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A systematic review on hyperspectral imaging technology with a machine and deep learning methodology for agricultural applications

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ABSTRACT

The globe's population is increasing day by day, which causes the severe problem of organic food for everyone. Farmers are becoming progressively conscious of the need to control numerous essential factors such as crop health, water or fertilizer use, and harmful diseases in the field. However, it is challenging to monitor agricultural activities. Therefore, precision agriculture is an important decision support system for food production and decision-making. Several methods and approaches have been used to support precision agricultural practices. The present study performs a systematic literature review on hyperspectral imaging technology and the most advanced deep learning and machine learning algorithm used in agriculture applications to extract and synthesize the significant datasets and algorithms. We reviewed legal studies carefully, highlighted hyperspectral datasets, focused on the most methods used for hyperspectral applications in agricultural sectors, and gained insight into the critical problems and challenges in the hyperspectral data processing. According to our study, it has been found that the Hyperion hyperspectral, Landsat-8, and Sentinel 2 multispectral datasets were mainly used for agricultural applications. The most applied machine learning method was support vector machine and random forest. In addition, the deep learning-based Convolutional Neural Networks (CNN) model is mainly used for crop classification due to its high performance with hyperspectral datasets. The present review will be helpful to the new researchers working in the field of hyperspectral remote sensing for agricultural applications with a machine and deep learning methods.

1. Introduction

The COVID-19 pandemic's effects have shaken the global and national food systems. The pandemic can immediately affect the demand channels and food supply, which suggests a fall in food resources and increased food prices. The shutdown and lockdown would cause tremendous agony for the poor and informal sector workers. Almost every step of the manufacturing process will be disrupted due to this. However, their significant reliance on farming would endanger their lives and lead to malnutrition and starvation. Furthermore, decreases in earnings and payments reduce people's ability to buy food and pay farmers for productivity. This has halted the entire economy (Workie et al., 2020).

In this circumstance, creating a sustainable agricultural system will always assist people in becoming self-sufficient by allowing them to farm crops for their families more organically and sustainably. In addition to these benefits, sustainable farming development generates potential jobs, ensuring food security while also helping to alleviate poverty. As a result, sustainable agriculture development is a critical strategy to address, as it creates a self-sufficient economy during pandemics like COVID-19 (Sridhar et al., 2022).

However, precision agriculture seeks to strengthen farmers' profitability and harvest yields while lowering the adverse effects of agriculture on the environment caused by excessive pesticide use. Predictive agriculture is a type of farming that collects and analyses data from plots to manage and optimize crop production. Precision agriculture is accomplished through the use of analytical software and technical equipment (Pascucci et al., 2021). Soil testing, weather pattern analysis, crop analysis, and plot measurement are all done with precision using sensor-equipped devices positioned throughout the fields (Vibhute and Gawali, 2013). Precision agriculture is one of the methods for gathering on-site data to aid decision-making and, as a result, to effectively

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manage crop yield and quality (Leonard, 2016). Precision agriculture has established itself as a critical instrument in agricultural management for forecasting production, monitoring plant stress, and optimizing fertilization, irrigation, and soil sowing operations for more sustainable farming methods and increased output for farmers (Awad, 2019; Vibhute and Gawali, 2013). Soil is the component that allows fertilizers and water to be absorbed through the roots, which are two essential elements for crop development (Navarro et al., 2016; Segarra et al., 2020).

Recently, remote sensing records have been used to determine crop production predictions, crop stress recognition, and yield modeling (Bishop, 2006). It is critical to detect and recognize plant disease (Ferentinos, 2018; Garcia and Barbedo, 2013) and prepare to ensure crop production for appropriate management estimations. Vibrant plants have a higher spectral response than in the visible spectrum in the near-infrared range. Plants that have been affected by the disease have a higher perceived reflectance and a lower infrared reflectance (Ennouri, 2019).

In this regard, hyperspectral remote sensing imagery (HRSI) is spectral signatures-based technology that can locate, identify, and differentiate spectrally distinct objects. Hyperspectral image analyses have revealed widespread use in precision farming, where the spectral signatures of crops at different production phases may be used to evaluate their health. Recently, efficient computer resources have been used to manage the enormous amount of hyperspectral data (Arias et al., 2021). The HRS image consists of hundreds of spectral data channels from the same scene. Detailed spectral information of HRS images enhances accurately identifying materials of interest while improving classification accuracy (Chen et al., 2016). In the current era, an artificial intelligence-based technology has been used in crop selection and to assist farmers with fertilizer selection. The machine interacted among them using the user's database and provided the system to determine which crop is appropriate for harvesting and the fertilizers that encourage maximum development (Jha et al., 2019). In this regard, deep learning-based methods may be used to identify weeds in diverse crops and control them autonomously with spray application. Autonomous pesticide spraying will benefit farmers by raising crop output and improving weed management accuracy. In addition, soil contamination will be prevented due to herbicides' regulated application (Moazzam, 2019). Crop biomass is increasingly being evaluated to improve the accuracy and efficiency of crop yield models using surface reflectance generated from remotely sensed space-borne multispectral broadband or narrowband hyperspectral data (Marshall and Thenkabail, 2015).

Conversely, monitoring the Spatio-temporal dynamics of earth surface activities and understanding their underlying mechanisms require mapping natural features' environmental, biological, or geographical characteristics (Lu et al., 2019). Deep learning algorithms (Yuan et al., 2020) have revolutionized image analysis and demonstrate an excellent method for examining high-dimensional HRS data and customizing their activity to the specific properties of HRS images. Convolutional Neural Network (CNN)-based models (Li et al., 2021) are particularly successful because they can extract features for classification and effectively utilize the spectral and spatial information included in HRS image cubes (Paoletti et al., 2019). However, the linear mixing model is the most widely used in hyperspectral unmixing, and a variety of methods based on it have been designed to retrieve end members and their abundances in hyperspectral images (Heylen et al., 2014). HRSI can perform direct assessments of the material under examination and show the geographical distribution of the selected parameters (Lodhi et al., 2019).

Fernández-Delgado et al., 2014 have analyzed 179 classifiers from 17 various families across the entire UCI machine learning classification database. They introduced the direct kernel perceptron in C, a whole and fast neural network, and the probabilistic neural network in Matlab, customizing the Gaussian kernel spread. They utilized 121 data sets, which represent the whole UCI database and other real-world situations, to draw significant conclusions about classifier behavior independent of data set collection. The classification methods are implemented in Matlab, C, R, and Weka using 121 datasets. The random forest (RF) is the most popular and accurate classifier (Son et al., 2018). The majority of the best classifiers are written in R and tuned with a caret, which appears to be a good thing. The random forest, SVM, neural networks, and boosting methods are best among other classification methods.

As there are practical situations where the standard of comparison does not have to be an expert, straw man bias can be challenging to detect. Regression (Hastie et al., 2009), classification, segmentation (Oliva et al., 2014; Zhu, 2017), and localization are some image analysis tasks that may be performed with machine learning. It needs a lot of computational capacity and hyperparameter optimization to training machine learning algorithms with enormous image data (England and Cheng, 2019).

Nevertheless, deep learning has been hailed as a game-changing technology in machine learning and data mining and the field of remote sensing research. Deep learning models were employed as an integrated framework that simultaneously collects features and performs classification, following the end-to-end approach, to eliminate the necessity for manual features and predefined functions. Deep learning is instrumental in image classification studies owing to its versatility in feature extraction, computing effectiveness, and automation through expert-free end-to-end learning (Zhong et al., 2019).

Consequently, several experiments were designed to determine which information is most helpful in training the machine learning approach (Sonobe et al., 2017) for crop-type classification and how various temporal and spatial factors affect crop-type classification performance to derive timely crop type information using a Deep Neural Network (DNN) and high-performance computing for intelligent and scalable computation of classifying methods (Cai et al., 2018).

One-dimensional convolutional neural networks (1D-CNNs) (Feng et al., 2017) are efficient deep learning techniques for end-to-end time series classification tasks. Long short-term memory RNNs (LSTM-RNNs) and gated recurrent unit RNNs (GRU-RNNs) are variations of RNNs that solve the issue of gradient disappearance or explosion seen with increasing time-series images. The main idea was that these three deep learning methods were trained on the complete time-series images to provide optimal architecture and hyper-parameters, resulting in better application efficiency for early crop classification (Zhao et al., 2020).

On the other hand, Salford Predictive Modeler (SPM) is a software package that combines machine learning with predictive analytics. It is called Minitab-SPM (https://www.minitab.com/en-us/products/spm/). It comprises clustering, association, classification, and prediction, among other data mining techniques. The CART, TreeNet, random forests, MARS, and significant new automation and modeling abilities not seen elsewhere, are all included in the SPM software. It's crucial to note that SPM is the more suitable alternative to R and Python, which perform very high, and that SPM is the only Random Forest code that Leo Breiman has approved.

Breiman, 2004 explained that a random forest would eventually find the best predictors by itself, and it will be able to handle enormous datasets and missing values. Random forests are a precise technique that can take thousands of variables without losing accuracy. Random forest will, in the end, automatically find the best predictors and will be able to handle enormous datasets and missing values. Their trees are formed with a modest number of cases in each terminal node, unlike single trees, where consistency is demonstrated by allowing the number of cases in each terminal node to grow big (Breiman, 2004). Since random forests efficiently model nonlinear relationships and variable interactions, more accurate models may be built using unclean data.

