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DEEP LEARNING BASED PLANT LEAF DISEASE DETECTION USING HYPERSPECTRAL IMAGES

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Abstract
Plant diseases pose a significant threat to global agricultural productivity, leading to substantial economic losses. Traditional methods of disease detection rely heavily on visual inspection and manual assessment, which can be time-consuming and subjective. The emergence of hyperspectral imaging technology, combined with deep learning techniques, has opened new avenues for the early detection and diagnosis of plant leaf diseases. Hyperspectral imaging captures detailed spectral information beyond the visible range, enabling the identification of subtle biochemical changes associated with plant health. This review paper aims to synthesize current research on the application of deep learning algorithms in processing hyperspectral images for plant leaf disease detection. A comprehensive analysis of various deep learning architectures, including Convolutional Neural Networks (CNNs) and other advanced models, is presented, highlighting their strengths and limitations. Additionally, the paper discusses preprocessing techniques, data augmentation strategies, and evaluation metrics that enhance detection accuracy. By analyzing existing literature, this review identifies key trends and advancements in the field while also addressing challenges such as data availability, computational requirements, and model interpretability. The findings underscore the superiority of deep learning approaches over traditional methods, paving the way for more efficient and reliable plant disease management solutions. Ultimately, this paper serves as a foundational resource for researchers and practitioners seeking to leverage hyperspectral imaging and deep learning for improved agricultural outcomes.
Keywords: Deep learning, hyperspectral imaging, plant disease detection, convolutional neural networks, agricultural technology.

1. Introduction
Plant diseases are a major cause of economic loss in global agriculture, significantly affecting crop yields and quality. Early detection and precise diagnosis of plant diseases are crucial for implementing effective management strategies and reducing the spread of pathogens[1]. Traditional methods for plant disease detection rely on manual visual inspection, which is labor-intensive, time-consuming, and prone to human error. Such methods also depend on the visible manifestation of symptoms, typically occurring in the later stages of infection, which limits timely intervention [2].
Determining uncertainty is crucial in many facets of climate change research, including biological systems where little is known or understood, as well as assumptions for stochastic or deterministic models. When the effects of climate change on food security are taken into account, however, it might be argued that the uncertainties increase[3]. However, a more straightforward definition might be "the risk of adequate food not being available." Food security can be defined as "when all people, at all times, have physical and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life" or "fair prices, choice, access through open and competitive markets[4], continuous improvements in food safety, transition to healthier diets, and a more environmentally sustainable food chain". It combines a number of problems with food access, availability, and utilisation. These risks are exacerbated by a variety of circumstances, including economic slump, currency fluctuations, water pollution, political turmoil, HIV/AIDS, conflict, trade agreements, and climate change[5]. Food insecurity is also attributed to a number of factors, including

property rights, unemployment, limited market access, poverty, education, and rising food prices. These have led to the creation of several "hotspots" for food security worldwide, especially in areas where several variables coexist. Countries in Sub-Saharan Africa rank highly on this list[6].
With advancements in imaging technologies, hyperspectral imaging (HSI) has emerged as a powerful tool for detecting plant diseases by capturing subtle changes in leaf biophysical and biochemical properties [7]. Unlike conventional RGB imaging, hyperspectral imaging provides detailed spectral data across hundreds of narrow bands, enabling the detection of early-stage stress indicators that are invisible to the naked eye. These indicators may include variations in chlorophyll content, leaf structure, or water retention, which are closely linked to the health of the plant [8].

