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Enhancing Agricultural Crop Management with Hyperspectral Images and Artificial Intelligence: A Comprehensive Review

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ABSTRACT

The primary objective of hyperspectral images was originally military-oriented; however, it has since expanded to include precision agriculture. The utilization of hyperspectral images related to machine learning algorithms takes into consideration exact crop classification and disease detection. These images capture a broad range of wavelengths, enabling the monitoring of various agricultural crops, including cereals, oilseeds, vegetables, and fruits. By utilizing hyperspectral images, farmers can assess crop conditions, including maturity index and nutrient status, and detect diseases that could lead to significant crop losses.Here we take a close look at the most important uses of hyperspectral images in farming, as well as the ways in which AI algorithms like ML and DL could be used to detect and identify crop diseases in cereals, oilseeds, fruits, and veggies. This research is the result of a comprehensive literature review that spanned a decade. The study looks at how these technological tools for sustainable agriculture are being integrated and highlights the most well-documented crops, like citrus fruits and some grains that are grown extensively and in great demand. In addition, the review lists and categorizes the main AI algorithms under development as well as the wavelength ranges that are being used to forecast, identify, and carry out other sustainable production-related tasks.In order to apply the best artificial intelligence algorithms, this review is a useful resource for future study on agricultural crop detection, categorization, and decision-making.

***Keywords* —** Hyperspectral image, Plant diseases, Disease detection, Machine learning, Deep learning, Precision agriculture, Artificial intelligence, Remote sensing, Crop classification.

I. INTRODUCTION

The population of the globe has increased significantly in recent years, according to reports from the United Nations (UN), and is expected to reach at least 9.1 billion by 2050[1]. The demand for food is predicted to rise dramatically as a result of this population boom, especially in emerging nations where worries about food security are becoming more pressing. Extended droughts, floods, and changes in temperature and rainfall patterns are some of the ways that climate change offers serious difficulties to agricultural production[2]. Using modern technology in agriculture to maximize crop yield and boost productivity in controlled situations is crucial to addressing these issues. Using artificial intelligence and hyperspectral cameras for image analysis is one such technology[3, 4]. The most crucial elements of integrating these technologies will be covered in this paper.

The electromagnetic spectrum is made up of several bands, each of which represents a particular kind of light energy (Figure 1). 400–700 nm wavelengths are visible to the human eye[5]. Conversely, hyperspectral sensors cover a wide range of spectral bands, from ultraviolet (UV) to longwave infrared (LWIR) wavelengths, and can often record over 200 of them. The agriculture industry has been greatly impacted by the new technology known as hyperspectral cameras in recent years. Farmers may identify possible problems with plant health and take preventive action before they worsen thanks to the high-resolution images and numerous wavelength bands that these cameras can capture[6, 7].

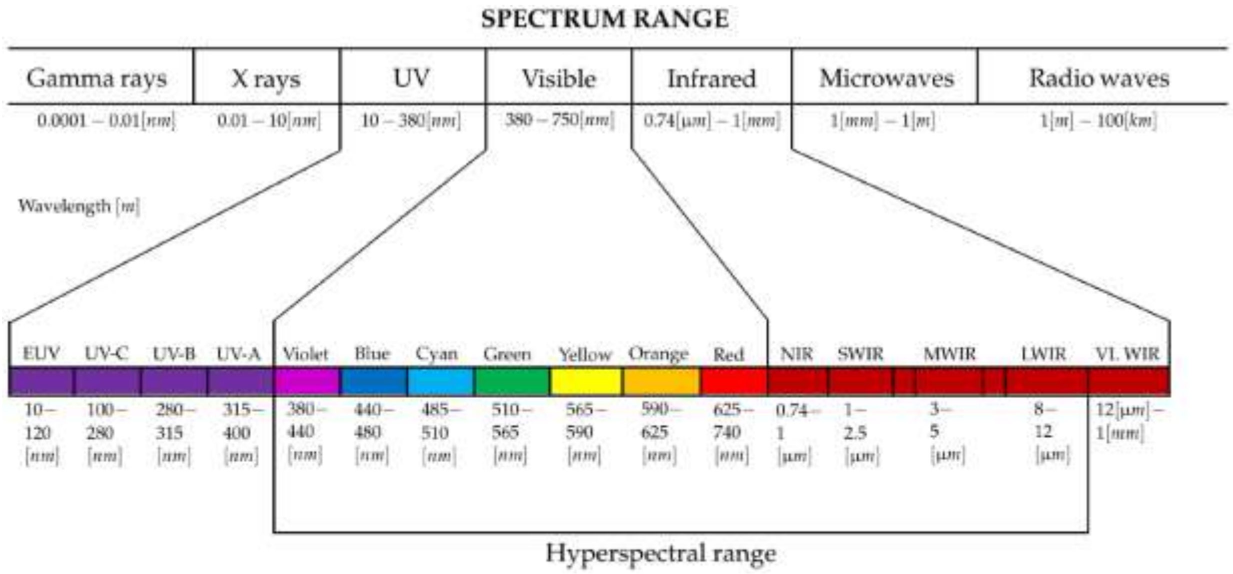


Figure 1: The hyper spectral range is situated within the electromagnetic spectrum (source: the authors).

Using multispectral pictures, scientists have been devoting a significant amount of effort and money to the diagnosis of plant diseases. The 3 to 20 non-contiguous bands that make up these images are typically crucial for identifying diseases [8]. Large-scale agricultural analysis has been made more viable by analysts utilizing machine learning and deep learning draws near [9]. As a substitute for multispectral photographs, hyperspectral images have just lately gained popularity.

By utilizing tight spectral bands and consolidating artificial intelligence, PC vision, and machine learning strategies, images offer a total understanding of the substance and organic properties of plants and soil [3].

Various studies have been carried out with an aim to improve agricultural crop management, specifically concentrating on non-invasive plant disease diagnosis methods. In these studies, hyperspectral camera remote sensing has shown to be an inventive tactic that has attracted a lot of interest.

[10,11]. Hyperspectral imaging is well known for its application in crop categorization, plant variety identification, and plant phenotyping—the study of a plant's morphology, physiology, and biochemistry. This approach offers a more thorough characterisation of plant performance and its interactions with the environment by evaluating these attributes over a broad range of neighboring bands [13]. Furthermore, research on disease detection in agricultural crops has made use of remote sensing techniques [14,15,16]. Machine learning is a useful tool in artificial intelligence that offers numerous applications when combined with hyperspectral images. Some research articles explore the potential of combining robotics with hyperspectral image processing, while others propose using robotic systems to replace human operators for capturing hyperspectral images at the leaf level in the field using low-cost, portable devices [17]. The detection of undesirable plants, or weeds, in particular agricultural crop varieties is one such use. This lessens the negative impacts on the environment by enabling farmers to apply herbicides to specific locations rather than the entire field [18]. Furthermore, individual crop and soil health can be evaluated using hyperspectral imaging and machine learning, allowing for the targeted delivery of pesticides to sick plants. Other tasks that machine learning can be utilized for include plant phenotyping, calculating nutrient levels, recognizing crop varieties, and detecting and categorizing crop illnesses [19, 20, 21].

This paper plans to investigate the utilization of hyperspectral images in horticultural crops, with an accentuation on essential calculations in light of machine learning and deep learning for detection and classification. It will likewise cover the ghastly ranges broadly utilized by crops like oats, oilseeds, and a few organic products. This is the way the article is organized: The initial segment gives a rundown of hyperspectral picture innovation and its applications in cultivating. In the subsequent part, we frame the examination approach that was followed for this audit. In the third segment, we analyze the innovation that depends on hyperspectral images and the aftereffects of this examination utilizing artificial intelligence approaches, for example, deep learning and machine learning. The difficulties introduced by this innovation are examined and deduced in the fourth and fifth segments, which likewise offer an outline of the perspectives and results.

II. METHODOLOGY

The article conducted three stages of work to assess and examine the bibliographic references cited, which are illustrated in Figure 2.

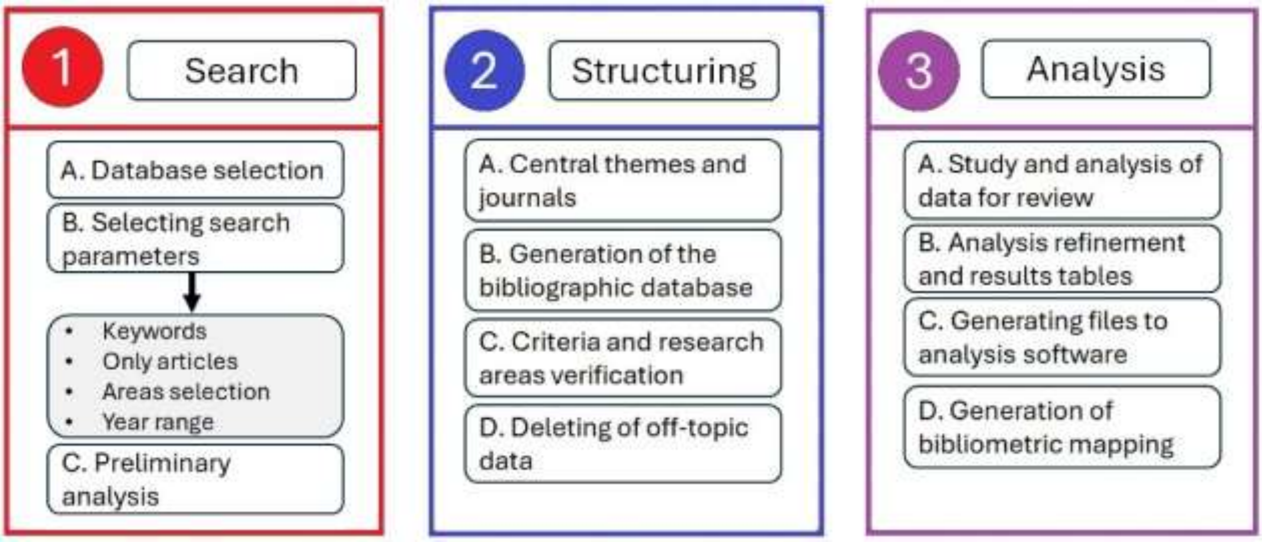


Figure 2: Depicts the stages implemented in the review analysis process as illustrated by the authors.