Therefore, the present review has compared the performance of multispectral and hyperspectral data to determine different plant characteristics. In addition, this article includes a brief background of hyperspectral imaging and a discussion of recent advances. This research aims to help agricultural practitioners and researchers better understand the benefits and disadvantages of hyperspectral imagery in precision agriculture. Future hyperspectral imaging research for crop monitoring is also discussed. The primary objectives are: (Abdulridha et al., 2019) to highlight the hyperspectral imaging platforms, (Ahmad et al., 2021) to compare hyperspectral data with multispectral datasets, (Ahmed et al., 2016) to show the status of hyperspectral data in the agricultural sectors in comparison with multispectral datasets, (A. R. Group, 2006) to emphasize the significance of deep learning in agricultural regions in comparison with machine learning, (Architecture et al., 2020) to demonstrate the hyperspectral system's development and recent trends.

The content of this article is arranged into seven sections. This section introduces the background of hyperspectral remote sensing. The searching strategy of research articles used in this paper is shown in section two. Section three focuses on remote sensing image sensors and their platforms. Analytical techniques used for remote sensing images are discussed in section four while focusing on unmixing problems and spectral classifications. Deep learning and machine learning technology are discussed in section five with their frameworks. Section six focuses on hyperspectral applications in agricultural sectors. Critical problems and challenges in hyperspectral data are highlighted in section seven.

2. Research articles searching strategy

The articles chosen for this review are based on two requirements: first, they must use hyperspectral imagery, and second, they must identify or classify multiple crops. However, multispectral imagery was also considered to compare it with HRSI. The publications were obtained by using the keywords "hyperspectral images," "deep learning," or "machine learning," and "application in agricultural," which are focused on feature extraction and classification of satellite data. These keywords were searched from reputable electronic databases, including IEEE, Springer, Elsevier, and Taylor & Francis Publishers, to provide a comprehensive review representative of updated techniques used in imaging sensors, preprocessing, feature extraction, and classification methods. 'Reputable databases' refers to a collection of publications that have been printed in reputable indexing such as SCI, Scopus, Web-of-Science, and journals such as IEEE, Taylor & Francis, Elsevier, and Springer. The required available literature is available in digital format on their official websites.

A total of 122 journal articles and conference papers were downloaded among those. Only the most recent publications were sorted out, with 11 reports demonstrating current deep learning methods for agricultural crop analysis and seven reports exhibiting machine learning techniques. The selected publications were discussed, and they were compared to give insight into hyperspectral advancement techniques. In addition, the imaging systems and sensors are discussed in the literature, and the analytical methods were also examined. The potential of hyperspectral imaging for various applications, including crop classification, disease detection, soil characteristics, and mapping crop biophysical and biochemical characteristics, was also explored.

3. Remote sensing image sensors and their platforms

Imaging spectrometry gave rise to hyperspectral imaging (Song et al., 2021). The physical technology used among hyperspectral and multispectral sensors is the same. They both measure brightness in the visible, near-infrared, and shortwave infrared parts of the spectrum, with the VNIR covering 400 nm to 1000 nm and the SWIR imagery from 1000 nm to 2400 nm, respectively. Hyperspectral sensors have many continuous and short spectral (5 to 15 nm) bands compared to multispectral sensors. Landsat-8(Peña and Brenning, 2015) has 11 bands and records a comparatively limited number of distinct spectral bands (ElMasry and Sun, 2010). Hyperspectral sensors can be mounted on various platforms, including airplanes, unmanned aerial vehicles (UAVs)(Dash et al., 2017), satellites, and close-range platforms, to capture images with different spatial and temporal resolutions (Lu et al., 2020).

Researchers have developed various hyperspectral earth observation remote sensing technology, evaluation techniques, and implementation strategies over the last few decades. Sentinel-2 multispectral satellite-based remote sensing, on the other hand, currently provides accessible, worldwide, and systematic high-quality visible and near-infrared images at a quick revisit time (Transon, 2018; Belgiu and Csillik, 2018). The Agricultural and food sectors have developed and deployed various imaging and spectroscopic techniques for assessing and classifying products based on their fundamental features and qualities during the last few decades (ElMasry and Sun, 2010; Ma et al., 2019). Fig. 1 illustrates the variety of sensor platforms used for hyperspectral imaging of various crops, with air-borne devices such as satellites leading the way, followed by airplanes, UAV- mounted sensors.

In addition, hyperspectral platforms with their sensors characteristics are also demonstrated in Table 1. Table 1 also shows the striking features of various remote sensing techniques widely used for multiple agriculture purposes. With a spatial resolution of 30 m and a spectral resolution of 10 nm, the EO-1 Hyperion is the most extensively used satellite-based hyperspectral sensor for agriculture. It captures data in the VNIR and SWIR ranges. Conversely, airborne HRSI has become famous for capturing hyperspectral imagery for monitoring the features of agriculture or forestry (Mahesh et al., 2015). An aerial visible/infrared imaging spectrometer (AVIRIS) was developed as the first hyperspectral sensor. Multispectral images have been widely used in agricultural studies to obtain soil and crop properties such as chlorophyll content, biomass, and crop yield estimation.

Table 2 highlights the agricultural applications carried out via multispectral and hyperspectral systems. The different hyperspectral imaging platforms, such as UAVs, satellites, helicopters, close-range imaging, and aircraft, offer varied benefits and drawbacks for precision agricultural applications. Satellite-based systems can cover huge areas but have a low spatial resolution and restricted data availability. For most agricultural applications, imaging platforms based on airplanes can collect data with sufficient geographical coverage and resolution. Close-range imaging systems can create images with extremely high spatial resolution, but only at the canopy or leaf level.

4. Analytical techniques for remote sensing images

Recently, deep learning algorithms have been utilized to identify the features from hyperspectral/multispectral images. The next section of the review is structured to assess the different techniques.

4.1. Pre-processing and normalization

Pre-processing techniques, also known as image rectification and restoration, are used to correct geometric and radiometric abnormalities in data caused by sensors and platforms. Variations in environment illumination and viewing geometry and atmospheric conditions, sensor noise, and response may require radiometric corrections. Each of these will be dissimilar depending on the sensor and platform used to collect the data and the conditions at the time.

Deep learning uses preprocessing and normalization techniques similar to machine learning. However, it is essential to note that most research relies on the stability of neural networks rather than band selection or saturated spectrum removal. In machine learning (Cruz-ramos et al., 2021), it is usual to pre-normalize data to rely on well-known assumptions for which classifiers are known to perform well, such as zero-mean and unit variance. Statistical techniques can significantly improve processing using standard strategies (Audebert et al., 2019). Feature extraction procedures such as the well-known principal component analysis (PCA) are among the different preprocessing methods for feature extraction that have been used (Rodarmel and Shan, 2002). Architecture et al. (2020) presented a cascaded encoder-decoder network (CED-Net) technique for semantic segmentation to differentiate weeds from crops. The proposed approach generates suitable abundance

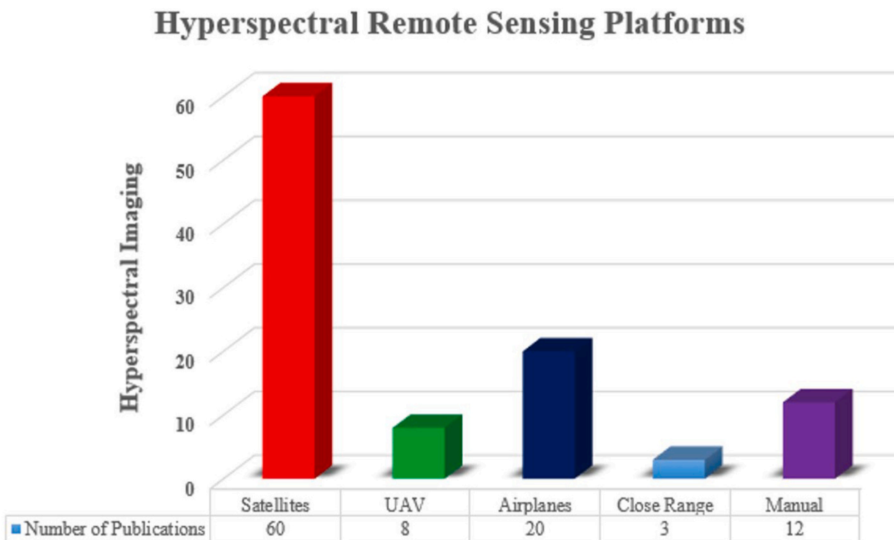

Fig. 1. Distribution of sensor platforms utilized for review.

Table 1
Comparison of Hyperion with AVIRIS, Sentinel-2, Landsat sensors characteristics.

Platform Name	Hyperion-1	AVIRIS	Sentinel-2	Landsat-8
Sensor type	Hyperspectral	Hyperspectral	Multispectral	Multispectral
Spectral range (nm) VNIR-SWIR	357–2576 357–1000 900–2576	400–2500	443–2190 2100–2280	350–1100 800–2600
Spectral bands	220	224	13	8
Spatial (m)	30	3–17	10–20–60	30
Temporal (days)	16–30	–	5	16
Spectral (nm)	10	10	15–180	–
Objective	Earth observation	Earth observation	Earth observation	Natural Resources like urban centres, farms, forests and other land uses. Cirrus cloud detection
Country Organization	USA-NASA	Jet Propulsion Laboratory, USA	Europe ESA	USA-NASA
Number of articles/ References	45	16	25	21

maps that may be utilized to build accurate thematic maps by applying spectral unmixing models that consider the spectral variability of various classes (Ibarrola-Ulzurrun et al., 2019). Different feature spaces are analyzed by authors (Dalmau et al., 2017) with six spectral bands from LANDSAT 5 TM images. They have used the first three principal components and ten vegetation indices to obtain crop classification results (Dalmau et al., 2017).