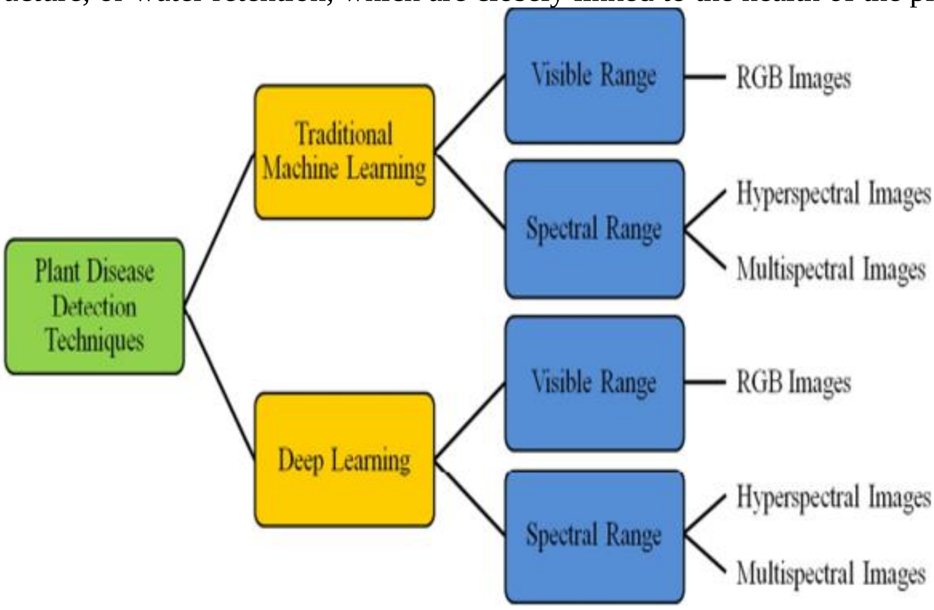

Fig Various techniques discussed for plant disease detection
The integration of deep learning techniques with hyperspectral imaging has revolutionized plant disease detection by automating the process of classifying healthy and diseased plants with high accuracy [9]. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated significant potential in learning both spectral and spatial features from hyperspectral data, outperforming traditional machine learning approaches. These models can process large amounts of data and extract complex patterns, making them well-suited for hyperspectral image analysis [10].
we explore the current advancements in using deep learning for plant leaf disease detection through hyperspectral imaging. We analyze various deep learning architectures, data preprocessing methods, and evaluation metrics employed in existing research [11]. The paper discusses the challenges associated with hyperspectral imaging, such as data complexity, computational requirements, and the need for large labeled datasets. By summarizing the latest developments and identifying potential gaps in research, this review aims to provide a comprehensive understanding of the role of deep learning in hyperspectral-based plant disease detection and its potential for improving agricultural practices [12].
Plant conditions can be monitored byobserving howleavesreflectlight. Hyperspectral imaging (HSI) is used to detect subtle changes in the spectral reflectance of plants [1]. HSI can collect spectral and spatial data from wavelengths outside human vision, providing more valuable data for disease detection than visual assessment, which only uses visible wavelengths. Additionally, HSI offers a potential solution for the scalability and repeata bility issues associated with traditional field inspection [13]. Agriculture is one of the most important economic activities of the Indian subcontinent and two-third population is directly involved in farming and related occupations. Agriculture has long been considered India’s backbone, dating back to the Indus Valley civilization. To earn income, mankind established their residence land according to agricultural facilities and favorable conditions. Agriculture is important in most developing countries because it provides jobs and contributes a significant portion to GDP [14].

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Traditional machine learning for plant disease detection

Machine learning methods are utilized to find important fundamental patterns within complex data. Early work in the area of disease detection used traditional machine learning methods for the classification of images. The generic steps used for plant disease recognition and classification with traditional machine learning algorithms. The first step is to create a database which may involve capturing the images using a suitable imaging system or using a publicly available dataset [15]. Image preprocessing is a vital start required to enhance image characteristics and to reduce the time required for processing in further steps. Some of the popular pre-processing steps involve image resizing, noise removal, contrast enhancement, conversion of color space, etc. Image segmentation is done to get the target region from the entire image. Few popularly used segmentation techniques are thresholding, K-means clustering, etc. After segmentation is done, relevant features such as shape, size, texture, and color are extracted from the segmented images. With the help of these extracted feature vectors, the machine learning algorithms are trained to label the images into given categories. Numerous classifiers, e.g., support vector machine (SVM), naive Bayes, artificial neural network (ANN), etc., are used for classifying images. The use of test data is done on the trained model to categorize the new data into one of the distinct classes. The potential of the model is assessed using various evaluation metrics such as accuracy, precision, F1-score, and area under curve (AUC) [16].

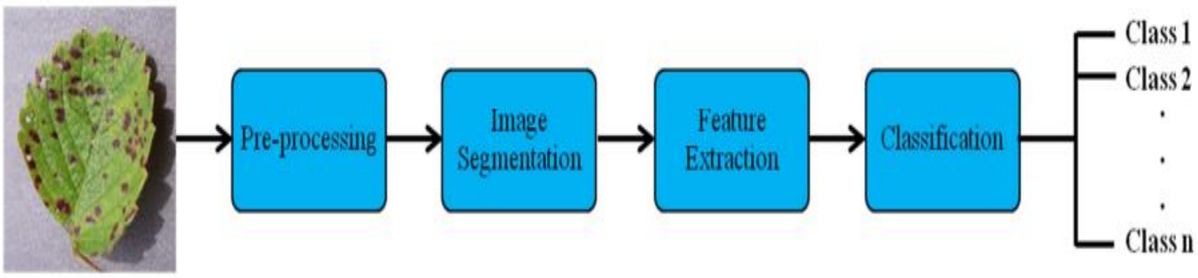

Fig General steps in traditional machine learning

1.1 Plant Disease

plant disease, an impairment of the normal state of a plant that interrupts or modifies its vital functions. All species of plants, wild and cultivated alike, are subject to disease. Although each species is susceptible to characteristic diseases, these are, in each case, relatively few in number. The occurrence and prevalence of plant diseases vary from season to season, depending on the presence of the pathogen, environmental conditions, and the crops and varieties grown. Some plant varieties are particularly subject to outbreaks of diseases while others are more resistant to them. See also list of plant diseases [17].