II.1. Stage 1: Search

The following describes the methodological approach that was used during the first phase of the search.

Selection of Database

A thorough search was done using a number of scholarly databases, including:

- Science Direct
- Web of Science
- Scopus
- MDPI
- Frontiersin Science
- GoogleScholar (for complementary grey literature).
- Keywords

The search strings used the following keywords and their combinations.

- Hyperspectral Imaging
- Machine learning
- Crop Disease Detection
- Crop Disease Identification
- Precision Agriculture.
- HSI and ML for Crop Disease Detection and Identification:

In-clusion Criteria:

- Peer-reviewed English-language research articles published between 2013 and 2023 that focus on the diagnosis and detection of agricultural diseases using hyperspectral imaging and machine learning.
- Research examining the benefits and drawbacks of several machine learning methods used for HSI data processing in connection to agricultural disease detection and classification

Ex-clusion Criteria:

- Research publications that specifically concentrate on the advancement or design aspects of HSI technology and refrain from investigating its use in disease diagnosis or categorization.
- Editorials, Conference proceedings, and opinions that don't present significant data or assessments.
- Articles published in languages other than English are not considered.

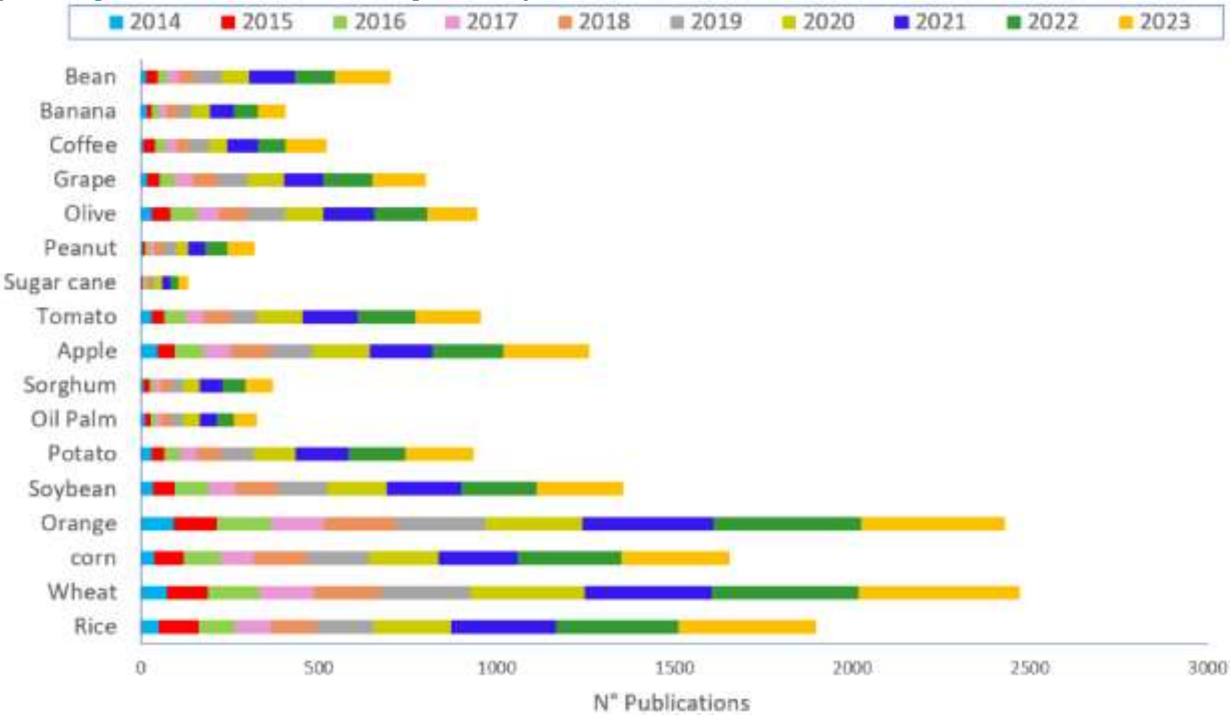
Section Process:

- Mendeley Desktop v1.19.8 or EndNote 21 were used as reference management tools to remove duplicates from the initial search results.
- This was followed by a thorough evaluation of the abstracts and titles using the inclusion and exclusion criteria.
- After that, the remaining papers were carefully scrutinized to make sure they answered the research topic.

Synthesis Process:

The selected study was analyzed and interpreted using a narrative synthesis methodology; key themes and supporting data about the use of HIS and other machine learning methods for agricultural disease detection and diagnosis were subsequently retrieved. Advantages of non-invasiveness, early disease detection, and potential species discrimination were the main points of the review. The difficulties posed by the volume of data, the expense, and the fluctuating field conditions were also covered. Finally, possible avenues for this field's future research were investigated.

Based on the gathered data, it can be concluded that hyperspectral cameras are very helpful in agricultural applications including early disease or insect identification, better irrigation and fertilizer application, and crop quality evaluation. These cameras are helpful in assessing crop ripeness as well. Research articles on the connection between hyperspectral photos and cropping have been published much more frequently throughout the last ten years. Figure 3 shows the results of a preliminary search using the terms kind of crop and hyperspectral, which produced a lot of hits.



In Figure 3: The number of annual publications featuring the terms crops and hyperspectral images is depicted (courtesy of the authors).

In the course of searching, it was uncovered that cereals, such as wheat, rice, and corn, are the crops that employ hyperspectral images most frequently, with 346, 346, and 291 publications in 2022, respectively. When it comes to fruit trees, citrus fruits, like oranges and apples, with 413 and 199 publications, respectively, are particularly noteworthy. Additionally, legumes, such as Soybeans with 211 publications and Beans with 112 publications, also deserve mention. It is worth noting that the total number of publications in 2023 surpasses that of 2022, with a total of 3297 compared to 2942.

Hyperspectral image-based non-invasive illness detection is used in a large number of published publications [14, 22–24]. This technique can be used in conjunction with neural networks and other tools to perform tasks related to disease identification and classification [25].

After preliminary analysis, two primary research areas were found: the identification of diseases in agricultural crops and the application of hyperspectral images for multiple applications, including crop phenotyping, nutrient identification, vegetable variety classification, leaf level assessment, maturity index determination, and more.

II.2. Stage 2: Structuring

In the second phase of the project, we identified the main themes and significant journals by conducting a preliminary analysis, the results of which are shown in Figure 3. Table 1, which is included in the crucial information we have compiled, lists the essential journals that were utilized in this extensive examination.

Table 1 offers a concise overview of the journals that were assessed. Based on the authors' reports, this table includes details about each journal's SJR (SCImago Journal Rank), JCR (Journal Citation Report), and ND (number of documents).

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

Journal	Cite Score	SJR	H-Index	JCR	ISSN	ND
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
Spectrochemical 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	7.50	1872-26X	2
Plant Methods	5.10	1.12	86	5.10	1746-4811	2
Ecological Informatics	6.10	0.92	66	5.10	1574-9541	2
IEEE Computer Science (miscellaneous)	3.50	0.93	204	3.90	2169-3536	2
International Journal of Remote Sensing	7.0	0.73	195	3.40	1366-5901	1
Frontiers of Plant Sciences	7.10	1.23	187	5.60	1664-462X	1

To ensure that the study remained focused and relevant, several steps were taken. Firstly, a bibliographic database was organized and all documents were closely monitored to verify the selection of articles. Secondly, each selected article was thoroughly inspected to confirm that it met the criteria and research areas. Thirdly, any articles that were deemed irrelevant to the study were eliminated. Finally, the remaining articles were carefully assessed to ensure that they were aligned with the research objectives.

II.3. Stage 3: Analysis

Data analysis was done throughout the project's final stages. First, every item was carefully examined, and relevant data was taken out. Second, each article's collected data was categorized and entered into the results tables. Following that, bibliometric analysis files were created for software that imports bibliometric mapping. The VOS viewer tool, a free, open-access program for scientific bibliometry, was used to build the bibliometric network. The bibliometric network was built and visualized using this program.

III. RESULT

III.1. Hyperspectral Images of Technology Based

The hyperspectral imaging sensors are widely recognized for their remarkable spectral resolution, despite their comparatively low spatial resolution. These sensors gather information about the spectral and spatial properties of every pixel. An array of numbers representing the intensities at a given position (x, y) over z distinct bands can be thought of as a pixel. A pixel's spectral signature at (x, y) is represented by a set of integers known as the pixel spectrum. The hyperspectral data acquired by means of a camera or sensor is shown in a three-dimensional representation in Figure 4.

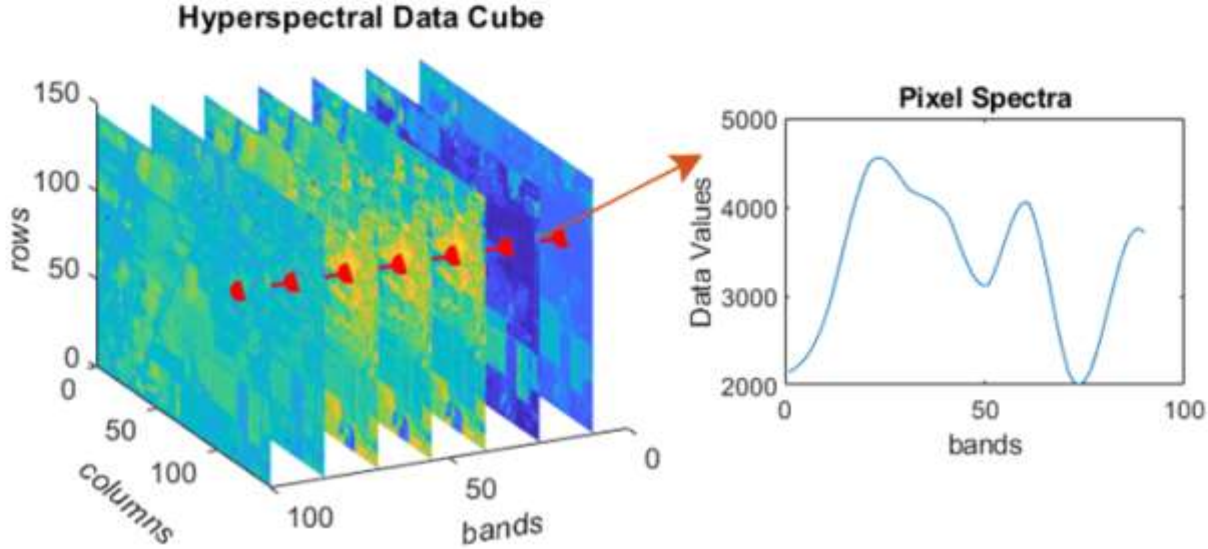


Figure 4 presents a hyper-spectral data cube, as depicted in the image sourced from Mathworks® located in Natick, Massachusetts (USA) (Source: Mathworks®, Natick, Massachusetts (USA))

From 2020 to 2023, hyperspectral imaging will see a dramatic uptick in agricultural applications, as examined in this study. Evidence also suggests that these pictures can help pinpoint instances of plant stress due to things like pest infestations, nutrient deficits, or drought. You can use them to classify early nutrient deficiencies, find diseases before they show symptoms, assess soil properties and composition, use spectral signatures to differentiate crops and weeds, keep an eye on pest infestations, study crop varieties, and figure out when to harvest using spectral analysis. Hyperspectral information can assist researchers and ranchers with fining tune watering, preparing, and pesticide applications. Better soil the board, designated bug control, and distinguishing the ideal opportunity to gather for most extreme yield and quality can be accomplished using this data, as can the convenient mediations to decrease pressure and further develop crop yield expectations. This, thus, will streamline asset use and diminish costs.