4.2. Spectral classification

The sensor's spectrums show spectral resolution proportional to the amount of spectral information in each band. High spectral resolution sensors have narrower bands than low-resolution sensors. Low-resolution sensors have larger bands that cover more of the spectrum in each band. Different machine learning approaches are used to develop crop classification models using multi-spectral and multi-temporal satellite images (Chakhar et al., 2020; Viskovic et al., 2019). Due to the ability to monitor the health of the vegetation, spectral measurements are used in many precision agricultural applications. Since they are linked to biophysical and biochemical crop characteristics, spectral vegetation indices (Dor et al., 2017) are one of the most often utilized methods in remote sensing (Ndossi and Avdan, 2016).

The dimensionality reduction (Jiao et al., 2014) and unsupervised classification algorithms are mainly used for hyperspectral image processing. The PCA was used to reduce the data's high dimensionality (Nyabuga et al., 2021; Setiyoko et al., 2017). The method successfully classified various crop stages with splitting and merging cluster centers and the niching process (Senthilnath et al., 2013). Crop types may be differentiated in the agricultural landscape from cultivated population crops. The Spectral Angle Mapper (SAM) method was used in conjunction with certain dissimilarity concepts (Sci et al., 2014). Spectral signatures were obtained from the input airborne hyperspectral images to map out selected crops (Sci et al., 2014).

Various agricultural land covers (Griffiths et al., 2019) or crop types with different spectral properties are demonstrated in Table 3. These studies have used hyperspectral images to identify the agricultural features correctly. Table 3 also indicates that different analytical methods such as linear mixing model, polynomial post-nonlinear mixing model, Gaussian processes regression, and machine learning algorithms like SVM and RF have various complexity, performance, and applicability. All methods have generally done well in past research.

4.3. Spectral unmixing for classification

A technique that retrieves the pure spectral components, known as end members, and a collection of fractional abundances that describe the proportion of each end member is referred to as spectral unmixing (Ibarrola-Ulzurrun et al., 2019) (Yang et al., 2018). One of the distinctive features of hyperspectral images for identifying species type is spectral unmixing (Jibreen et al., 2018). Such images have a high spectral resolution, making signal processing at each pixel a traditional problem known as mixed pixels (Wardlow et al., 2007). It may be

Table 2
Application of Multispectral / Hyperspectral imagery in agriculture.

Type of Sensor / platform used	Applications	Research Emphasis	References
Close-range hyperspectral imaging	Investigating biochemical components	A hyperspectral camera's ear and a halogen lamp were installed on a moving platform, and this imaging system was utilized to estimate the sugar and nitrogen contents of tomato leaves.	(Zhu et al., 2020)
Agricultural robotics system	Crop/weed classification	A deep learning-based technique uses two Convolutional Neural Networks applied to RGB images to allow a robot to conduct accurate weed/crop classification.	(Fawakherji et al., 2019)
Sentinel-2	Crop Classification	In comparison to SVM, RF has a more substantial potential for correctly classifying crops, and Sentinel-2 has much potential for vegetation mapping within the remote sensing sector.	(Saini and Ghosh, 2018)
Sentinel-2A and Sentinel-2B satellites	To Classify different crops	Different machine learning techniques were adopted to identify seven different crop types using multi-spectral and multi-temporal satellite images.	(Viskovic et al., 2019)
Sentinel-2	Vegetation cover classification	The NDVI and unsupervised k-means clustering algorithms have been used to analyze vegetation's seasonal dynamics and classify vegetation cover.	Gaikwad et al., 2021
Sentinel-1A	Phenological sequence patterns for classifying crops	Within a thick stack of multi-temporal Sentinel-1 images, a novel classification technique (PSP) has been developed that detects crop-specific sequences.	(Bargiel, 2017)
EO-1 Hyperion	Soil type classification	Hyperion image was used to classify various soil types using SVM method.	Vibhute et al., 2015
Air-SAR	Crop classification	The efficiency of a neural network-based crop classification technique that uses backscattering coefficients gathered in various C-band SAR configurations was examined.	(Del Frate et al., 2003)
EO-1 Hyperion	Disease detection	The potential of high spectral resolution data obtained by the EO-1 Hyperion polar orbiting sensor for disease identification and severity assessment of sugarcane orange rust has been demonstrated.	(A. R. Group, 2006)
Close-range hyperspectral	Monitoring soil properties	Hyperspectral imaging was used to investigate soil macro and micro-elements set on a linear stage.	(Malmir et al., 2019)
UAV-SAR	Crop classification with a heterogeneous distribution of crop categories	The capacity of time-series L-band UAVSAR for crop classification was examined using the RF technique. Polarimetric parameters from Cloude–Pottier and Freeman–Durden decompositions outperformed linear polarizations in crop discrimination.	(Li et al., 2020)

required to use mixing models to unmix these mixed pixels to discover the abundance of any characteristics of a class or end-member (Dixit and Agarwal, 2021).

Since unmixing spectral needs prior information of the end-members that participated in the mixed pixels (Kumar et al., 2012), the selection is essential and can substantially influence the outcomes. Hence, users must take precautions when picking end members. These end-members may be obtained from the image directly or can be provided by the user. This classification separates spectral unmixing into unsupervised and supervised types (Dixit and Agarwal, 2021).

Spectral diversity in hyperspectral data obtained from aerial or satellite sources is in-evitable, making spectral unmixing challenging to use appropriately to predict abundance maps. The LMM, a basic unmixing approach, typically fails to manage this tricky issue adequately. Hong et al. (2019) presented the augmented linear mixing model (ALMM), a new spectral mixture model that uses a data-driven learning technique to handle spectral variation in inverse issues of hyperspectral unmixing. In conclusion, Table 4 highlights the applications of hyperspectral linear unmixing and nonlinear unmixing for mapping green vegetation, exploration of minerals, crop classification, disease detection, and distinguishing dry soil cover, concrete, and other vegetation.

5. Significance of deep learning and machine learning

Due to the benefits of deep learning, Chen et al. (2016) consider a regularized deep feature extraction approach for hyperspectral image classification using CNN. The suggested 3-D deep CNN has shown excellent classification efficiency despite small datasets by utilizing proper architectural and robust regularization (Chen et al., 2016). Deep Learning has an advantage over all other machine learning-based algorithms. It can discover characteristics on its own, saving process by reducing the necessity to compute and construct features manually. Moreover, the deep learning approach produces infinite precision; more excellent training or more data input may result in higher accuracy (Moazzam, 2019).

For instance, Su et al. (2019) proposed a novel unsupervised unmixing approach based on a deep autoencoder network (DAEN) with two new elements. The first part of the network uses stacked autoencoders (SAEs) to learn spectral signatures and produce a suitable initialization for the unmixing process. A variational autoencoder (VAE) is used in the second half of the network to simultaneously conduct blind source separation to acquire end member signatures and abundance fractions (Su et al., 2019). On the other hand, the crop classification techniques are generated using different machine learning algorithms on multi-temporal and multi-spectral satellite imagery. The techniques are only applied to agricultural regions identified using existing land use classification models (Viskovic et al., 2019).

For precision agriculture (Khaliq et al., 2018), researchers have used a variety of machine learning approaches and hyperspectral imagery (Table 5). Research Scholars have also generated a set of deep learning-based remote sensing data analysis methods to achieve exceptional

Table 3
Various research findings using hyperspectral data to determine agricultural characteristics.

Type of Sensor / platform used	Application of Extracted Features	Processing and analyzing techniques	Research Emphasis	References
Hyperion (EO-1)	Plant species classification	Support vector machine	Hyperspectral data was used to ensure the application of binary encoding and support vector machine algorithms for plant recognition, mapping, and classification.	(Varpe et al., 2015)
CHRIS images	Estimating leaf chlorophyll	Gaussian Processes regression	Gaussian Processes regression (GPR) is a versatile nonlinear regression model that is used to build complicated relationships at the canopy level with parameters of interest such as chlorophyll.	(Verrelst et al., 2013)
ASD Field Spec Pro FR Spectroradiometer	Early detection and classification of plant diseases	SVM, ANN	Nine spectral vegetation indicators connected to physiological parameters were used as features for automated classification. An SVM with a radial basis function kernel can spot the difference between healthy and infected plants and specific diseases.	(Rumpf et al., 2010)
ASD Field Spec-4	Determination of soil properties	Partial least squares regression (PLSR)	The PLSR-based models were developed to determine the various soil properties.	Vibhute et al., 2018
EO-1Hyperion	Grass, dry Soil, Concrete, teak tree	Linear mixing model, Polynomial post-nonlinear mixing model	Modified mixing model was utilized for spectral unmixing that includes a linear and a non-linear mixing model. Overall accuracy was calculated using abundance accuracy, reconstruction accuracy, and other statistical metrics, and the results show that Modified Polynomial Post-nonlinear mixing model beats, Polynomial Post-nonlinear mixing model (PPNMM), and Linear Mixing Model (LMM).	(Dixit and Agarwal, 2021)

Table 4
Various research findings using hyperspectral images to determine spectral unmixing for classification.