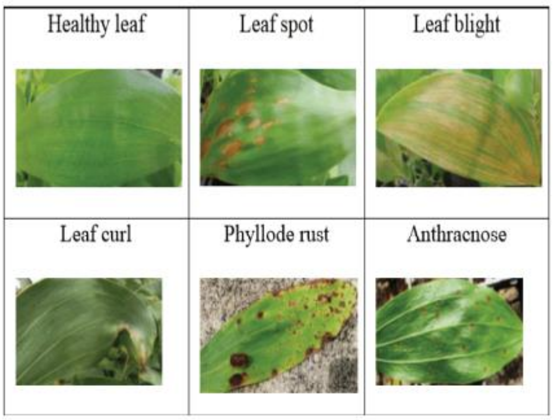

Fig Various Plant Diesease [18].

1. Fungi

Most phytopathogenic fungi are Ascomycetes or Basidiomycetes. They reproduce both sexually and asexually via the production of spores and other structures. Spores may be spread long distances by air or water, or they may be soil borne. Many soil inhabiting fungi can live saprotrophically, carrying out the role of their life cycle in the soil. These are facultative saprotrophs. [19].

Fig Fungi Diesease

2. Bacteria

Most bacteria associated with plants are saprotrophic and do no harm to the plant itself. However, a small number, around 100 known species, cause disease, especially in subtropical and tropical regions of the world. Most plant pathogenic bacteria are bacilli. Erwinia uses cell wall–degrading enzymes to cause soft rot. Agrobacterium changes the level of auxins to cause tumours with phytohormones[20].

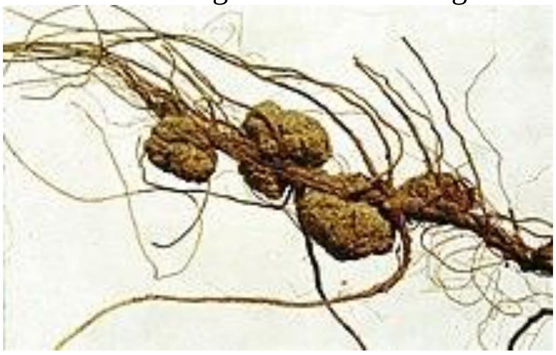

Fig Bacterial Diesease

3. Mollicutes

Phytoplasma and Spiroplasma are obligate intracellular parasites, bacteria that lack cell walls and, like the mycoplasmas, which are human pathogens, they belong to the class Mollicutes. Their cells are extremely small, 1 to 2 micrometres across. They tend to have small genomes (roughly between 0.5 and 2 Mb). They are normally transmitted by leafhoppers (cicadellids) and psyllids, both sap-sucking insect vectors. These inject the bacteria into the plant's phloem, where it reproduces [20].

Fig Mollicutes Diesease

4. Viruses

Many plant viruses cause only a loss of crop yield. Therefore, it is not economically viable to try to control them, except when they infect perennial species, such as fruit trees. These may encode only three or four proteins: a replicase, a coat protein, a movement protein to facilitate cell to cell movement through plasmodesmata, and sometimes a protein that allows transmission by a vector[21].

Fig Viruses On Leaf

5. Nematodes

Some nematodes parasitize plant roots. They are a problem in tropical and subtropical regions. Potato cyst nematodes (Globodera pallida and G. rostochiensis) are widely distributed in Europe and the Americas, causing $300 million worth of damage in Europe annually. Root knot nematodes have quite a large host range, they parasitize plant root systems and thus directly affect the uptake of water and nutrients needed for normal plant growth and reproduction, whereas cyst nematodes tend to be able to infect only a few species[22].

Fig Nematodes On Root

Leaf Disease Detection by Well Known Deep Learning Architectures

Since each disease region has its own characteristics, discussed the use of individual lesions and spots rather than considering the whole leaf. The advantages of this method were that occurrence of multiple diseases on the same leaf could be detected and the data can be augmented by cutting up the leaf image into multiple sub-images. diseases of 14 species of plants in the experimental environment and complex field environment as the research object and used the GoogLeNet model to identify diseases. The overall accuracy of using a single lesion and spot was 94%, which was higher than using the whole image (82%). put forward a new view of leaf disease detection that focused on identifying diseases disease area method (i.e. by the common name of disease rather than crops - diseases on the target category), and through the experiments showed that whatever crops, the model training with the common disease were more universal, especially for the new data obtained in different fields or that crops have not been seen[23].