Real-Case Studies

Case models showing the use of hyperspectral imaging and machine learning incorporate the development of grapevines for winemaking. Fine mold and fleece buildup are two of the most well-known grapevine diseases, and the two of them can prompt huge crop misfortunes. The visual examination used in conventional disease detection approaches is time-consuming and often not conducted quickly enough to prevent widespread contamination. In an early stage of a review conducted at a grape farm in Napa Valley, California, hyperspectral imaging linked to machine learning was utilized to identify and categorize grapevine illnesses. [27]. A 400-1000 nm unearthly reach camera mounted on a robot created the hyperspectral photographs. The capacity to recognize minute varieties in reflectance among solid and diseased grapevines was made conceivable by the extensive ghostly data these photographs provided for each pixel. To order the disease states in light of their ghastly marks, an irregular woods classifier — a machine learning strategy eminent for its sturdiness and exactness in handling high-layered information — was utilized. The marked examples of both solid and sick grapevines made up the preparation dataset. The review's discoveries exhibited that hyperspectral imaging and machine learning together may productively recognize and sort grapevine diseases at a beginning phase, which might bring down crop misfortunes and improve the viability of disease control in grape plantations.

The project's result was an extremely accurate detection system with a rate of over 90%. This technique might identify diseases like powdery mildew before symptoms were apparent to the unaided eye. With this skill, vineyard managers may apply focused treatments only when required, cutting costs and usage of pesticides while enhancing the general health of the vineyard. Classifying three key crops grown worldwide—corn, soybeans, and winter wheat—is the subject of another noteworthy study [28]. In the United States, these crops are widely grown, especially in the Midwest, which includes Ponca City, Oklahoma. The study demonstrates how well cloud computing systems such as Google Earth Engine (GEE) work when processing large-scale hyperspectral information. enormous-scale crop categorization jobs require the ability to analyze enormous amounts of data efficiently, which is made possible by this approach. The research opens up new avenues for the advancement of machine learning pipelines in the cloud that are tailored for hyperspectral data processing in agriculture. The ability of CNNs to capture complex spectral patterns allowed them to outperform other models in the results, which showed great accuracy in crop classification. Because DESIS data has a higher spatial resolution than Hyperion, it often gave higher accuracy. Large datasets could be processed more effectively thanks to cloud computing, which also greatly cut down on computation time. The study found that a potent tool for precision agriculture is the integration of hyperspectral imagery and machine learning on cloud platforms, which enables more precise and scalable crop classification and improved crop management and yields.

III.2. Identification of Plant Leaf Diseases Using Hyperspectral Images

Hyperspectral imaging has garnered significant attention as a means of tracking and forecasting agri-food output. By analyzing components and identifying biological microbiological pollutants, these images facilitate the diagnosis of plant illnesses in agricultural crops. Highly developed sensors detect the radiation that plants emit or reflect over a wide range of spectral bands, yielding a wealth of information on features including the composition of the leaves and stems and the amount of nutrients in the soil. This information is vital for recognizing anomalies and diseases in crops [16, 29].

Hyperspectral images are particularly useful for cereal crops like rice and wheat[30]. In these applications, the images are used to detect H_2O levels and nitrogen concentrations in the plants [31]. For instance, the detection of wheat leaf rust, a common disease affecting wheat crops worldwide, has been improved by the development of deep learning-based tools that achieve around 84.1% prediction accuracy [32].

Researchers like those mentioned in ref. [33] have also explored the use of chlorophyll fluorescence together with hyperspectral images to identify Common illnesses, including wheat head blight caused by Fusarium, are prevalent. The studies conducted by researchers are carried out in both laboratory and field settings and employ a method that integrates chlorophyll fluorescence (CFI) during the initial inspection phase with hyperspectral imaging for monitoring the disease [33].

III.3. Machine Learning

ML is an application of AI that improves efficiency in predicting and categorizing unknown data while imitating human learning processes by optimizing preexisting knowledge structures. Because machine learning can handle large volumes of data, it is a very effective technique for processing hyperspectral photographs of crops in the context of agricultural disease identification [3,34].

Numerous investigators, as referenced in [35], have employed machine learning algorithms that integrate SVM and LDA approaches to evaluate the severity of Verticillium wilt disease in olive crops throughout a vast 300-hectare area. The LDA technique used by the researchers yielded a general precision level of 59%, whereas the SVM approach produced a precision level of 79.2%.

Chlorophyll content in crops such as potatoes has been estimated by previous studies using machine learning methods [36]. To illustrate the point, a study that looked at different models for measuring chlorophyll content in potato crops at different phases of growth also recommended an SVM-based model that was more accurate. Machine learning methods such as support vector machines (SVMs), random forests (RFs), and gradient boosting (GB) are useful for analyzing reflectance spectra and vegetation indices in crop samples [37]. What follows is a segment with more information about some of the most popular algorithms.

3.3.1. Supervised Machine Learning

The term "supervised learning" describes the method by which a machine learning algorithm learns to make predictions using a set of labeled examples as input. A variety of analysis and prediction tasks, including those in agriculture, can benefit from this method, which finds extensive application in machine learning. In such cases, supervised machine learning models extract patterns linked to various crop characteristics, diseases, or quality parameters from tagged datasets that contain images, sensor data, or other pertinent information[38].

Artificial Neural Networks

This The agricultural industry has seen a significant increase in the use of artificial neural networks (ANNs) for a variety of applications, such as crop quality evaluation, production monitoring, and disease and pest identification. In this situation, hyperspectral photos are very useful since they can be used with artificial neural networks (ANNs) and hold a lot of information about crops. For instance, hyperspectral pictures are employed in cereals like wheat to assess grain hardness, identify fungal infections, and assess damage from cold. The approach is frequently used to train ANNs, especially in supervised learning environments with classifiers that are recognized for their high levels of automation, simplicity, robustness, sensitivity, and accuracy in classification [25,41]

Support Vector Machine(SVM)

The main function of support vector machines (SVMs) is to classify objects according to particular properties or features. The ultimate goal of SVMs is to find the best separation line that maximum divides objects into distinct classes. SVM-based techniques have been widely used for disease detection, crop classification, and classification of a wide range of food items [41, 42]. In a different study, a pixel-based method for extracting hyperspectral images was used to classify diseased corn kernels. The results showed that using the pixel technique improved the SVM's accuracy to 100%, indicating that the data derived from pixels was more complete and accurate than the data derived from objects [43].

K-Nearest Neighbor (K-NN)

In machine learning, the k-nearest neighbors (K-NNs) technique is a popular choice for regression and classification tasks. In contrast to other algorithms that need explicit model learning during training, the K-NNs method remembers the training instances and uses them to make predictions based on how similar the new input is to the data. Numerous applications have demonstrated the great efficacy and efficiency of this instance-based technique[44].

Classification and Decision Tree (CART)

Decision trees provide a powerful and easily understood machine learning technique that can be used for classification problems, especially in the agricultural domain when combined with hyperspectral imagery. The ability to distinguish between different crop varieties, identify stress or disease, and track crop health are some of its benefits. Decision trees are a useful tool for processing multi-dimensional data obtained from hyperspectral pictures because of their capacity to constantly segment the data space based on feature values. This ability is what makes decision trees effective [45].

Logistic Regression (LR)

In machine learning, the k-nearest neighbors (K-NNs) technique is a popular choice for regression and classification tasks. In contrast to other algorithms that need explicit model learning during training, the K-NNs method remembers the training instances and uses them to make predictions based on how similar the new input is to the data (characteristics).

Linear Regression

By collecting data at a broad range of wavelengths, hyperspectral imaging makes it possible to conduct a thorough analysis of the chemical makeup of plants. The motivation behind this technique is to develop a straight line relationship utilizing at least one free factors, such unearthly groups, and a reliant variable, similar to crop yield, chlorophyll content, or the presence or nonappearance of disease [47].

Multivariate Linear Regression (MLR)

A famous factual method for dissecting the connection between a few ward factors and no less than one free factor is multivariate straight relapse (MLR). This strategy goes past single-subordinate variable essential direct relapse. Utilizing the range information from hyperspectral sensors, MLR can be utilized in crop examination through hyperspectral imaging to figure various huge agronomic attributes, including biomass, chlorophyll content, dampness levels, and yield, among other quantitative characteristics [29,48].

Deep Forest

This machine learning approach is very new and has demonstrated excellent results in many fields, including remote sensing applications and picture categorization, including hyperspectral imaging in agriculture. Unlike more conventional models like neural networks, deep forests use an ensemble learning technique inspired by decision trees, leading to efficient feature learning and representation due to their hierarchical structure. With this method, different crop kinds can be reliably classified by deep forests using their spectral fingerprints that are taken from hyperspectral pictures[49].