Type of Sensor / platform used	Application of Extracted Features	Classification techniques	Research Emphasis	References
EO-1 Hyperion	To classify various minerals found in the Cuprite mining district	Unsupervised unmixing based on a deep autoencoder network (DAEN).	The results of the experiment, that were acquired using both synthetic and real data sets, show that the proposed DAEN can effectively deal with problems involving significant outliers.	(Su et al., 2019)
Hyperspectral Digital Imagery Collection Experiment (HYDICE)	spectral variabilities caused by environmental conditions	Spectral unmixing with augmented linear mixing model (ALMM),	The approach may learn the spectral variability dictionary while estimating the abundance maps at the same time.	(Hong et al., 2019)
Multispectral, synthetic and real hyperspectral datasets	Identify end members	Nonlinear unmixing process using Unsupervised modified bilinear model	Overall, the MBM model has shown to be more efficient in unmixing.	(Vani, 2018)
HYDICE Hyperspectral Data sets	Estimated abundances obtained for each endmember material like road, soil, water and tree	Pixel-based CNN for HSI unmixing	By incorporating the spatial correlation between the image components, the cube-based CNN provides superior performance in the unmixing process than the pixel-based CNN.	(Zhang et al., 2018)
EO-1 Hyperion satellite data	To distinguish dry soil, concrete, grass and teak tree	Linear mixing model ad non-linear mixing model	The modified technique is the ultimate performer since it is consistent and robust during accuracy assessment	(Dixit and Agarwal, 2021)

outcomes. Table 5 focuses on the work done by several researchers using deep learning and machine learning methods for various agricultural applications such as crop classification (Case et al., 2019), (Viskovic et al., 2019), (Cai et al., 2018), (Zhong et al., 2019), leaf disease detection (Ashourloo et al., 2016), and detection of citrus canker disease (Abdulridha et al., 2019).

5.1. Software packages available for machine learning and deep learning

The present review provides machine learning and deep learning frameworks available in public repositories (Figs. 2 and 3). We have also provided a comparative analysis and specified the various models used for developing various applications. Due to versatility and adaptability, python has been recognized as one of the most often used programming languages for developing deep learning frameworks. Tensor Flow is a more advanced approach and supports a broader range of programming languages. Many supporting technologies are available with Tensor Flow. Keras received much attention, similar to Tensor Flow. The comparative search volume scores for PyTorch and other frameworks were low. TensorFlow is a large-scale machine learning system that works in various environments. TensorFlow enables developers to try out new optimizations and training algorithms. TensorFlow supports a wide range of applications, emphasizing deep neural network training and validation, and various real-world examples demonstrate TensorFlow's incredible performance (Gerard, 2021).

6. Hyperspectral applications in agriculture

Agriculture is ideal for hyperspectral imaging technology due to its biological complexity and wide range of growing conditions, weather, soil and crop types, crop variations, and other factors. There is significant interest in using HSI to monitor and forecast agro-food production through component studies and online detection of microbial, biological, diseases, and chemical contaminants (Taylor et al., 2013). Hyperspectral imaging has been widely used in agriculture to estimate crop biochemical and biophysical properties such as carotenoids, chlorophyll, LAI, and water contents (Surase et al., 2019) to identify vegetation physiological status yield prediction, assess crop nutrient content, monitor plant diseases, and investigation crop disease.

6.1. High throughput phenotyping (HTP) in the field

Incorporating heterogeneous data from consistent, automatic, multifunction, and high-throughput phenotyping systems will necessitate the continuous development of novel technologies, focusing on high-performance HTP technologies and low-cost. Multifunctional

Table 5
Selected previous research work for investigating deep learning and machine learning algorithms.

Application of extracted features	Deep Learning /Machine Learning Techniques Used	Research Emphasis	References
Crop classification	Deep neural network	The machine learning model used for crop identification revealed that spatial and temporal variables influence crop-type classification performance.	(Cai et al., 2018)
Wheat leaf rust disease detection	Gaussian process regression, PLSR, ν support vector regression (ν-SVR)	In this study, it is evident that GPR's accuracy is higher than other approaches due to its performance with a small training sample.	(Ashourloo et al., 2016)
Detect citrus canker disease	K nearest neighbor, radial basis function	In all category, the RBF classifications exceed the KNN classifications. The greatest significant distinction was made between a healthy and asymptomatic leaf, which was 96% and 94% accurate, respectively, using the RBF and KNN approaches.	(Abdulridha et al., 2019)
Crop classification	Random forest SVM, K- nearest neighbor, neural network	Random forest model exhibited the highest accuracy for classifying crop.	(Viskovic et al., 2019)
Crop classification	1D-CNN, LSTM-RNN, and GRU-RNN	Deep Learning algorithms have been used to extract temporal characteristics efficiently from 1D-CNNs, gated recurrent unit RNNs and LSTM-RNNs.	(Case et al., 2019)
Crop classification	Long Short-Term Memory (LSTM)	With time series representation in classification tasks, the Conv1D layer-based deep neural network architecture is a potential alternative.	(Gadiraju et al., 2020; Zhong et al., 2019)
Review studies	Deep learning models	CNN-based models have been demonstrated to be very effective in identifying high-level characteristics for classification while also efficiently utilizing the spectral information and spatial-contextual available in HSI data cubes.	(Paoletti et al., 2019)
Review studies	Machine learning, deep learning models	The study utilized machine learning-based hyperspectral image analysis algorithms and covers image analysis tasks such as target/anomaly detection, land cover classification, physical/chemical parameter estimate and unmixing.	(Gewali et al., 2018; Hennessy et al., 2020)

phenotyping devices generate massive amounts of sensor data and images. However, crop HTP faces new challenges in data storage, management, and analysis (Shakoor et al., 2017). Recently, plant breeding and crop production uses have benefited from high-throughput phenotyping or phenomics technologies. Researchers have developed and tested several sensors, platforms, and image processing algorithms for field-based phenotyping (Zhang et al., 2020).

6.2. Chlorophyll content

Chlorophyll content can be estimated using hyperspectral remote sensing with high spatial resolution. Accurate canopy chlorophyll content assessment is critical in measuring biotic and abiotic stresses (Yang et al., 2015). The findings show that using hyperspectral remote sensing images to extract chlorophyll content at the leaf and canopy level is reliable. The use of chlorophyll content to assess forest growth stages and diseases can be beneficial (Yang et al., 2015).

The modified spectral signatures caused by fungal infection can be detected through hyperspectral imaging. The reduced physiological activity of tissues caused by Fusarium forms the basis for conducting chlorophyll fluorescence analysis. The symptoms of this disease can be easily identified via image analysis (Bauriegel and Herppich, 2014; England and Cheng, 2019). The average spectra of millet leaves were obtained by intelligently extracting the region of interest. The hyperspectral imaging technique was used to collect spectral and image information from millet leaves at different periods of development. The CNN model proved efficient in estimating the chlorophyll content of millet leaves as it can mine the interior features of spectral data while also simplifying preprocessing (Maria and Xiaoyan, 2020).

6.3. Fungal diseases detection

The changes in spectral characteristics caused by fungal contamination allow hyperspectral imaging to detect it while reducing the physiological activity of tissues caused by Fusarium effects. These effects serve as the foundation for chlorophyll fluorescence imaging analyses (Bauriegel and Herppich, 2014).

6.4. Drought stress detection

Hyperspectral imaging is a non-invasive method of collecting high-resolution data from plants. Several data analysis approaches are available to identify abiotic and biotic stress in plants (Sahoo et al., 2015), emphasizing the classification of healthy and sick plants, disease severity, and early identification of stress symptoms (Lowe et al., 2017). HRSI is gaining popularity as a promising proximal and remote sensing tool for detecting agricultural drought stress (Gerhards et al., 2019). The most significant result was that the multiple index standard deviations consistently increased as the hydric environment deteriorated. Improvements were seen in the dry treatment and plants subjected to recurrent drought occurrences (Variability, 2020).

6.5. Weeds detection and management

The use of deep learning in automated weeding is innovative, and it offers greater accuracy than any other method. Deep learning might be utilized in different crops for weed detection (Knoll et al., 2018)and automated spray application, bridging a study gap (Moazzam, 2019). Architecture et al. (2020) presented a conceptual segmentation technique based on a cascaded encoder-decoder network to detect crop weeds. Present weed and crop categorization systems are incredibly complicated, involving millions of variables that require more training time. To resolve these drawbacks, the researchers recommended micro training networks in a cascade to get coarse-to-fine predictions, which would then be combined to get the outcome (Architecture et al., 2020).

