant amount of research studies related to techniques used for applications, which are summarized in Table 6; some of them correspond to classification tasks such as aromatic varieties such as coffee [134,135]. In other works, machine learning algorithms are applied to verify the state of maturity in fruits such as blueberries, grapes, or citrus fruits [108,136,137]. In other crops, such as citrus, machine learning algorithms are used for the early detection of deterioration, particularly in fruits such as oranges in the early estimation of their maturity, which could influence the future market price and allow producers to plan the harvest in advance and thus reduce costs [138].

Table 6. Summary of techniques used for multiple tasks (other crops) (source: authors).

Reference	Crops	Disease	Bandwidths (nm)	Algorithms
[139]	Lettuces	Phenotypes	(400–1000)	Recurrent neural networks (RNNs), long short-term memory (LSTM)
[135]	Coffee	Coffee bean varieties	(973–1630)	Wavelet transform (WT), support vector machine (SVM)
[135]	Coffee	Coffee bean varieties	(973–1629)	Moving average smoothing (MA), wavelet transform (WT), support vector machine (SVM), empirical mode decomposition (EMD)
[134]	Coffee	Consistency	(408–1008)	Partial least squares (PLS)
[140]	Weed	Indicator of competition for water	Variable	Analysis of variance (ANOVA)
[136]	Blueberry	Growth stages	Variable	Spectral angle mapping (SAM), multinomial logistic regression (MLR)
[141]	Blueberry	Internal quality	(400–100)	Partial least squares (PLS)
[142]	Strawberry	Strawberry ripeness	(503, 604 528, 715)	Support vector machine (SVM), convolutional neural network (CNN)
[143]	Apple	Bruise region	(675–960)	Principal component analysis (PCA), random forest (RF)
[31]	Apple	Bruise damage	(930–2500)	K-nearest Neighbor (k-NN), linear discriminant analysis (LDA), support vector machine (SVM)
[55]	Grape	Predicting sugar, total flavonoid, and total anthocyanin contents	(411–1000)	Multiple linear regression (MLR), partial least squares (PLS)
[144]	Grape	Pigment composition	(400–1000)	Radiative transfer model (RTM)
[137]	Grape	Maturity of grapes	(900–1700)	Modified partial least squares regression (MPLS)
[145]	Banana	Banana grading	(1069.21)	Convolutional neural network (CNN), multilayer perceptron (MLP)
[146]	Potato	Water content	(1400–1450)	Partial least squares (PLS), competitive adaptive reweighting algorithm (CARS)
[101]	Orange	Orange quality	(900–1700)	Artificial neural network (ANN)
[147]	Orange	Pectin content	(900–2500)	Principal component analysis (PCA), partial least squares regression (PLSR)
[138]	Orange	Distinction between green oranges and leaves	(400–100 900–2500)	Analysis of variance (ANOVA)
[108]	Citrus	Early decay	(325–1100)	Principal component analysis (PCA)
[148]	Tea	Green tea quality	(379–1040)	K-nearest neighbor (k-NN), support vector machine (SVM)
[149]	Peanut	Peanut maturity	(545, 660, 790)	Partial least squares (PLS)

4. Discussion

Compared to other review articles [3,9], this review paper focuses on the benefits and applications of HSI in precision agriculture, particularly for crop diseases detection and classification. This review article highlights the machine learning methods employed for detecting and classifying diseases in agricultural crops. It emphasizes the significance of AI in enhancing crop health, ensuring food security, and promoting sustainable agricultural practices. By focusing on these aspects, the review aims to consolidate current knowledge and advancements in the field, providing a comprehensive understanding of how HSI coupled with machine learning can revolutionize crop disease detection and identification management in agriculture.