Back Propagation Neural Network(BPNNs)

Through the fusion of genetic algorithms (GAs) and neural networks, robust computational tools are created that significantly enhance the analysis of hyperspectral imaging in agriculture. By integrating these two methodologies, neural networks are capable of capturing intricate patterns while genetic algorithms refine model parameters, resulting in a highly potent combination. This combination holds great potential for advancing precision agriculture applications by enabling the extraction of critical features and the discovery of intricate relationships. However, selecting the most appropriate model for specific requirements requires careful assessment of factors such as computational costs, data needs, and interpretability constraints [25].

Linear Discriminant Analysis(LDA)

A popular machine learning and statistical technique in multivariate analysis for supervised classification is called linear discriminant analysis (LDA). Finding a linear feature mixture that can successfully distinguish between different classes or groups within a dataset is its primary objective. According to references in, LDA has been extensively utilized in the categorization of agricultural products and in the hyperspectral image-based weed distinction in crops such as wheat and rice [35,50,51].

Naive Bayes Algorithm

The Bayes theorem is used by the incredibly efficient and straightforward generative machine learning classifier Naive Bayes to calculate the probability that connected events will occur. A lot of agricultural crops are classified using this method [52, 53]. Other researchers have also used hyperspectral cameras with sensors that record data in the visible, near-infrared (NIR), and short-wavelength infrared (SWIR) regions to apply this technology to the detection of blemishes or bruising on apples [45].

In addition, studying the maturation of crops like rice using Naive Bayes classification methods [47]. Nitrogen characteristic calculations in this study rely heavily on the correlation between nitrogen characteristics and chlorophyll in the visible and near-infrared (VNIR) spectrum, as detected by distant sensors.

Modified Partial Lease Squares Regression (MPLSR)

Modified partial least squares regression (MPLSR) is a popular measurable procedure for creating expectation models, especially while managing datasets that show unconventional qualities. Hyperspectral images, for instance, can keep data in a few aspects because of the many phantom groups they regularly contain. MPLSR does an excellent job of preserving the most crucial information required for crop analysis while lowering the dimensionality of this data. This is accomplished by finding the spectral bands and crop qualities that capture the most variance in the predictor and responder variables, respectively, as latent variables [54,55].

Light gradient Boosting Machine(LightBGM)

Gradient boosting decision tree framework LightGBM is an open-source tool that has gained widespread acclaim for its outstanding performance in a variety of machine learning tasks, such as regression, classification, and ranking. It is especially helpful for examining hyperspectral photos of crops and has shown to be a vital resource for tasks involving regression and classification [56,57].

3.3.2. Unsupervised Machine Learning

The goal of the research of unsupervised machine learning is to find hidden structures and patterns in data without the need for labels or predefined answers. When there are few labels or when revealing hidden information in the data is the goal, this method is quite helpful. Unsupervised learning algorithms have made significant strides in the categorization of remote sensing photos in recent years and are now widely recognized as a successful substitute for traditional feature extraction techniques [58].

K-Means Clustering

Intending to sort data into bunches with low between bunch closeness and high intra-bunch similitude is what's really going on with the k means technique. Utilizing the k-implies algorithm, the creators of reference [59] characterized an image of wheat crop ears in light of the average variety values in every super pixel zone. To build the accuracy of PLDA models in assessing potato quality, creators like Ref. [60] used the k-implies algorithm's unrivaled division.

Hierarchical Clustering

A popular technique in data mining called hierarchical clustering puts data points in a structure like a tree called a dendrogram. Subsequently, this technique clusters the data points by combining or dividing groups according to similarity or distance metrics. Finding inherent clusters in data and revealing hidden linkages is the main focus of hierarchical clustering methods. When it comes to crop monitoring using hyperspectral images, this strategy is invaluable. It simplifies the understanding and management of agricultural fields by illuminating links and patterns in spectral data. Incorporating hierarchical cluster analysis and hyperspectral imaging into crop health monitoring, crop type categorization, and early problem detection processes can greatly benefit researchers and agronomists. In the long run, this will boost crop yields [25,61].

WEKAXMeans (WXM)

The WEKAXMeans utility carries out the X-implies bunching procedure from the Weka machine learning software suite. This strategy automatically determines the optimal number of bunches utilizing the data. Since the objective is often to partition or sort separate regions in view of spectral marks without the prerequisite for predefined class names, this capacity is exceptionally helpful while doing hyperspectral imaging of crops. In addition to other things, by gathering pixels with comparable spectral marks, WEKAXMeans can assist with recognizing regions with solid plants, pushed plants, or various sorts of soil. For more on this, see [62].

Iterative Self-Organizing Data Analysis Technique (ISODATA)

Without assuming anything about the distribution of the data, the ISODATA algorithm is a method for grouping data based on their commonalities. This approach isn't parametric. A field's plant composition can be thoroughly studied using hyperspectral imaging, which records information over a broad spectrum of wavelengths. No pre-labeled information regarding the crops' condition is needed for this process [63,64].

Dimensionality Reduction

The goal of "dimensionality reduction," a well-liked technique in machine learning and data analysis, is to reduce the number of features in a dataset while preserving their significance. The "curse of dimensionality," which increases computational complexity and the likelihood of overfitting, can be brought on by datasets that are too multidimensional and so difficult to manage [65].

Principal Component Analysis (PCA)

A well-liked technique for analyzing multivariate data is principal component analysis (PCA), which entails selecting a smaller group of uncorrelated variables to represent a larger group of possibly associated variables. This method is frequently used to classify and diagnose diseases in a variety of cereal kinds, including rice [43,66].

Singular Value Decomposition (SVD)

The goal of this extremely sophisticated and adaptable instrument is to improve the hyperspectral picture processing and analysis for agricultural applications. It efficiently decreases the number of dimensions, minimizes noise, and recovers important information from the images by using Singular Value Decomposition (SVD). This novel method greatly enhances the ability to identify crop types, track crop health, and forecast critical agricultural attributes. This technology maximizes agricultural management by utilizing SVD, which raises crop productivity and quality [37,67].

Partial Least Squares Regression (PLSR)

The partial least squares regression (PLSR) technique aims to determine a link between a set of independent factors and a set of dependent variables [68]. The very dependable technique of PLSR is widely used in cereal crops like wheat to identify micronutrients such as Ca, Mg, Mo, and Zn.[12]. To accomplish this goal, researchers frequently combine hyperspectral pictures with PLSR modeling. When working with high-dimensional datasets exhibiting strong correlations among predictor variables, PLSR proves to be an invaluable tool for dimensionality reduction and multivariate regression analysis [69]. Within principal component regression (PLSR) lies principal component analysis (PCA). The output of PLSR is continuous, as opposed to the discrete output of linear regression [70].

3.3.3. Deep Learning(DL)

Deep learning is an advanced representation learning technique that makes use of an intricate artificial neural network with several layers of neurons. Although its use in agriculture is still relatively new, it is being used more and more for crop image classification, such as determining the tomato plants' hardness level [71, 72]. Furthermore, deep learning is used for applications such as weed detection in soybean fields [39]. This approach has shown exceptional categorization skills and surpasses traditional machine learning methods when it comes to extracting high-level abstract traits. The classification model's most sensitive wavelength range is the near-infrared (NIR) region, which is commonly used to evaluate plant health. A 5-layer convolutional neural network and over 400 pictures were utilized to attain a detection accuracy of 97.7 percent, according to a study published in the journal Remote Sensing [4].

Convolutional Neural Network (CNN)

This is a very powerful and adaptable tool for crop hyperspectral picture analysis. It is helpful in a variety of precision agriculture applications because it is excellent at handling non-linear relationships, automatically detecting characteristics, and storing spatial information. Its black box characteristics, data requirements, and computing costs must be carefully considered. Convolutional neural networks (CNNs), which examine local patterns and correlations between nearby pixels, are crucial for maintaining spatial data. Particularly for cereals like rice, this geographical context is essential for identifying spatially spread crop problems [74–77].

Recurrent Neural Network(RNNs)

Neural networks succeed at handling successive data, making them ideal for time-series analysis and other consecutive data sets like hyperspectral imaging in agriculture. Notwithstanding their standard relationship with tasks, for example, discourse acknowledgment and natural language handling, their usage in hyperspectral photography empowers the assessment of spatial and temporal examples in crop data gathered over many spectral bands [11].

Long Short-Term Memory(LSTM)

The LSTM model of recurrent neural networks (RNNs) is ideal for processes that involve both time-series information and sequential data. Hyperspectral imaging of crops is an extraordinary application for LSTM models because of their capacity to take utilization of the consecutive idea of the ghastly groups or changes in crop conditions over the long haul. By recognizing pressure factors like irritations, diseases, and supplement lacks, LSTM can assess hyperspectral information to decide the strength of crops. In addition, LSTM can recognize patterns in the planning of crop wellbeing markers, which permits it to give supportive alerts and bits of knowledge. To work on the exactness of crop creation gauges, LSTM examinations hyperspectral information over the long haul and records for changes in unearthly marks as the development season advances [3].

Stacked Denoising Autoencoder(SDAE)

A model made up of several sequentially organized stacked denoising autoencoders (SDAEs) is shown in the image. Each layer feeds its output into the one after it, allowing it to recognize more abstract representations of the input data. In hyperspectral data analysis, SDAEs have shown to be a very effective deep learning method for obtaining useful features, especially for applications involving crop health monitoring and categorization [32].

Residual Attention Convolutional Neural Networks(RACNNs)

A developing number of agricultural applications are making utilization of them, including weed ID, crop disease detection, and yield expectation. A neural network design with convolutional layers, wavelet analysis, and attention methods accomplishes this. Especially for applications including image analysis and sign handling, this plan intends to extract important elements from data. Utilizing wavelet transforms, attention systems, and convolutional processes, this engineering can break down and interaction data quickly for agricultural applications. [78,79].

Wavelet transforms and attention mechanisms are used in (WACNNs)

In WACNNs, attention components and wavelet transforms are utilized to improve highlight extraction and lift model performance. Concentrates by have demonstrated the way that involving WACNNs in agriculture can be especially useful for tasks like plant classification, soil dampness appraisal, and crop disease ID [80,81].