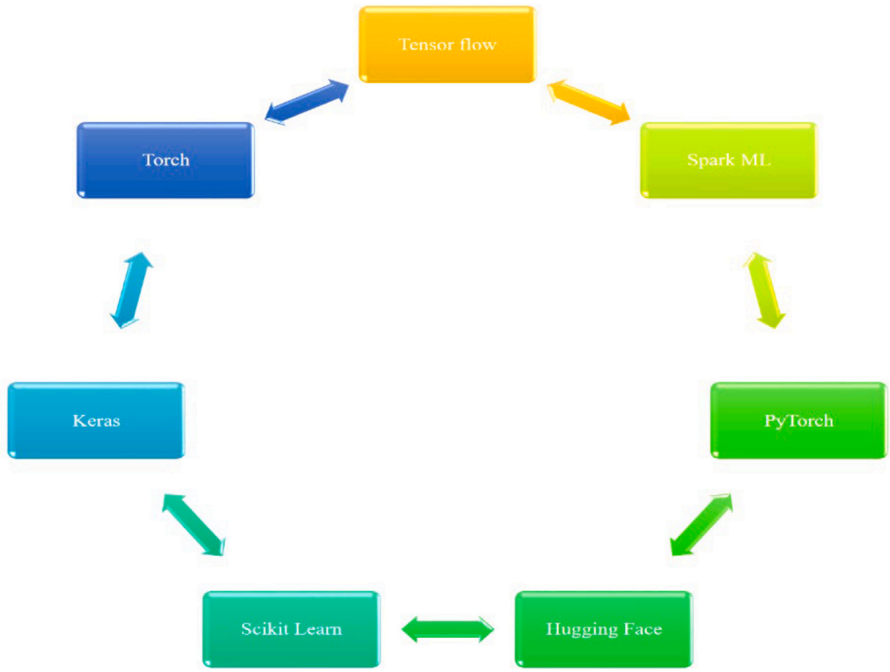

Fig. 2. Machine learning Framework.

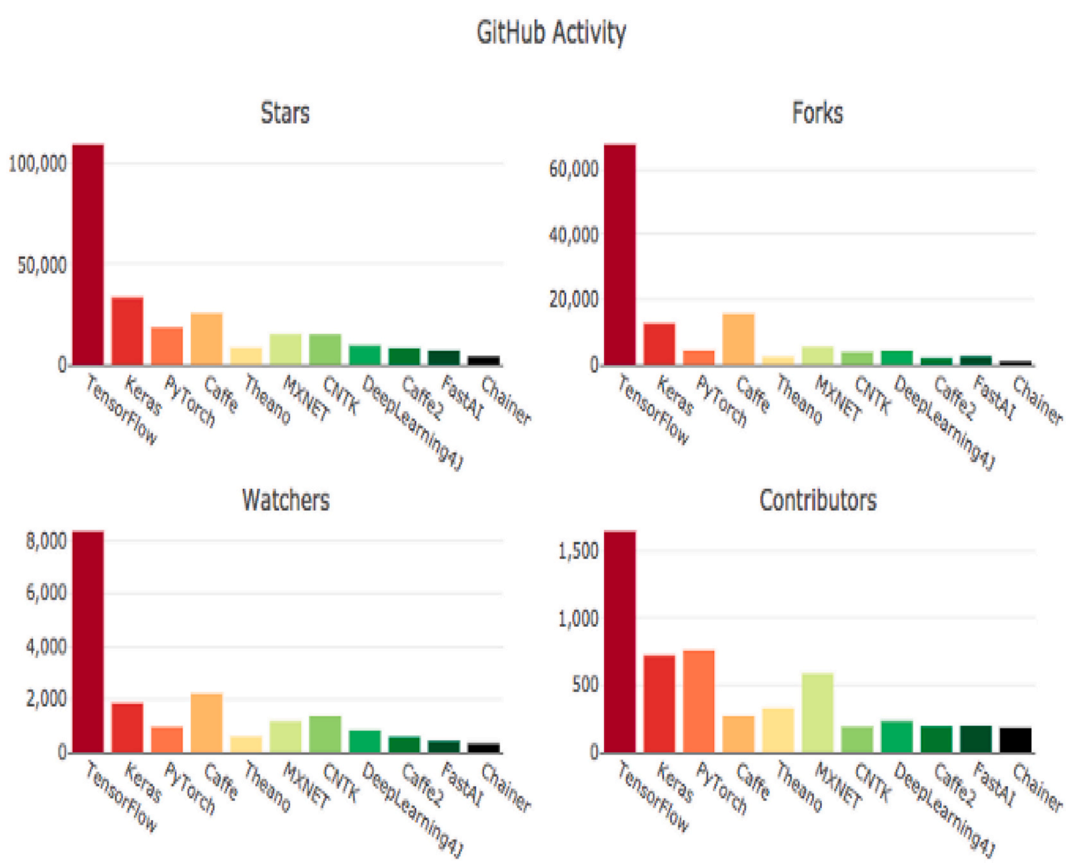

Fig. 3. Deep Learning Framework GitHub Activity Jeff Hale (2018).

6.6. *Crop classification*

Data from hyperspectral remote sensing may extract and classify crop characteristics. Data from remote sensing is unorganized, and CNN can handle unstructured data effectively (Bhosle and Musande, 2020). HRS data have precisely identified crop types and varieties and acquired spatial distribution maps and planting structure information of crops due to their multiple bands, rich spectral information, and sensitivity to minor spectral variations among ground objects. Hyperspectral data is inappropriate for good crop classification in large-scale regions due to its high dimension and extensive data processing effort. As a result, establishing a dimension reduction strategy and classifier capable of speeding up hyperspectral data processing is crucial for future fine classification of crops using hyperspectral remote sensing at a broad regional scale (Zhang et al., 2019).

7. Key problems and challenges

7.1. Limitation of standard datasets and experiment analysis

Datasets are essential in evaluation and research; it has been discovered that there are fewer benchmark hyperspectral datasets that are publicly available. Furthermore, researchers might not apply the proper technique for the challenging task without following the conventional approach for evaluation in the actual situation. Various researchers have developed different datasets by modifying the experimental settings, making it very unlikely for a real-time situation and making it difficult to do a comparative analysis by comparing the two techniques (Babu and Padma, 2019).

Techniques that work effectively on these few and small images will be easily translated to large real-world images. For all of these considerations, creating new open data sets should be one of the hyperspectral remote sensing communities (Gewali et al., 2018).

7.2. Dimensionality problem

Hyperspectral data's high dimensionality is a well-studied challenge in remote sensing. The number of spectrally unique signatures in hyperspectral data is originally termed virtual dimensionality (VD). In the past, virtual dimensionality (VD) was frequently used to calculate the number of end members. In comparison to intrinsic dimensionality, virtual dimensionality is a relatively novel concept that, if properly understood, can have a considerable impact on hyperspectral data processing (Gewali et al., 2018).

Due to high dimensions, HSI data contains several artifacts that make misclassification. HSI data has significant intraclass variability, similar to very high-resolution (VHR) images, as a result of uncontrollable variations in the reflectance detected by the spectrometer, which generally happens due to changes in atmospheric conditions or occlusions because of clouds present and variations in illumination, among other environmental interferers (Paoletti et al., 2019).

7.3. Deep learning limitations

An unsupervised deep learning system is the best model of hyperspectral data utilizing enormous amounts of already accessible labeled images, but supervised deep learning requires large-scale datasets. The transferability of learned unsupervised characteristics between images of various types has already been investigated in studies.

Deep generative models like generative adversarial networks and variational autoencoders appear to be highly promising for modeling unlabeled hyperspectral data. By simulating the generative distribution of spectra, GANs and VAs might be used to quantify spectral variability (Arisoy et al., 2021; Gewali et al., 2018). A deep model's many variables require a high computational cost and intensive memory (Cheng et al., 2017). Researchers must correctly select the most appropriate models that best suit HSI data, considering the aforementioned fundamental HSI dataset issues and the restrictions of deep models. As a result, reducing calculation time requires selecting suitable architectures, proper learning methods, and procedures that better fit the data.

7.4. Mixed pixel classification

The significant primary issue of hyperspectral is unlabeled data. Compared to multispectral remote sensing sensors like Sentinel or Landsat, the number of active space-borne spectrometers constantly capturing images is still restricted, and the generated data is frequently unavailable publicly. In addition, compared to satellite-based sensors, airborne spectrometers span a much-limited area. The number of HSI datasets is also relatively restricted (Paoletti et al., 2019). Hyperspectral images include a large number of pixels. Thus, manually selecting the optimal vegetation and bare soil spectra is quite challenging. As a result, unsupervised end member extraction approaches can outperform supervised ones. On the other hand, the unmixing methods (Bioucas-dias, 2013) used are based on linear mixture models, and estimated faults are typically focused on areas with significant nonlinear effects (Wei et al., 2017). These impacts would be interesting to explore further processing (Luo et al., 2013).

8. Conclusions

The present study reviewed the selected publications focusing on agricultural applications derived from hyperspectral data and advanced machine and deep learning methods. These publications use various features depending on the scope of the studies and usage of remote sensing datasets. Every study focuses on agricultural applications with either multispectral or hyperspectral datasets. Since hyperspectral imaging has been widely accepted for agricultural applications, particularly precision agriculture, due to its wide range of spectrum information. Several platforms such as satellites, aircraft, UAVs, and close-range systems have been used in hyperspectral data acquisition. Several studies have been focused on either machine or deep learning methods. The results demonstrate that no precise assumption can be made about the suitable method. However, several machine learning methods have provided satisfactory results for various agricultural applications. SVM, random forest, neural networks, LMM, PLSR, and SVR, are the most used methods. Some studies have also used various methods to verify which method is suitable for their research since deep learning is the most applied model for complex data due to its higher performance. Additionally, deep learning methods have transformed image analysis and proven valuable for processing high-dimensional remote sensing data. It is concluded that the CNN, RNN, and LSTM methods are the most used by researchers for agricultural applications. In addition, Python is the most preferred language for developing deep learning models. We believe that the present review will discover the way for further studies on agricultural applications with hyperspectral and deep learning models.

In the future, we will develop a deep learning-based model for automatic crop classification from time-series data.

Ethics approval and consent to participate

Not applicable.