Among the findings of the documentary review, it is also possible to highlight that integrating hyperspectral imaging with genomics holds significant potential for advancing agricultural research and applications. Hyperspectral imaging provides detailed spectral data reflecting the physiological and biochemical state of plants, while genomics offers insights into the genetic makeup and traits of crops [150]. By combining these technologies, researchers can correlate specific genetic markers with spectral signatures, enabling the identification of traits linked to disease resistance, nutrient use efficiency, and stress tolerance. This can facilitate the development of precision breeding programs aimed at creating crop varieties with desirable traits. For example, hyperspectral data could be used to non-invasively monitor the expression of certain genes under different environmental

conditions, accelerating the selection process in breeding programs and improving crop resilience and productivity. Hyperspectral imaging can monitor plant health and stress responses in real time across various climatic conditions. By integrating these data with climate models, researchers can predict how crops will respond to future climate scenarios, aiding in the development of climate-resilient agricultural practices. Additionally, hyperspectral imaging can detect subtle changes in plant physiology that precede visible symptoms of stress caused by drought, temperature extremes, or other climatic factors. This information can be used to develop early warning systems for farmers, allowing for timely interventions to mitigate the effects of adverse weather conditions.

The integration of advanced technologies into agriculture, particularly through precision farming, has profound implications for global agricultural practices and the advancement of sustainable agriculture [151]. Precision agriculture involves the use of data analytics, satellite imagery, and various sensors to optimize the use of resources such as water, fertilizers, and pesticides, enhancing both productivity and sustainability. Furthermore, precision agriculture facilitates the early detection of crop diseases and pest infestations through continuous monitoring and advanced data analysis. Technologies like remote sensing and AI-driven analytics can identify subtle changes in crop health that may indicate the onset of disease, allowing farmers to take proactive measures before significant damage occurs.

As examples of hyperspectral platforms (see Figure 6), the following stand out. **Unmanned aerial vehicles (UAVs): Advantages:** they have a high spatial resolution for smaller areas and lower operational cost than airplanes, and provide easier access to specific target areas. Spatial resolution: UAVs can fly at low altitudes, capturing high-resolution images that provide detailed spatial information. **Drawbacks:** they have a limited flight time and range, weather dependence, and regulatory restrictions.

Lab hyperspectral platform: Advantages: high spatial resolution: field-based sensors can capture data at very high resolutions, allowing for detailed analysis of small features or samples. Non-destructive in situ measurements: measurements can be taken directly on the target object without harming it, making them ideal for studying sensitive materials or analyzing objects in their natural environment. Portability and adaptability: these systems are lightweight and portable, allowing researchers to easily move them around and collect data in diverse field settings. Controlled environment: by setting up the platform in a controlled environment (indoors or with a portable tent), researchers can minimize the impact of external factors like wind or sunlight variations. **Drawbacks:** limited coverage area: field-based systems can only collect data over a small area at a time. Analyzing large areas requires collecting and stitching together multiple datasets, which can be time-consuming. Time-consuming data acquisition: depending on the size and complexity of the target area, data collection can be slow and laborious.

Field hyperspectral platform: Advantages: high spatial resolution: unlike satellite or airborne hyperspectral sensors, field platforms capture data at very high resolutions. This allows for detailed analysis of small features or samples, like examining individual leaves on a plant or cracks in a rock. Portable and adaptable: these compact and lightweight systems can be easily transported and deployed in diverse field settings. **Drawbacks:** limited coverage area: the trade-off for high resolution is coverage area. These systems can only analyze a small area at a time. Studying large fields might require collecting and piecing together multiple datasets, which can be time-consuming. Environmental dependence: field measurements can be affected by external factors like changing sunlight or strong winds. Careful planning and consideration of weather conditions are crucial.