One-Dimensional Convolutional Neural Network(ID CNN)

This particular neural network architecture is intended to handle text or time series data that are organized sequentially in a single dimension. This architecture is tailored to handle one-dimensional input, in contrast to traditional convolutional neural networks (CNNs), which are generally used for two-dimensional data, such as photographs.

In Figure 5, you can see a comprehensive overview of the machine learning algorithms that the authors employed to classify agricultural products and identify diseases in them. Deep learning and conventional machine learning are the two main groups into which the classification methods are split in this review article. Rather than conventional ML strategies that depend on pre-handling, deep learning procedures can naturally separate the most important classification qualities. Figure 5 shows the most famous ML and DL calculations utilized for disease detection in crops and for arranging different agrarian information focuses, for example, supplement levels, crop types, development, chlorophyll records, weed detection, nitrogen levels, and natural product development files.

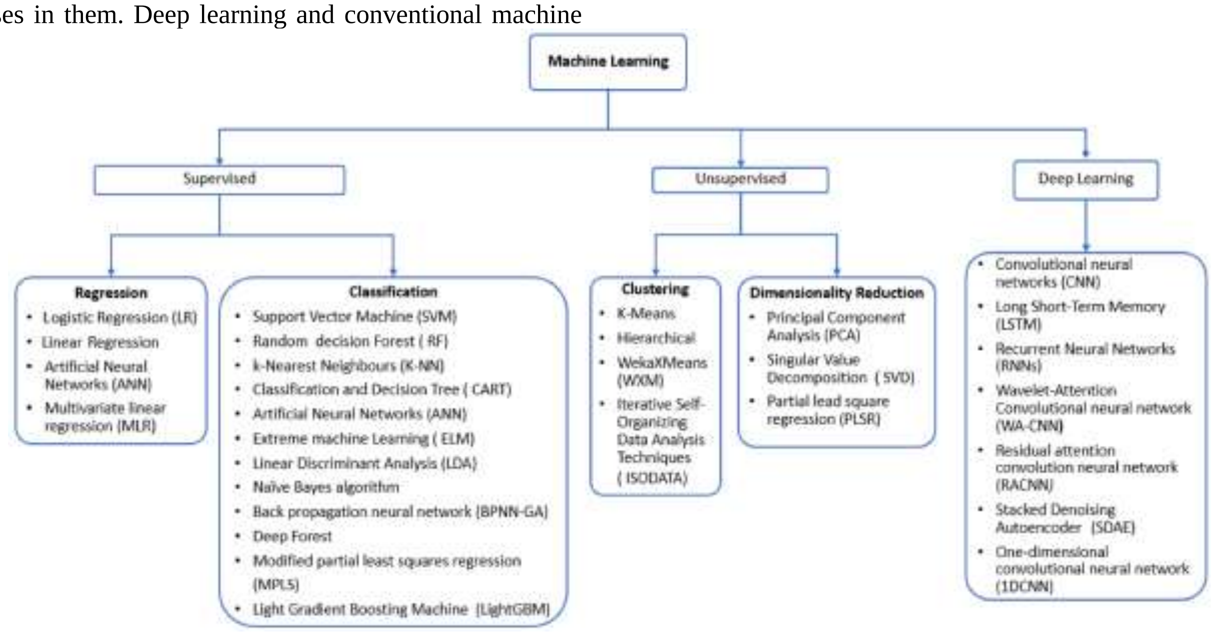


Figure 5 displays the machine learning algorithms that are utilized in crops, as depicted in the authors' source material.

One powerful tool for material identification and classification is hyperspectral imaging, which gathers data over a broad range of spectral bands. However, in order to glean useful insights from such intricate datasets, specific methods are required. There are a number of machine learning models that work well with hyperspectral image processing, including support vector machines (SVMs), recurrent neural networks (RNNs), deep forests, k-nearest neighbors (k-NNs), extreme learning machines (ELMs), and backpropagation neural networks (BPNNs). When it comes to hyperspectral data processing, every model has its own set of pros and cons. It is vital to choose the appropriate methodologies based on requirements and limits, and the optimum model to utilize will vary depending on the application. In Table 2, you can see a summary of a few of the most common machine learning approaches to hyperspectral image processing.

Table 2 shows the machine learning algorithms' performance evaluation (according to the authors' source).

Model	Performance	Advantages	Drawbacks
SVMs	Support vector machines (SVMs) perform exceptionally well in high-dimensional situations for the classification of hyperspectral imagery.	Machine learning models, particularly those based on decision trees, are less likely to overfit when dealing with scenarios that have limited amounts of training data.	The process of selecting parameters, which involves determining the regularization parameter and kernel type, is computationally complex and demands considerable thought.

Model	Performance	Advantages	Drawbacks
CNNs	CNNs are particularly adept at handling image processing tasks, particularly in the domain of hyperspectral imaging, by taking advantage of spatial and spectral relationships.	Feature learning enables AI models to autonomously extract and learn hierarchical features from data, integrating spatial and spectral information while tolerating noise. This enhances classification accuracy, scalability, and flexibility in network design, and facilitates transfer learning.	Data Requirements: The effective training of CNNs necessitates a substantial amount of labeled data. Computational Resources: Training CNNs is a resource-intensive process that often necessitates the use of GPUs.
BPNNs	BPNNs offer a flexible and effective way to analyze hyperspectral imaging data, which may be applied to various applications such as feature extraction, regression, classification, and dimensionality reduction.	Bidirectional Probabilistic Neural Networks (BPNNs) are applicable in hyperspectral imaging classification tasks, with the objective of assigning each pixel to predefined classes. BPNNs are trained on labeled hyperspectral data and can recognize the spectral fingerprints of different materials or types of land cover. Transfer Learning can be utilized with BPNNs that have been trained on substantial datasets, such as natural images, by adapting the pre-trained models to hyperspectral data to fine-tune them for hyperspectral imaging tasks.	Optimizing BPNNs requires fine-tuning of hyperparameters such as layer count, neuronal density, learning rate, and activation functions. Nevertheless, it is not always easy to determine the best combination; in fact, it frequently requires a great deal of trial and error.
RFs	RFs are successful in handling both classification and regression tasks in hyperspectral data processing by utilizing an ensemble of decision trees.	Nonlinearity Management: These models possess the ability to capture intricate connections. Feature Significance: These models offer insights into the significance of various spectral bands. Scalability: They are adept at handling extensive datasets.	Interpretability is a concern with these models as they are not as easy to understand as simpler ones. Overfitting might be an issue if not properly validated, but it is generally less of a problem compared to other methods.
DF	The potential of deep forests for analyzing hyperspectral images is significant due to their proficiency in managing intricate, multidimensional data.	Managing high-dimensional data, specifically hyperspectral images that contain numerous spectral bands, can be challenging. However, deep forests overcome this issue by employing hierarchical feature learning, which creates hierarchical representations of spectral information. Deep forests provide durability in the face of noise in hyperspectral pictures due to	Deep forests, especially for big hyperspectral imaging datasets, can result in lengthier training durations and higher processing demands due to their multiple decision tree levels, which add to the model's complexity. Understanding the prediction principles of deep forests can be difficult because, while they offer hierarchical data representations, they are more complicated and challenging to

Model	Performance	Advantages	Drawbacks
		atmospheric conditions or sensor constraints, which makes them suitable for real-world scenarios where data quality may vary.	interpret than simpler models like decision trees. This complexity can be a disadvantage in applications that require high interpretability.
RNNs and LSTM	The optimal networks for sequential data are RNNs and LSTM networks, particularly for hyperspectral data that needs to be flexible in terms of spectral dimension.	Since of their memory capacity, LSTM networks are useful for learning patterns across the spectral sequence since they can capture dependencies across spectral bands.	Training can be challenging because of factors like vanishing gradients, which can make them difficult to train. Additionally, they require a high amount of computational resources for both training and inference.
k-NNs	A popular non-parametric machine learning technique with a variety of uses, including hyperspectral image classification, is k-nearest neighbors, or k-NNs.	k-NNs are known for their uncomplicated and approachable methodology. They use the label that is most frequently used by a sample's k-nearest neighbors to classify it. Since k-NN is a lazy learning algorithm, it can be implemented more quickly and easily without the need for a separate training phase, in contrast to some other models that require lengthy training.	The distances between each training sample and the test sample must be calculated by the algorithm. This may incur significant processing costs, particularly when working with the big datasets used in hyperspectral imaging. Moreover, storing every training sample for distant computing could need a significant amount of memory.
ELMs	Hyperspectral image analysis can benefit greatly from the use of extremely learning machines (ELMs), as they offer a number of advantages over traditional techniques.	ELMs offer several benefits, especially in terms of their ability to quickly train and process high-dimensional and computationally complex hyperspectral data. They can also perform well on unseen data, which makes them appropriate for real-world applications where adaptation to variances not present in the training data is necessary. Reduced Risk of Overfitting: The procedure of randomly assigning weights in ELMs reduces the likelihood of overfitting, a prevalent problem in high-dimensional hyperspectral image analysis. The accuracy of Extreme Learning Machines (ELMs) can rival that of other methods, such as Support Vector Machines (SVMs), with substantially quicker training times.	Vulnerability to Initialization: Extreme Learning Machines (ELMs) are vulnerable to the effects of initialization due to their reliance on randomly generated input-to-hidden layer weights. Despite this randomness accelerating the training process, it may cause inconsistencies in the model's performance, making it essential to carefully adjust hyperparameters.