Consent for publication

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Availability of data and material

Data Sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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Authors' contributions

Atiya Khan: Conceptualization, Data curation, Writing draft. Amol D.

Vibhute: Scientific analysis, Investigation, Validation, Technical assistance, Writing - review & final editing. Shankar Mali: Formal analysis. C. H. Patil: Formal analysis, Edited the manuscript, Correction, Evaluation. All authors read and approved the final manuscript.

Authors' information (optional)

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Declaration of Competing Interest

The authors declare that they have no competing interests.

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References

A. R. Group, 2006. EO-1 HYPERION Satellite Data, 34.

Abdulridha, J., Batuman, O., Ampatzidis, Y., 2019. UAV-Based Remote Sensing Technique to Detect Citrus Canker Disease Utilizing Hyperspectral Imaging and Machine Learning.

Ahmad, M., Mazzara, M., Distefano, S., 2021. Regularized CNN Feature Hierarchy for Hyperspectral Image Classification, pp. 1–11.

Ahmed, M.R., Yasmin, J., Mo, C., Lee, H., Kim, M.S., 2016. Outdoor applications of hyperspectral imaging technology for monitoring agricultural crops : a review. J. Biosytm Eng. 41 (4), 396–407.

Architecture, E., Khan, A., Ilyas, T., Umraiz, M., Mannan, Z.I., 2020. CED-Net : Crops and Weeds Segmentation for Smart Farming Using a Small Cascaded.

Arias, F., Zambrano, M., Broce, K., Medina, C., Pacheco, H., 2021. Hyperspectral imaging for rice cultivation. Applicat. Meth. Challeng. 6 (1), 273–307. https://doi.org/10.3934/agrfood.2021018.

Arisoy, S., Nasrabadi, N.M., Kayabol, K., 2021. GAN-based hyperspectral anomaly detection. In: Eur Signal Process Conf 2021-Janua: 1891–1895. https://doi.org/10.23919/Eusipco47968.2020.9287675.

Ashourloo, D., Aghighi, H., Matkan, A.A., Mobasheri, M.R., Rad, A.M., 2016. An Investigation Into Machine Learning Regression Techniques for the Leaf Rust Disease Detection Using Hyperspectral Measurement, pp. 1–8.

Audebert, N., Saux, B., Lefèvre, S., Learning, D., Audebert, N., Le, Saux B., 2019. Deep Learning for Classification of Hyperspectral Data : A Comparative Review To Cite this Version: HAL Id : hal-02104998 Deep Learning for Classification of Hyperspectral Data : A Comparative Review.

Awad, M.M., 2019. Toward Precision in Crop Yield Estimation Using Remote Sensing and Optimization Techniques. https://doi.org/10.3390/agriculture9030054.

Babu, M.C.G., Padma, M.C., 2019. A efficient solution for classification of crops using hyper spectral satellite images. Int J Innov Technol Explor Eng 9 (2), 5204–5211. https://doi.org/10.35940/ijitee.b7311.129219.

Bargiel, D., 2017. A new method for crop classification combining time series of radar images and crop phenology information. Remote Sens. Environ. 198, 369–383. https://doi.org/10.1016/j.rse.2017.06.022.

Bauriegel, E., Herppich, W.B., 2014. Hyperspectral and chlorophyll fluorescence imaging for early detection of plant diseases, with special reference to fusarium spec. Infect. Wheat. 32–57. https://doi.org/10.3390/agriculture4010032.

Belgiu, M., Csillik, O., 2018. Sentinel-2 cropland mapping using pixel-based and object-based time-weighted dynamic time warping analysis. Remote Sens. Environ. 204, 509–523. https://doi.org/10.1016/j.rse.2017.10.005. January 2017.

Bhosle, K., Musande, V., 2020. Evaluation of CNN model by comparing with convolutional autoencoder and deep neural network for crop classification on hyperspectral imagery. Geocarto Int 0 (0), 1–15. https://doi.org/10.1080/10106049.2020.1740950.

Bioucas-dias, J.M., 2013. Hyperspectral Remote Sensing Data Analysis and Future Challenges. https://doi.org/10.1109/MGRS.2013.2244672.

Bishop, Christopher M., 2006. Pattern Recognition and Machine Learning (Information Science and Statistics). Springer, Verlag New York, Inc., Secaucus, NJ, USA.

Breiman, L., 2004. Technical Report 670 Statistics Department. Statistics (Ber).

Cai, Y., Guan, K., Peng, J., Wang, S., Seifert, C., Wardlow, B., Li, Z., 2018. A high-performance and in-season classification system of field-level crop types using time-series Landsat data and a machine learning approach. Remote Sens. Environ. 210, 35–47. https://doi.org/10.1016/j.rse.2018.02.045 (April 2017).

Case, S.A., Zhao, H., Chen, Z., Jiang, H., Jing, W., Sun, L., 2019. Evaluation of Three Deep Learning Models for Early Crop Classification Using Sentinel-1A Imagery Time.

Chakhar, A., Ortega-Terol, D., Hernández-López, D., Ballesteros, R., Ortega, J.F., Moreno, M.A., 2020. Assessing the accuracy of multiple classification algorithms for crop classification using landsat-8 and sentinel-2 data. Remote Sens. 12 (11), 1–19. https://doi.org/10.3390/rs12111735.

Chen, Y., Jiang, H., Li, C., Jia, X., Member, S., 2016. Deep feature extraction and classification of hyperspectral images based on convolutional neural networks, 54 (10), 6232–6251.

Cheng, Y., Wang, D., Zhou, P., Zhang, T., 2017. A survey of model compression and acceleration for deep neural networks. arXiv preprint 1, 1–12. https://doi.org/10.48550/arXiv.1710.09282. arXiv:1710.09282.

Cruz-ramos, C., Garcia-salgado, B.P., Reyes-reyes, R., Ponomaryov, V., 2021. Gabor Features Extraction and Land-Cover Classification of Urban Hyperspectral Images for Remote Sensing Applications, 1–21.

Dalmau, O.S., Alarcón, T.E., Oliva, F.E., 2017. Crop classification in satellite images through probabilistic segmentation based on multiple sources. Sensors (Switzerland) 17 (6), 1–15. https://doi.org/10.3390/s17061373.

Dash, J.P., Watt, M.S., Pearse, G.D., Heaphy, M., Dungey, H.S., 2017. ISPRS journal of photogrammetry and remote sensing assessing very high resolution UAV imagery for monitoring forest health during a simulated disease outbreak. ISPRS J. Photogramm. Remote Sens. 131, 1–14. https://doi.org/10.1016/j.isprsjprs.2017.07.007.

Del Frate, F., Schiavon, G., Solimini, D., Borgeaud, M., Hoekman, D.H., Vissers, M.A.M., 2003. Crop classification using multiconfiguration C-band SAR data. IEEE Trans. Geosci. Remote Sens. 41 (7 PART I), 1611–1619. https://doi.org/10.1109/TGRS.2003.813530.

Dixit, A., Agarwal, S., 2021. Applied computing and geosciences non-linear spectral unmixing of hyperspectral data using Modi fi ed PPNMM. Appl Comput Geosci 9 (January), 100053. https://doi.org/10.1016/j.acags.2021.100053.

Dor, F., Disease, G., Al-saddik, H., 2017. Development of Spectral Disease Indices for. https://doi.org/10.3390/s17122772.

ElMasry, H.G., Sun, D.W., 2010. Principles of hyperspectral imaging technology. In: Chapter 1 Hyperspectral Imaging for Food Quality Analysis and Control, pp. 3–43.

England, J.R., Cheng, P.M., 2019. Artificial intelligence for medical image analysis: a guide for authors and reviewers. AJR 212 (3), 513–519. https://doi.org/10.2214/AJR.18.20490.

Ennouri, K., 2019. Remote Sensing : An Advanced Technique for Crop, p. 2019. https://doi.org/10.1155/2019/9404565.

Fawakherji, M., Youssef, A., Bloisi, D.D., Pretto, A., Nardi, D., 2019. Crop and Weeds Classification for Precision Agriculture using Context-Independent Pixel-Wise Segmentation. https://doi.org/10.1109/IRC.2019.00029.

Feng, F., Li, W., Du, Q., Zhang, B., 2017. Dimensionality reduction of hyperspectral image with graph-based discriminant analysis considering spectral similarity. Remote Sens. 9 (4), 323. https://doi.org/10.3390/rs9040323.

Ferentinos, K.P., 2018. Deep learning models for plant disease detection and diagnosis. Comput. Electron. Agric. 145 (January), 311–318. https://doi.org/10.1016/j.compag.2018.01.009.

Fernández-Delgado, M., Cernadas, E., Barro, S., Amorim, D., 2014. Do we need hundreds of classifiers to solve real world classification problems? J. Mach. Learn. Res. 15 (1), 3133–3181.

Gadiraju, K.K., Ramachandra, B., Chen, Z., Vatsavai, R.R., 2020. Multimodal deep Learning based crop classification using multispectral and multitemporal satellite imagery. In: Proc ACM SIGKDD Int Conf Knowl Discov Data Min, pp. 3234–3242. https://doi.org/10.1145/3394486.3403375.

Gaikwad, S.V., Vibhute, A.D., Kale, K.V., Mane, A.V., 2021. Vegetation cover classification using Sentinal-2 time-series images and K-Means clustering. In: 2021 IEEE Bombay Section Signature Conference (IBSSC). IEEE, pp. 1–6.