Unmanned aerial vehicles (UAVs)

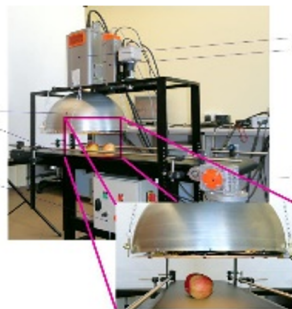


(a)

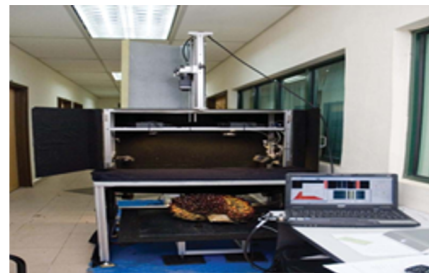


(b)

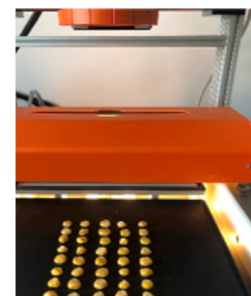
Lab hyperspectral platform



(c)



(d)

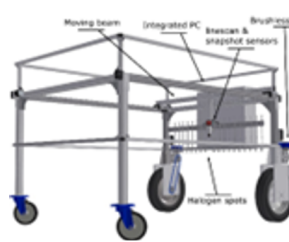


(e)

Field Hyperspectral platform



(f)



(g)

Figure 6. Examples of hyperspectral platforms for field applications. (a) Cubert S185 hyperspectral camera onboard and (b) DJI M600 [37,152]. (c) Setup for hyperspectral measurements consisting of (a) SWIR spectral camera; (b) VNIR spectral camera; (c) diffuser with halogen lamps; (d) belt conveyor with photocells for controlling the direction of movement; (e) system for regulation of belt conveyor speed; (f) stepper motor. (d) The spectral camera (Imperx IPX-2 M 30). (e) SisuCHEMA hyperspectral imaging system (Specim, Finland) [45,114,132]. (f) FX 10, Specim, Finland. (g) (Prism–grating–prism) spectrograph (Inspector V9, Specim) [59,102].

Figure 7 summarizes the concurrence of studies that implement artificial intelligence techniques and hyperspectral cameras. The results show that, between years 2020 and 2023, the use of hyperspectral images in agriculture has increased exponentially, mainly in cereals such as wheat, soybean, corn, and rice, and in fruits such as oranges and apples, especially in the detection of diseases in crops and classification of nutrient levels, crop types, and weed detection. The results show that it has not been determined which is the most precise or appropriate method; however, it is confirmed that techniques based on machine learning and deep learning with more use in crops of cereals, oilseeds, vegetables, and fruits are the models SVMs, RFs, PLS, LSTM, LMMs, CNNs, RNNs, and artificial neural networks. On the other hand, the chosen wavelengths in a wide range of the electromagnetic spectrum

depend on the purpose of each study, where the choice of appropriate wavelengths depends on the specific disease being investigated and the spectral characteristics of the plants and pathogens involved. Also, the combination of various spectral band analysis techniques can improve the accuracy of disease detection and help monitoring in crops. Deep learning is presented as an alternative that has been adapted by many authors and a tool used to manipulate massive information obtained by hyperspectral images.