Model	Performance	Advantages	Drawbacks
PLSR	Regression and dimensionality reduction are two common uses for PLSR. However, it can also be used to achieve classification goals, especially in the field of hyperspectral imaging.	Commonly used in hyperspectral data reduction efforts, principal component analysis (PCA) preserves important spectral details while reducing data dimensionality. One advantage of principal component analysis (PCA) is that it produces very simple and easy-to-understand models, in contrast to more complex machine learning methods like deep learning. Principal component analysis (PCA) is used to extract principle components, which are linear combinations of the original spectral bands. They can be used by researchers to gain a better understanding of the ways in which various spectral parameters influence the target variable's prediction.	The foundation of PLSR is the idea that there is a linear relationship between the target variable and the spectral data. Nevertheless, PLSR might not adequately represent a highly nonlinear underlying relationship, which could lead to less-than-ideal predictions. In addition, overfitting can happen utilizing PLSR, especially in the event that the quantity of idle factors or parts isn't selected cautiously. Unfortunate speculation execution on obscure information is brought about by overfitting, which happens when the model distinguishes clamor in the preparation information as opposed to the fundamental sign. Notwithstanding this, PLSR gives models that are more conceivable than those of some other machine learning draws near, such deep learning models. However, it very well may be hard to decipher stowed away factor commitments in high-layered datasets.
Naïve Bayes	An approach that is frequently used to solve classification problems is the Naïve Bayes algorithm.	Naive Bayes is an extremely efficient method that works well with hyperspectral data since it can easily handle a lot of spectral bands. For quick analysis and prototyping, its simplicity also makes it easy to understand and apply. Naive Bayes is a good choice for hyperspectral imaging since it can also handle high-dimensional data without issue. By estimating class probabilities, this approach also provides probabilistic forecasts, which are useful for making decisions and determining the accuracy of predictions. Naive Bayes has many benefits, yet there are situations when it shouldn't be utilized because it doesn't always produce reliable results.	The naive assumption that each feature is independent is often made in hyperspectral data analysis. Due to the strong correlation across spectral bands, this assumption might not be true, which would result in less than ideal performance when features are dependant. When feature dependencies are high, naive Bayes models may also find it difficult to capture complicated linkages and interactions between spectral bands, which will lead to lower performance than more sophisticated models.
CART	Decision trees are a well-liked supervised learning method that	A highly interpretable model type that works well for interpreting hyperspectral imaging	Overfitting of decision trees occurs when their depth is not sufficiently regulated. When evaluating

Model	Performance	Advantages	Drawbacks
	has several uses in the fields of classification and regression.	data is the decision tree. Their capacity to give experiences into direction is worked with by their various leveled structure portrayal. Likewise, choice trees can order the most instructive unearthly groups, which assists with include determination and dimensionality decrease, and hence proficiently handles high-dimensional data. These high-dimensional data sets include things like hyperspectral images.	unknown data, a deeply rooted tree may absorb random fluctuations from the training set, resulting in inadequate generalization. Because decision trees have a high degree of variability, slight variations in the training set can result in various trees being produced for the same dataset. Decision trees may be less trustworthy as a result of their sensitivity to changes in the data.

Table 3 provides an extensive overview of the important research on the use of hyperspectral imaging and machine learning to identify illnesses in agricultural crops, including oilseeds and cereals. While many articles focus on cereal crops, such rice and wheat, it is difficult to define a particular wavelength range for disease detection in these crops. For example, the wheat disease Fusarium head blight (FHB) lacks a distinct spectral signature; yet, alterations in the plant and afflicted tissues can produce recognizable patterns in hyperspectral photos. However, some research does use particular wavelength ranges [59].

Table 3 provides a concise overview of the diagnostic techniques employed to detect diseases in cereals and oilseeds, as described by the authors.

Ref	Crops	Disease	Bandwidths (nm)	Algorithms
[83]	Wheat	Frost and drought stress	(280 to 500)	PLSR
[42]	Wheat	Fusarium head blight	(400 to 2500)	SVM
[59]	Wheat	Fusarium head blight	(600 to 1100)	SVM, ANN and LR
[59]	Wheat	Fusarium head blight	(400 to 750)	CNN
[84]	Wheat	Fusarium head blight	(450 to 950)	RF algorithm
[85]	Wheat	Fusarium head blight	(1100, 1197, 1308, 1394)	PLSDA
[86]	Wheat	Fusarium head blight	(941, 876, 732)	CARS
[79]	Wheat	Fusarium head blight	Variable	RACNN
[87]	Wheat	Yellow rust	(400 to 1000)	SVM
[88]	Wheat	Rice weevil	(866.4 to 1701)	LDA, SVM and PCA
[89]	Rice	Insect damage	Variable	PCA

Ref	Crops	Disease	Bandwidths (nm)	Algorithms
[90]	Rice	Sheath blight	(726 to 930)	Support vector machine (SVM)
[91]	Rice	Nitrogen deficiency	(550 to 690)	LTSM and MLR
[92]	Rice	Rice false smut	(874.41 to 1734.91)	PCA
[93]	Corn	GR	(400 to 900)	k-NN), RF and SVM
[94]	Corn	Cold damage	(395 to 885)	CNN
[95]	Corn	Aflatoxin contamination	Variable	PLSDA

Detection of plant diseases in legumes has been extensively studied; studies on drought stress in chickpea, for instance, have shown a range of responses, as outlined in Table 4 [96]. When evaluating hyperspectral data, researchers typically focus on particular spectral signatures and areas of interest to determine drought stress in plants. This is due to the fact that drought stress modifies how plants absorb and reflect certain wavelengths of light.

Using near-infrared (NIR) wavelengths, scientists have studied diseases such as basal stem rot, prevalent in oil palm and other crops, as reported in [97]. Diseases such as late blight in potatoes or bacterial wilt in peanuts can be identified in a similar way, with the sensitivity of NIR wavelengths changing significantly throughout the disease's progression [99].

Wavelength ranges—400–1000 nm for the first author and 900–1700 nm for the second—are the primary determinants of citrus fruit quality. The second author used optimal clustering for spatial data reduction to generate quantitative maps of certain quality attributes in fresh oranges. Evaluation of citrus fruits, such as oranges, is the primary focus of these writers [100,101].

Table 4 presents an overview of methodologies employed in detecting diseases in other crops, as reported by the authors.

Reference	Crops	Disease	Bandwidths (nm)	Algorithms
[102]	Potato	Alternaria solani	(550 to 750)	PLS-DA and SVMs
[98]	Potato	Late blight	(450 to 950)	3D-CNN
[60]	Potato	Bruised	(450 to 1000)	PCA
[103]	Strawberry	Leaves	(359 to 1020)	ELM, k-NN and SVM
[104]	Leek	White tip	(800 to 870)	SVM
[64]	Tea	Anthracnose	(450 to 950)	ISODATAs
[105]	Chickpea	Ascochyta blight	(666 to 840)	DA and SVM
[99]	Peanut	Bacterial wilt	(730 to 900)	ANOVA and MLP
[106]	Cucumber	Powdery mildew	(400 to 900)	SVM
[107]	Tobacco	Spotted wilt virus	(400 to 1000)	RT and CART
[108]	Citrus	Fungal infection	(325 to 1100)	PCA

Reference	Crops	Disease	Bandwidths (nm)	Algorithms
[109]	Citrus	Diagnosis of citrus Hangdogging	(450 to 1023)	LS-SVM
[66]	Green-peel citrus	Thrips defect	(523, 587, 700, 768)	PCA
[110]	Tomato	Firmness estimation	(400 to 1000)	1D convolutional ResNet
[110]	Tomato	Early blight	(380 to 1023)	ELM
[35]	Olive	Verticillium wilt	(650 to 720 680 to 800 8000 to 15000)	SVM and LDA
[111]	Grape	Leafroll	(690, 715, 731, 1409, 1425, 1582)	LS-SVM
[44]	Apple	Marssonina blotch	(800 to 1100)	OSP
[45]	Apple	Bruising	(400 to 1000) 1000 to 2500	LDA and SVM
[46]	Apple	Bitter pit detection	(550 to 1700)	PLSR
[57]	Beet	Seed Ggrmination	(1000 to 2500)	RF, SVM, and LightGBM

Table 5 provides a concise summary of significant research focusing on the categorization of agricultural crops such as cereals and oilseeds, including studies that classify the various types of crops [80,112], as well as those that specifically identify crop varieties like wheat or rice [75,76].

In research and evaluation of nitrogen content, works like ref. [113] have examined the deficiency of nitrogen in rice crops. Furthermore, hyperspectral images are employed to assess chlorophyll content, as demonstrated in another study [33].

Machine learning techniques are used in crops like corn to estimate biomass content [51] and determine soil moisture levels [114]. Similarly, research has been conducted on identifying early mosaic virus in soybeans [115,116].

Table 5 Presents a concise overview of the various techniques utilized for multiple tasks related to cereals and oilseeds, as reported by the authors.

Ref	Crops	Disease	Bandwidths (nm)	Algorithms
[28]	Various	Classification	(400 to 2500)	RF, SVM, NB and WXM
[80]	Various	Classification	(400 to1000)	WA-CNN
[112]	Various	Classification	(400 to 2500)	CNN
[50]	Wheat	Wheat and weed discrimination	(400 to 1000)	PLS-DA and SVM
[40]	Wheat	Kernel presence	(990 to 1200)	PLS-DA
[12]	Wheat	Predicting micronutrients	(375 to 1000)	PLSR

Ref	Crops	Disease	Bandwidths (nm)	Algorithms
[30]	Wheat	Nitrogen and water status	(400 to 850 95 to 1750)	ANOVA
[117]	Rice	Rice variety	(400 to 1000)	PCAN
[76]	Rice	Rice varieties	(400 to 950)	CNN
[118]	Rice	Rice vigor	(873 to 1374)	CNN
[119]	Rice	Chlorophyll content estimation	(450 to 950)	PLSR, SVM and ANN
[75]	Rice	Rice classification	(450 to 950)	CNN
[113]	Rice	Nitrogen stress	Variable	CNN
[76]	Rice	Rice classification	(320 to 1100)	CNN
[47]	Rice	Nitrogen content	Variable	PLSR, SVM and ANN
[120]	Rice	Rice flour intensity	(500 to 900)	SMLRs and RF
[121]	Rice	Rice seeds vigor	(874.41 to 1734.91)	DCNN and PCA
[91]	Rice	Nitrogen concentration	Variable	MLR and LSTM
[122]	Corn	Corn seedling recognition	(400 to 1000)	CNN
[51]	Maize	Biomass estimating	(450 to 950)	RF
[53]	Maize seed	Moisture content	(930 to 2548)	PLSR and LS-SVM
[123]	Maize	Hardness for maize	(399.75 to 1005.8)	PLSR
[114]	Corn Maize	Moisture detection	(968.05 to 2575.05)	CNN and LSTM
[112]	Corn Soybean Wheat Alfalfa	NDVI and MNDWI	(400 to 2500)	CNN
[124]	Maize	Crop traits in maize	Variable	RF, PLS, SPA and CARS
[125]	Maize	Water and nitrogen status	(325 to 1075)	ANOVA
[126]	Barley	Nutrient concentration	(1000 to 2500)	PLS
[127]	Barley	Phenology of barley	(395 to 793)	SVMs
[128]	Barley	Phenolic compounds	(950 to 1760)	PCA) and SVMs
[129]	Sorghum	Sorghum purity	(935 to 1720)	PCA
[115]	Soybean	Soybean crop variables	(350 to 2500)	PLS
[130]	Soybean	soybean seed varieties Identification	(874 to 1734)	CNNs

Ref	Crops	Disease	Bandwidths (nm)	Algorithms
[131]	Oil Palm	Weight and ripeness	(560, 680, 740 and 910)	MLR
[132]	Oil Palm	Fruit grading	(750 to 910)	ANN
[133]	Peanut	Peanut maturity	(400 to 1000)	LMM

Studies have looked into a range of approaches for different goals, as Table 6 shows. Certain research works concentrate on classification tasks, including identifying between several aromatic coffee kinds [134, 135]. Citrus fruits, blueberries, and grapes are among the fruits whose maturity is evaluated by other studies using machine learning algorithms [108,136,137]. Machine learning algorithms are used in the case of citrus crops to detect deterioration early on, particularly in fruits like oranges, which enables an early estimate of their ripeness. Producers might use this information to save costs by planning their crops ahead of time and influencing future market pricing [138].