Garcia, J., Barbedo, A., 2013. Digital Image Processing Techniques for Detecting, Quantifying and Classifying Plant Diseases, pp. 1–12.

Gerard, C., 2021. TensorFlow.js. Pract Mach Learn JavaScript 25–43. https://doi.org/10.1007/978-1-4842-6418-8_2.

Gerhards, M., Schlerf, M., Mallick, K., 2019. Challenges and Future Perspectives of Multi-/ Hyperspectral Thermal Infrared Remote Sensing for Crop Water-Stress Detection : A Review.

Gewali, U.B., Monteiro, S.T., Saber, E., 2018. Machine Learning based Hyperspectral Image Analysis: A Survey.

Griffiths, P., Nendel, C., Hostert, P., 2019. Intra-annual reflectance composites from Sentinel-2 and Landsat for national-scale crop and land cover mapping. Remote Sens. Environ. 220, 135–151. https://doi.org/10.1016/j.rse.2018.10.031. October 2018.

Hastie, Trevor, Tibshirani, Robert, Friedman, Jerome, 2009. Overview of Supervised Learning, in the Elements of Statistical Learning. Springer, pp. 9–39.

Hennessy, A., Clarke, K., Lewis, M., 2020. Hyperspectral Classification of Plants : A Review of Waveband Selection Generalisability.

Heylen, R., Parente, M., Gader, P., 2014. A review of nonlinear hyperspectral unmixing methods. IEEE J Sel Top Appl Earth Obs Remote Sens 7 (6), 1844–1868. https://doi.org/10.1109/JSTARS.2014.2320576.

Hong, D., Yokoya, N., Chanussot, J., Zhu, X.X., 2019. An augmented linear mixing model to address spectral Variability for hyperspectral Unmixing. IEEE Trans. Image Process. 28 (4), 1923–1938. https://doi.org/10.1109/TIP.2018.2878958.

Ibarrola-Ulzurrun, E., Drumetz, L., Marcello, J., Gonzalo-Martin, C., Chanussot, J., 2019. Hyperspectral classification through unmixing abundance maps addressing spectral variability. IEEE Trans. Geosci. Remote Sens. 57 (7), 4775–4788. https://doi.org/10.1109/TGRS.2019.2892903.

Jha, K., Doshi, A., Patel, P., Shah, M., 2019. Arti fi cial Intelligence in Agriculture A comprehensive review on automation in agriculture using arti fi cial intelligence. Artif Intell Agric 2, 1–12. https://doi.org/10.1016/j.aiia.2019.05.004.

Jiao, X., Kovacs, J.M., Shang, J., McNairn, H., Walters, D., Ma, B., Geng, X., 2014. Object-oriented crop mapping and monitoring using multi-temporal polarimetric RADARSAT-2 data. ISPRS J. Photogramm. Remote Sens. 96, 38–46. https://doi.org/10.1016/j.isprsjprs.2014.06.014.

Jibreen, A., Alqahtani, N., Bchir, O., 2018. Performance evaluation of various hyperspectral nonlinear unmixing algorithms, 8 (1), 1–8. https://doi.org/10.5923/j.ajsp.20180801.01.

Khaliq, A., Peroni, L., Chiaberge, M., 2018. Land cover and crop classification using multitemporal sentinel-2 images based on crops phenological cycle. In: EESMS 2018 - Environ Energy, Struct Monit Syst Proc, 1–5. https://doi.org/10.1109/EESMS.2018.8405830.

Knoll, F.J., Czymmek, V., Poczihoski, S., Holtorf, T., Hussmann, S., 2018. Improving e fficiency of organic farming by using a deep learning classi fi cation approach, 153 (August), 347–356. https://doi.org/10.1016/j.compag.2018.08.032.

Kumar, U., Raja, K.S., Mukhopadhyay, C., Ramachandra, T.V., 2012. A neural network based hybrid mixture model to extract information from non-linear mixed pixels. Inf 3 (3), 420–441. https://doi.org/10.3390/info3030420.

Leonard, E.C., 2016. Encyclopedia of Food Grains (Second Edition).

Li, H., Zhang, C., Zhang, S., Atkinson, P.M., 2020. Crop classification from full-year fully-polarimetric L-band UAVSAR time-series using the random Forest algorithm. Int. J. Appl. Earth Obs. Geoinf. 87, 102032. https://doi.org/10.1016/j.jag.2019.102032 (December 2019).

Li, D., Wang, R., Xie, C., Liu, L., Zhang, J., Li, R., 2021. A Recognition Method for Rice Plant Diseases and Pests Video Detection Based on Deep Convolutional.

Lodhi, V., Chakravarty, D., Mitra, P., 2019. Hyperspectral imaging system : development aspects and recent trends. Sens Imaging. https://doi.org/10.1007/s11220-019-0257-8.

Lowe, A., Harrison, N., French, A.P., 2017. Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. Plant Methods 1–12. https://doi.org/10.1186/s13007-017-0233-z.

Lu, B., He, Y., Dao, P.D., 2019. Comparing the performance of multispectral and hyperspectral images for estimating vegetation properties. IEEE J Sel Top Appl Earth Obs Remote Sens 12 (6), 1784–1797. https://doi.org/10.1109/JSTARS.2019.2910558.

Lu, B., Dao, P.D., Liu, J., He, Y., Shang, J., 2020. Recent Advances of Hyperspectral Imaging Technology and Applications in Agriculture, pp. 1–44.

Luo, B., Yang, C., Chanussot, J., Zhang, L., 2013. Crop yield estimation based on unsupervised linear unmixing of multidate hyperspectral imagery. IEEE Trans. Geosci. Remote Sens. 51 (1), 162–173. https://doi.org/10.1109/TGRS.2012.2198826.

Ma, J., Sun, D., Pu, H., Cheng, J., Wei, Q., 2019. Advanced techniques for hyperspectral imaging in the food industry. Princ. Rec. Applicat. 1–24.

Mahesh, S., Jayas, D.S., Paliwal, J., White, N.D.G., 2015. Hyperspectral imaging to classify and monitor quality of agricultural materials. J. Stored Prod. Res. 61, 17–26. https://doi.org/10.1016/j.jspr.2015.01.006.

Malmir, M., Tahmasbian, I., Xu, Z., Farrar, M.B., 2019. Geoderma prediction of soil macro- and micro-elements in sieved and ground air-dried soils using laboratory-based hyperspectral imaging technique. Geoderma 340, 70–80. https://doi.org/10.1016/j.geoderma.2018.12.049 (July 2018).

Maria, S., Xiaoyan, W., 2020. Chlorophyll Content for Millet Leaf using Hyperspectral Imaging and an Attention- Convolutional Neural Network, pp. 1–12.

Marshall, M., Thenkabail, P., 2015. ISPRS Journal of Photogrammetry and Remote Sensing Advantage of hyperspectral EO-1 Hyperion over multispectral IKONOS, GeoEye-1, WorldView-2, Landsat ETM +, and MODIS vegetation indices in crop biomass estimation. ISPRS J. Photogramm. Remote Sens. 108, 205–218. https://doi.org/10.1016/j.isprsjprs.2015.08.001.

Moazzam, S.I., 2019. A Review of Application of Deep Learning for Weeds and Crops Classification in Agriculture.

Navarro, A., Rolim, J., Miguel, I., Catalão, J., Silva, J., Painho, M., Vekerdy, Z., 2016. Crop monitoring based on SPOT-5 Take-5 and sentinel-1A data for the estimation of crop water requirements. Remote Sens. 8 (6) https://doi.org/10.3390/rs8060525.

Ndossi, M.I., Avdan, U., 2016. Application of Open Source Coding Technologies in the Production of Land Surface Temperature (LST) Maps from Landsat : A PyQGIS Plugin. https://doi.org/10.3390/rs8050413.

Nyabuga, D.O., Song, J., Liu, G., Adjeisah, M., 2021. A 3D-2D Convolutional Neural Network and Transfer Learning for Hyperspectral Image Classification, p. 2021.

Oliva, F.E., Dalmau, O.S., Alarcón, T.E., 2014. A supervised segmentation algorithm for crop classification based on histograms using satellite images. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 8856 (November), 327–335. https://doi.org/10.1007/978-3-319-13647-9_30.

Paoletti, M.E., Haut, J.M., Plaza, J., Plaza, A., 2019. ISPRS J. Photogr. Rem. Sens. Deep Learning Classifiers for Hypersp. Imaging : A Rev. 158 (September), 279–317.

Pascucci, S., Pignatti, S., Darvishzadeh, R., 2021. Special Issue " Hyperspectral Remote Sensing of Agriculture and Vegetation", pp. 1–7.

Peña, M.A., Brenning, A., 2015. Assessing fruit-tree crop classification from Landsat-8 time series for the Maipo Valley, Chile. Remote Sens. Environ. 171, 234–244. https://doi.org/10.1016/j.rse.2015.10.029.

Rodarmel, C., Shan, J., 2002. Principal component analysis for hyperspectral image classification. Surv L Inf Sci 62 (2), 115–122.

Rumpf, T., Mahlein, A., Steiner, U., Oerke, E., Dehne, H., Plümer, L., 2010. Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. Comput. Electron. Agric. 74 (1), 91–99. https://doi.org/10.1016/j.compag.2010.06.009.

Sahoo, R.N., Ray, S.S., Manjunath, K.R., 2015. Hyperspectral remote sensing of agriculture, 108 (5).