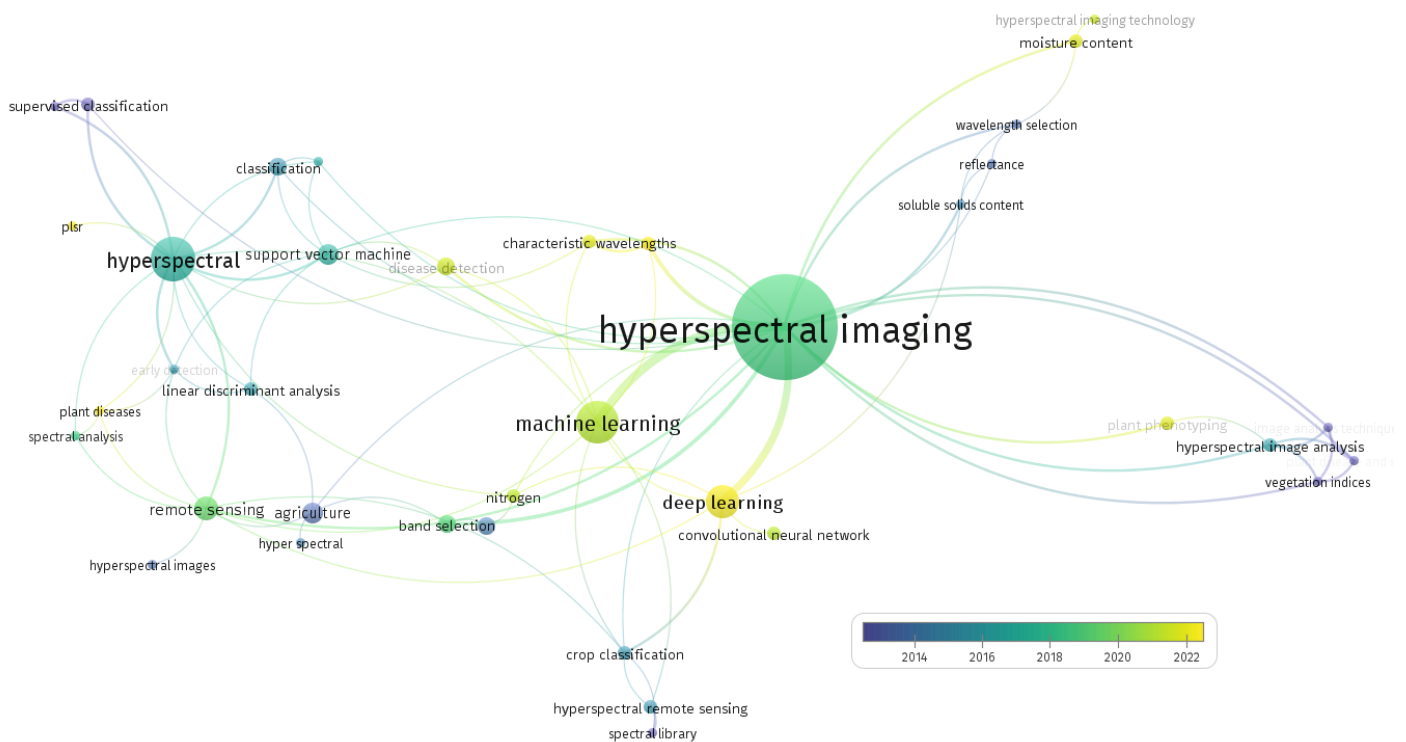


Figure 7. Scientific network mapping of the most used keyword terms in papers reviewed; the lines represent co-occurrence link strength among terms (source: authors).

With respect to hyperspectral imaging vs. RGB imaging, within the findings, it can be highlighted that they are both valuable tools in agriculture, but hyperspectral imaging offers several distinct advantages over traditional RGB imaging [153–155], which are summarized in Table 7.

Table 7. Summary of advantages of using hyperspectral images over RGB images in agriculture (source: authors).

Advantage	Hyperspectral Imaging	RGB Imaging
Spectral Resolution	Captures a wide spectrum of light across many narrow, contiguous bands, ranging from the visible to the near-infrared and even further. This allows for the detection of subtle differences in plant properties.	Captures light in only three broad bands (red, green, and blue), limiting the amount of information that can be obtained about the vegetation.
Detailed Analysis of Plant Health	Can detect specific wavelengths that are indicative of particular plant health issues, such as nutrient deficiencies, water stress, disease, or pest infestations, often before these issues are visible to the naked eye.	Provides limited information, mainly based on color changes that are visible to the human eye, which usually appear at later stages of plant health problems.
Enhanced Crop Monitoring	Allows for the detailed monitoring of plant growth and development, enabling precision agriculture practices such as variable rate application of fertilizers and pesticides.	Can provide basic information about plant growth stages and general health but lacks the detailed spectral information necessary for precise monitoring.