Table 6 presents a summary of techniques used for various tasks related to other crops, as reported by the authors.

Reference	Crops	Disease	Bandwidths (nm)	Algorithms
[139]	Lettuces	Phenotypes	(400 to1000)	RNNs and LSTM
[135]	Coffee	Coffee bean varieties	(973 to 1630)	WT and SVM
[135]	Coffee	Coffee bean varieties	(973 to 1629)	MA, WT, SVM, and EMD
[134]	Coffee	Consistency	(408 to 1008)	PLS
[140]	Weed	Indicator of competition for water	Variable	ANOVA
[136]	Blueberry	Growth stages	Variable	SAM and MLR
[141]	Blueberry	Internal quality	(400 to 100)	PLS
[142]	Strawberry	Strawberry ripeness	(503, 528, 604, 715)	SVM and CNN
[143]	Apple	Bruise region	(675 to 960)	PCA and RF
[31]	Apple	Bruise damage	(930 to 2500)	k-NN, LDA and SVM
[55]	Grape	Predicting sugar, total flavonoid, and total anthocyanin contents	(411 to 1000)	MLR and PLS
[144]	Grape	Pigment composition	(400 to 1000)	RTM
[137]	Grape	Maturity of grapes	(900 to 1700)	MPLS
[145]	Banana	Banana grading	(1069.21)	CNN and MLP
[146]	Potato	Water content	(1400 to 1450)	PLS and CARS

Reference	Crops	Disease	Bandwidths (nm)	Algorithms
[101]	Orange	Orange quality	(900 to 1700)	ANN
[147]	Orange	Pectin content	(900 to 2500)	PCA and PLSR
[138]	Orange	Distinction between green oranges and leaves	(100 to 2500)	ANOVA
[108]	Citrus	Early decay	(325 to 1100)	PCA
[148]	Tea	Green tea quality	(379 to 1040)	k-NN and SVM
[149]	Peanut	Peanut maturity	(545, 660, 790)	PLS

IV. DISCUSSION

The major reason for this audit paper is to analyze the advantages and uses of HSI in precision agriculture, explicitly comparable to the ID and classification of crop diseases. Highlighting the job of artificial intelligence (artificial intelligence) in improving crop wellbeing, guaranteeing food security, and creating supportable agricultural practices, it draws attention to the machine learning methods used to distinguish and arrange crop issues. The motivation behind this survey is to consolidate existing knowledge and accomplishments in the field by zeroing in on these areas and offering an exhaustive grasp of how HSI and machine learning could upset agricultural crop disease recognizable proof and control. The documentary review's findings suggest that hyperspectral imaging and genetics together have a lot of potential to advance agricultural applications and research. While genomics sheds light on the genetic composition and characteristics of crops, hyperspectral imaging collects fine-grained spectral data that represents the physiological and biochemical condition of plants [150]. Combining these technologies allows researchers to identify features associated with stress tolerance, nutrient utilization efficiency, and disease resistance by connecting certain genetic markers with spectral signatures. This can make it easier to create crop types with desired features through precision breeding techniques. Hyperspectral data, for instance, can be used to non-invasively track the expression of particular genes in various environmental settings, which can speed up breeding program selection and increase crop productivity and resilience.

Modern imaging techniques, such hyperspectral imaging, make it possible to track plant health and stress reactions in real time under a variety of climatic circumstances. Through the integration of this data with climate models, these technologies facilitate the prediction of crop responses to future climate scenarios, hence assisting in the development of agricultural practices that are resilient to climate change. Furthermore, minor alterations in plant physiology that occur before obvious signs of stress brought on by drought, extremely high or low temperatures, or other climatic conditions can be identified using hyperspectral imaging. By using this data, early warning systems for farmers can be created, allowing them to take prompt action to lessen the consequences of unfavorable weather conditions.

Global agricultural practices and the advancement of sustainable agriculture are significantly impacted by the application of cutting-edge technologies in agriculture, particularly through precision farming [151]. Precision agriculture optimizes the use of resources like water, fertilizer, and pesticides while fostering sustainability and productivity through the use of data analytics, satellite imaging, and a range of sensors. Furthermore, precision agriculture enables the early detection of pest infestations and crop diseases through continuous monitoring and sophisticated data analysis. By identifying minute changes in crop health that could be signs of an impending disease, technologies such as remote sensing and AI-driven analytics enable farmers to take preventive action before serious harm is done.

Unmanned aerial vehicles are one type of hyperspectral platform (UAVs). UAVs have several advantages over airplanes, including as quicker access to target locations, lower operating costs, and excellent spatial resolution for smaller areas. They are able to obtain detailed spatial information from low-altitude high-resolution image capturing. However, UAVs are subject to regulatory restrictions, have a limited flight time and range, and are weather-dependent.

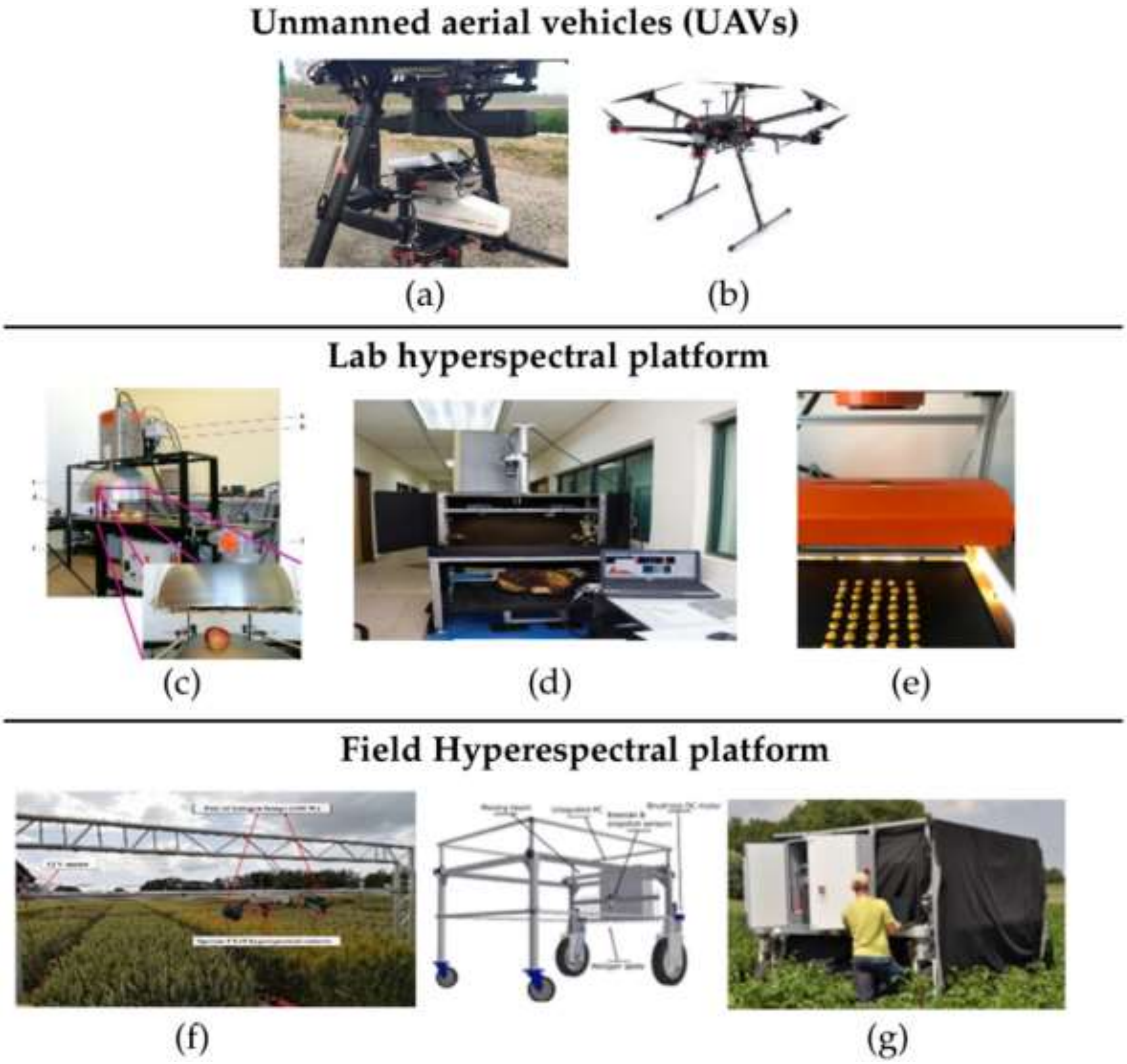


Figure 6 The following instances show how hyperspectral platforms can be used in diverse contexts for practical purposes. (a) depicts an airplane with the Cubert S185 hyperspectral camera installed, whereas (b) uses the DJI M600 [37,152] for the same purpose. In (c), the setup for hyperspectral measurements consists of a visible and near-infrared (VNIR) spectral camera, a shortwave infrared (SWIR) spectral camera, a diffuser with halogen lamps, a belt conveyor with photocells to control movement direction, a system to regulate the belt conveyor speed, and a stepper motor. (d) features the Specim, Finland-based SisuCHEMA hyperspectral imaging system, while (e) showcases the Imperx IPX-2 M 30 spectral camera [45,114,132]. (f) displays the FX 10 system made by Specim in Finland, and (g) shows the Imspector V9 spectrograph made by Specim, which is a (prism-grating-prism) system

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Lab hyperspectral platform: Advantages: Field-based sensors can be used by researchers to collect high-resolution data, allowing for the accurate examination of small features or samples. Non-destructive in situ measurements are provided by these sensors, which are perfect for inspecting delicate materials or monitoring items in their native environments. Furthermore, field-based sensors are lightweight and flexible, making it possible for researchers to effectively gather data in a variety of environments. Researchers can reduce the impact of outside elements like wind and sunshine fluctuations by setting up the platform in a controlled space, either within or beneath a movable tent.