Saini, R., Ghosh, S.K., 2018. Crop classification on single date Sentinel-2 imagery using random forest and suppor vector machine. In: Int Arch Photogramm Remote Sens Spat Inf Sci XLII–5(November), pp. 683–688. https://doi.org/10.5194/isprs-archives-xlii-5-683-2018.

Sci, J.E., Change, C., Case, L.A., Hills, T., 2014. Earth science & climatic change using hyperspectral data to identify crops in a cultivated agricultural, 5 (9). https://doi.org/10.4172/2157-7617.1000232.

Segarra, J., Buchaillot, M.L., Araus, J.L., 2020. Rem. Sens. Prec. Agricult. Sentinel-2 Impr. Feat. Applicat. 1–18. https://doi.org/10.3390/agronomy10050641.

Senthilnath, J., Omkar, S.N., Mani, V., Karnwal, N., Shreyas, P.B., 2013. Crop Stage Classification of Hyperspectral Data using Unsupervised Techniques. https://doi.org/10.1109/JSTARS.2012.2217941.

Setiyoko, A., Dharma, I.G.W.S., Haryanto, T., 2017. Recent development of feature extraction and classification multispectral/hyperspectral images: a systematic literature review. J. Phys. Conf. Ser. 801 (1), 012045. IOP Publishing.

Shakoor, N., Lee, S., Mockler, T.C., 2017. High throughput phenotyping to accelerate crop breeding and monitoring of diseases in the field Nadia Shakoor, Scott Lee, Todd C. Mockler Donald Danforth Plant Science Center, United States.

Son, N.T., Chen, C.F., Chen, C.R., Minh, V.Q., 2018. Assessment of Sentinel-1A data for rice crop classification using random forests and support vector machines. Geocarto Int 33 (6), 587–601. https://doi.org/10.1080/10106049.2017.1289555.

Song, X.-P., Huang, W., Hansen, M.C., Potapov, P., 2021. An evaluation of Landsat, Sentinel-2, Sentinel-1 and MODIS data for crop type mapping. Sci Remote Sens 3 (January), 100018. https://doi.org/10.1016/j.srs.2021.100018.

Sonobe, R., Yamaya, Y., Tani, H., Wang, X., Kobayashi, N., Mochizuki, K., Sonobe, R., Yamaya, Y., Tani, H., Wang, X., Kobayashi, N., 2017. Assessing the suitability of data from sentinel-1A and 2A for crop classification. GIScience Remote Sens 00 (00), 1–21. https://doi.org/10.1080/15481603.2017.1351149.

Sridhar, A., Balakrishnan, A., Jacob, M.M., Sillanpää, M., Dayanandan, N., 2022. Global impact of COVID-19 on agriculture: role of sustainable agriculture and digital farming. Environ. Sci. Pollut. Res. https://doi.org/10.1007/s11356-022-19358-w.

Su, Y., Member, S., Li, J., Member, S., Plaza, A., Marinoni, A., Member, S., Gamba, P., Chakravortty, S., 2019. DAEN : deep autoencoder networks for hyperspectral Unmixing. IEEE Trans Geosci Remote Sens PP:1–13. https://doi.org/10.1109/TGRS.2018.2890633.

Surase, R.R., Kale, K.V., Varpe, A.B., Vibhute, A.D., Gite, H.R., Solankar, M.M., Nalawade, D.B., 2019. Estimation of water contents from vegetation using hyperspectral indices. In: Microelectronics, Electromagnetics and Telecommunications. Springer, Singapore, pp. 247–255.

Taylor, P., Dale, L.M., Dardenne, P., Baeten, V., Pierna, J.A.F., 2013. Hyperspectral Imaging Applications in Agriculture and Agro-Food Product Quality and Safety Control : A Review Hyperspectral Imaging Applications in Agriculture and Agro-Food Product Quality and Safety Control (January), pp. 37–41. https://doi.org/10.1080/05704928.2012.705800.

Transon, J., 2018. Survey of Hyperspectral Earth Observation Applications from Space in the Sentinel-2 Context, 8, pp. 1–32. https://doi.org/10.3390/rs10020157.

Vani, K.N.K., 2018. Unsupervised nonlinear spectral unmixing of satellite images using the modified bilinear model. J Indian Soc Remote Sens 7 (1999). https://doi.org/10.1007/s12524-018-0907-7.

Variability, S., 2020. Drought Stress Detection in Juvenile Oilseed Rape Using Hyperspectral Imaging with a Focus on Spectra Variability. https://doi.org/10.3390/rs12203462.

Varpe, A.B., Rajendra, Y.D., Vibhute, A.D., Gaikwad, S.V., Kale, K.V., 2015. Identification of plant species using non-imaging hyperspectral data. In: 2015 International Conference on Man and Machine Interfacing (MAMI). IEEE, pp. 1–4.

Verrelst, J., Alonso, L., Pablo, J., Caicedo, R., Moreno, J., Camps-valls, G., Member, S., 2013. From imaging spectroscopy data, 6 (2), 867–874.

Vibhute, A.D., Gawali, B.W., 2013. Analysis and modeling of agricultural land use using remote sensing and geographic information system: a review. Int. J. Eng. Res. Appl. 3 (3), 081–091.

Vibhute, A.D., Kale, K.V., Dhumal, R.K., Mehrotra, S.C., 2015, December. Soil type classification and mapping using hyperspectral remote sensing data. In: 2015 International Conference on Man and Machine Interfacing (MAMI). IEEE, pp. 1–4.

Vibhute, A.D., Kale, K.V., Mehrotra, S.C., Dhumal, R.K., Nagne, A.D., 2018. Determination of soil physicochemical attributes in farming sites through visible, near-infrared diffuse reflectance spectroscopy and PLSR modeling. Ecol. Process. 7 (1), 1–12.

Viskovic, L., Kosovic, I.N., Mastelic, T., 2019. Crop classification using multi-spectral and multitemporal satellite imagery with machine learning. In: 2019 27th Int Conf Software, Telecommun Comput Networks, 2019. SoftCOM, pp. 1–5. https://doi.org/10.23919/SOFTCOM.2019.8903738.

Wardlow, B.D., Egbert, S.L., Kastens, J.H., 2007. Analysis of time-series MODIS 250 m vegetation index data for crop classification in the U.S. Central Great Plains. Remote Sens. Environ. 108 (3), 290–310. https://doi.org/10.1016/j.rse.2006.11.021.

Wei, Q., Chen, M., Tourneret, J., Member, S., Godsill, S., 2017. Unsupervised nonlinear spectral unmixing based on a multilinear mixing model, 1 (3), 1–11.

Workie, E., Mackolil, J., Nyika, J., Ramadas, S., 2020. Deciphering the impact of COVID-19 pandemic on food security, agriculture, and livelihoods: a review of the evidence from developing countries. Curr Res Environ Sustain 2, 100014. https://doi.org/10.1016/j.crsust.2020.100014.

Yang, B., Wang, B., Wu, Z., 2018. Unsupervised nonlinear hyperspectral unmixing based on bilinear mixture models via geometric projection and constrained nonnegative matrix factorization. Remote Sens. 10 (5), 1–34.

Yang, X., Yu, Y., Fan, W., 2015. Chlorophyll Content Retrieval from Hyperspectral Remote Sensing Imagery Chlorophyll Content Retrieval from Hyperspectral Remote Sensing Imagery. https://doi.org/10.1007/s10661-015-4682-4.

Yuan, Q., Shen, H., Li, T., Li, Z., Li, S., Jiang, Y., 2020. Remote sensing of environment deep learning in environmental remote sensing : achievements and challenges. Remote Sens. Environ. 241 (January), 111716 https://doi.org/10.1016/j.rse.2020.111716.

Zhang, X., Sun, Y., Zhang, J., Wu, P., Jiao, L., 2018. Hyperspectral Unmixing via deep convolutional neural networks. IEEE Geosci. Remote Sens. Lett. 15 (11), 1755–1759. https://doi.org/10.1109/LGRS.2018.2857804.

Zhang, Y., Wang, D., Zhou, Q., 2019. Advances in crop fine classification based on Hyperspectral Remote Sensing. In: 2019 8th Int Conf Agro-Geoinformatics, pp. 1–6.

Zhang, C., Marzougui, A., Sankaran, S., 2020. High-Resolution Satellite Imagery Applications in Crop Phenotyping : An Overview, 175 (June).

Zhao, F., Wu, X., Wang, S., 2020. Object-oriented vegetation classification method based on UAV and satellite image fusion. Procedia Comput Sci 174 (2019), 609–615. https://doi.org/10.1016/j.procs.2020.06.132.

Zhong, L., Hu, L., Zhou, H., 2019. Deep learning based multi-temporal crop classification. Remote Sens. Environ. 221, 430–443. https://doi.org/10.1016/j.rse.2018.11.032. March 2018.

Zhu, Z., 2017. ISPRS journal of photogrammetry and remote sensing change detection using landsat time series : a review of frequencies, preprocessing, algorithms, and applications. ISPRS J. Photogramm. Remote Sens. 130, 370–384. https://doi.org/10.1016/j.isprsjprs.2017.06.013.

Zhu, W., Li, J., Li, L., Wang, A., Wei, X., Mao, H., 2020. Nondestructive diagnostics of soluble sugar, total nitrogen and their ratio of tomato leaves in greenhouse by polarized spectra – hyperspectral data fusion, 13 (2), 189–197. https://doi.org/10.25165/j.ijabe.20201302.4280.