Table 7. Cont.

Advantage	Hyperspectral Imaging	RGB Imaging
Soil and Crop Differentiation	Can distinguish between different soil types, crop species, and even different varieties of the same crop by analyzing their unique spectral signatures.	Often struggles to differentiate between similar-looking soils and crops due to its limited spectral information.
Yield Prediction	Enables more accurate yield predictions by analyzing the spectral signatures related to plant biomass, chlorophyll content, and other growth parameters.	Provides more general estimates based on visible growth, which may not be as precise.
Environmental Monitoring	Can detect environmental stressors such as pollution, soil contamination, and water quality issues by analyzing specific spectral features.	Limited in its ability to detect such detailed environmental conditions.

5. Conclusions

This study also concludes that using these tools has benefits, such as non-invasive monitoring, because hyperspectral imaging allows crops to be monitored without any physical contact or damage. The technology provides detailed and precise information on crop conditions, which is not possible with traditional imaging methods. Additionally, it increases efficiency by enabling precision agriculture practices and improved resource utilization, leading to cost savings and higher yields.

Additionally, there are challenges such as the high cost of integrating these technologies, as the initial investment in hyperspectral sensors and data processing and storage infrastructure can be high [156]. Managing and interpreting the large volumes of data generated also require advanced expertise and computational resources. Other operational challenges to consider include weather conditions, sensor calibration, and data acquisition protocols, all of which need to be carefully managed for accurate results. Hyperspectral camera spectrometers can detect different reflectance conditions that generally occur due to changes in atmospheric conditions, the presence of clouds, variations in lighting, other environmental interferences, and others related to proper illumination effects correction [157]. In the case of large cultivation areas, taking hyperspectral images requires the use of unmanned aerial vehicle (UAV) systems, which must fly at a low speed below 100 m to avoid blurred images. Therefore, a complete field study requires a Global Positioning System (GPS) and ground data acquisition using a spectrometer [21].

The future prospects of hyperspectral imaging combined with artificial intelligence in agriculture look promising, with advancements in sensor technology and data analytics. As the cost of technology decreases and data processing becomes more efficient, hyperspectral imaging is expected to become more accessible to researchers and farmers worldwide, revolutionizing agricultural practices and contributing to sustainable farming.

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Nomenclature and Abbreviations

The following abbreviations are used in this manuscript:

ANOVA	Analysis of Variance
ANN	Artificial Neural Network
BPNN-GA	Backpropagation Neural Network
CART	Classification And Regression Tree
CNN	Convolutional Neural Network
CARS	Competitive Adaptive Reweighting Algorithm
DA	Discriminant Analysis
DCNN	Deep Convolution Neural Network
EMD	Empirical Mode Decomposition
ELM	Extreme Learning Machine
k-NN	K-Nearest Neighbor
LDA	Linear Discriminant Analysis
LightGBM	Light Gradient Boosting Machine
LSTM	Long Short-Term Memory
CFI	Chlorophyll Fluorescence Imaging
CNN	Convolutional Neural Network
LR	Logistic Regression
MA	Moving Average Smoothing
MLR	Multivariate Linear Regression
MLP	Multilayer Perceptron
MPLS	Modified Partial Least Squares Regression
NB	Naive Bayes
NIR	Near-Infrared Light
NDVI	Difference Vegetation Index
OSP	Orthogonal Subspace Projection
PCA	Principal Component Analysis
PLSR	Partial Least Squares Regression
PLS	Partial Least Squares
PLSDA	Partial Least Squares Discriminant Analysis
RF	Random Forest Algorithm
RACNN	Residual Attention Convolution Neural Network
RNNs	Recurrent Neural Networks
SAM	Spectral Angle Mapping
SVD	Singular Value Decomposition
SMLR	Stepwise Multiple Linear Regression
SDAE	Stacked Denoising Autoencoder
SWIR	Short-Wave Infrared

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