Drawbacks: Field-based systems face constraints in data collection due to their capacity to gather information over a narrow area at any given moment. To analyze larger areas, multiple datasets must be collected and integrated, which can be a protracted process. The process of collecting data can be arduous and require significant effort, especially when considering the size and intricacy of the target region.

Field hyperspectral platform: Advantages: Field platforms exhibit a notable edge over hyperspectral sensors mounted on satellites or aircraft, as they attain exceptionally high spatial resolutions. Unlike these sensors, field platforms capture data at much finer scales, enabling in-depth examination of minute features or specimens. For example, field platforms can be utilized to scrutinize individual leaves on a plant or fissures in a rock. These portable and versatile systems are designed for ease of transport and deployment in various field conditions.

Drawbacks: These systems have a high resolution, but their coverage area is constrained. Although the amount of space they may study at once is restricted, studying large fields might need compiling and combining several datasets, which can take a while. Furthermore, field measurements may be impacted by environmental variables like shifting sunshine or high winds, which highlights the significance of meticulous planning and consideration of meteorological conditions.

The agreement between investigations using hyperspectral cameras and artificial intelligence techniques is shown in Figure 7. According to the findings, hyperspectral image usage in agriculture increased dramatically between 2020 and 2023, especially for crops like wheat, soybeans, corn, and rice as well as fruits like oranges and apples. This expansion is important for weed detection, crop type classification, nutrient level classification, and crop disease detection. Which method is the most accurate or appropriate has not yet been established. Nonetheless, research has demonstrated that the machine learning and deep learning methods most commonly applied in cereals, oilseeds, vegetables, and fruits are the models SVMs, RFs, PLS, LSTM, LMMs, CNNs, RNNs, and ANNs. The choice of wavelengths throughout a broad spectrum of the electromagnetic spectrum depends on the goals of specific research projects. The selection of appropriate wavelengths is influenced by the specific disease being studied as well as the spectral characteristics of the plants and pathogens involved in the investigation. Additionally, combining various spectral band analysis techniques can increase the precision of crop monitoring and disease diagnosis. The enormous amount of data gathered from hyperspectral photos is processed using deep learning, an alternative that has been embraced by numerous writers. The agreement between research projects using hyperspectral cameras and artificial intelligence techniques is shown by the graph in the above image. According to the findings, hyperspectral image usage in agriculture increased dramatically between 2020 and 2023, especially for crops like wheat, soybeans, corn, and rice as well as fruits like oranges and apples. This expansion is important for weed detection, crop type classification, nutrient level classification, and crop disease detection. Which method is the most accurate or appropriate has not yet been established. Nevertheless, research has demonstrated that the most common machine learning and deep learning approaches utilized in crops such as cereals, oilseeds, vegetables, and fruits include SVMs, RFs, PLS, LSTM, LMMs, CNNs, RNNs, and ANNs. The goals of certain investigations dictate the selection of wavelengths from a vast array of electromagnetic spectrum bands. The specific illness being studied, together with the spectral characteristics of the plants and viruses involved, dictate the wavelengths that are considered suitable. For more precise crop monitoring and disease identification, it is recommended to combine multiple spectral band analysis approaches. One solution that has gained support from many authors is deep learning, a technique for handling the enormous amount of data obtained from hyperspectral photos.

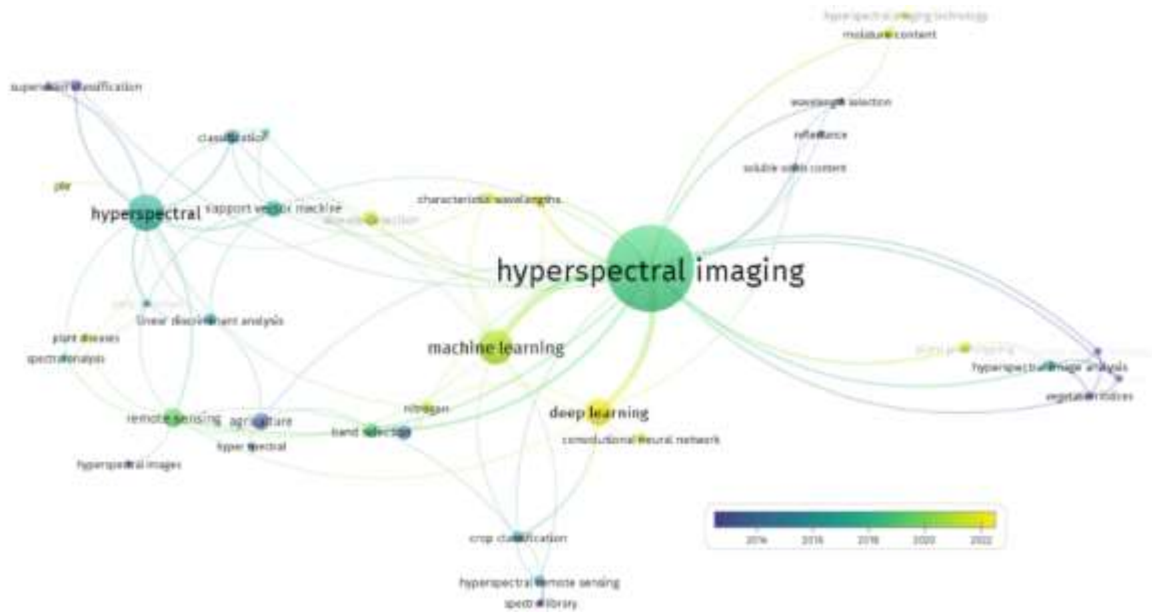

Figure 7. A scientific network map has been created to illustrate the most commonly used keywords in the papers reviewed. The lines on the map represent the strength of co-occurrence links among the terms (Source: Authors).

When it comes to comparing hyperspectral imaging to RGB imaging, it is important to note that both have their own unique advantages in the field of agriculture [153,154,155]. Although hyperspectral imaging has several benefits over traditional RGB imaging, these advantages are best summarized in Table 7.

Table 7. Summary of the benefits of employing hyperspectral images instead of RGB images in agriculture, as detailed by the authors.

Advantage	**Hyperspectral Imaging**	**RGB Imaging**
Spectral Resolution	The device captures a vast range of light, covering numerous closely spaced wavelengths from the visible to the near-infrared spectrum and beyond, which enables the identification of minute variations in the characteristics of plants.	The sentence you provided captures light in three distinct color bands (RGB), which limits the amount of information that can be obtained about vegetation.
Plant Health Analysis Detailed	Can pinpoint particular wavelengths that signal plant health problems, like nutrient shortages, water scarcity, illness, or infestations, frequently before they are perceptible to the naked eye..	Offers minimal information, primarily relying on visible color changes that typically manifest in the later stages of plant health issues.
Enhanced Crop Monitoring	Enhances agricultural precision through precise application of fertilizers and pesticides, while simultaneously promoting the growth and development of plants, thus enabling the use of precision agriculture techniques.	Paperpal co-pilot can offer fundamental knowledge about the different stages of plant growth and overall health, but it is unable to deliver precise spectral data required for meticulous monitoring.
Crop and Soil Differentiation	Identifies soil types, crop varieties, and specific crop species by examining their unique spectral patterns.	Frequently has difficulty distinguishing between visually similar soils and crops, as its spectral data is limited.
Yield Prediction	Increases the accuracy of agricultural yield predictions by examining the spectral properties	Provides the less precise, broader estimates based on visible growth.

Advantage	Hyperspectral Imaging	RGB Imaging
	associated with plant biomass, chlorophyll concentrations, and other growth-related factors.	
Environmental Monitoring	By analyzing specific spectral characteristics, this study aims to investigate the impact of environmental stressors including pollution, soil contamination, and water quality issues.	The capacity to recognize intricate environmental circumstances is restricted.

Table 7. Summary of benefits of employing hyperspectral images over RGB images in agriculture, as outlined by the authors.

V. CONCLUSION

According to this study, hyperspectral imaging has a number of advantages, one of which is the capacity to monitor crops non-invasively—that is, without causing any harm or physical touch. Conventional imaging techniques are unable to yield the exact and comprehensive information regarding crop conditions that this technology offers. Additionally, it increases productivity through the facilitation of precision agriculture methods and the optimization of resource consumption, which results in lower costs and higher crop yields.

Hyperspectral imaging technology has its advantages and disadvantages. On one hand, it can provide detailed and valuable information about crop health and soil properties, which can lead to more informed decision-making. On the other hand, the high cost of sensor equipment and data processing infrastructure can pose a significant barrier to its widespread adoption. Furthermore, for effective interpretation, the enormous volumes of data produced by this technology call for sophisticated knowledge and powerful computers. To guarantee correct results, additional operational difficulties including weather, sensor calibration, and data collection procedures must also be properly handled. When paired with artificial intelligence, hyperspectral imaging in agriculture appears to have a bright future despite these obstacles. It is anticipated that developments in sensor and data analytics technologies will increase the efficiency and accessibility of this technology, revolutionizing agricultural methods and promoting sustainable farming in the process. There is a great chance that technology will transform the agriculture sector as costs come down and data processing becomes more effective.

Nomenclature and Abbreviations

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

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