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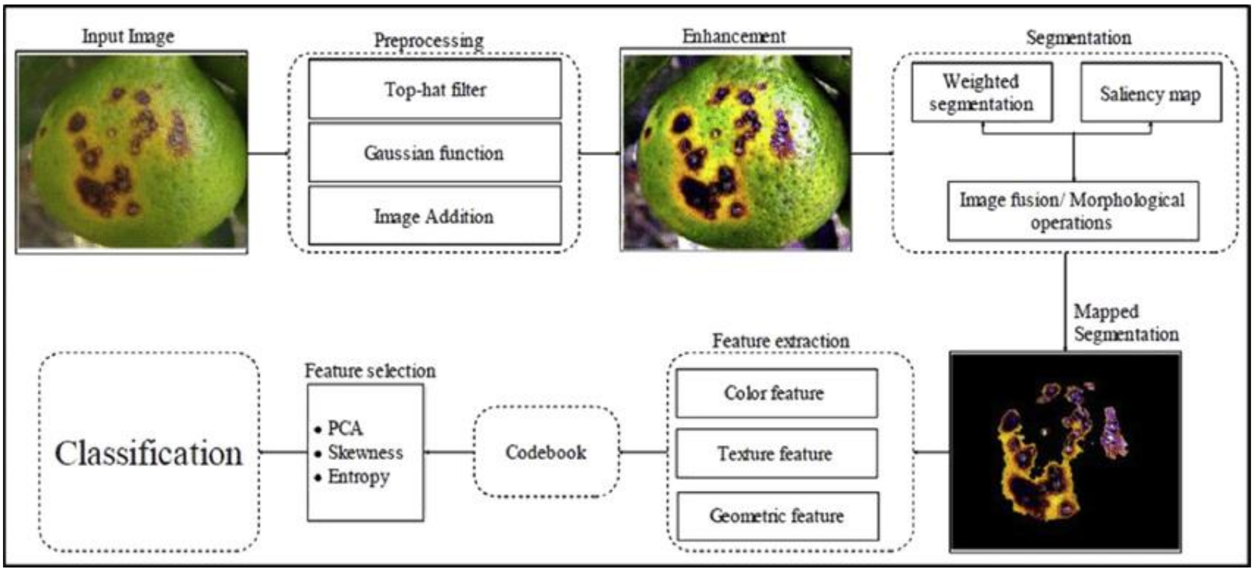
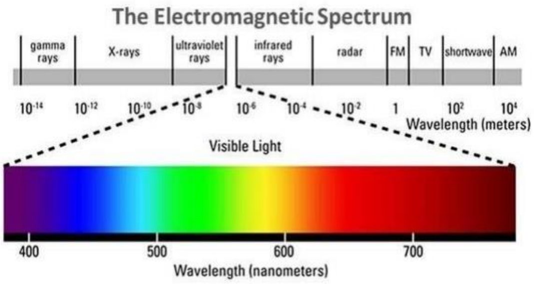


Hyperspectral Images

Hyperspectral imaging is a technique that collects and processes information across the electromagnetic spectrum to obtain the spectrum for each pixel in an image. This allows for the identification of objects and materials by analyzing their unique spectral signatures. Applications of hyperspectral imaging include food quality & safety, waste sorting and recycling, and control and monitoring in pharmaceutical production [24].



A standard RGB image consists of 3 subcomponents; on the other hand, the hyperspectral image consists of hundreds of subcomponents. After the image is acquired, a data cube (hypercube) consisting of spatial and spectral information appears. The dimensions of the data cube are the resolution of the image and the number of bands in the image. The 'X' and 'Y' components of the hyperspectral data cube are derived from the resolution of the image and the depth is related to the number of bands in the image. In Figure 2, the comparison between RGB and Hyperspectral Images can be seen [25].

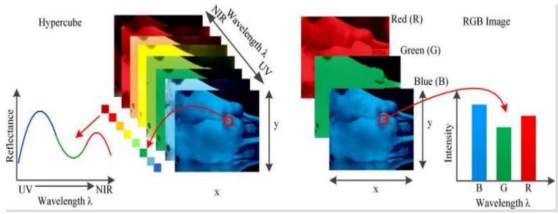


Fig Hyperspectral and RGB Image Components

For each pixel in the hyperspectral image, there is a vector consisting of reflections in each electromagnetic band. At the same time, this vector expresses a spectral signature for each pixel in the hypercube. Figure 3 shows a sample pixel vector and a sample spectral signature.

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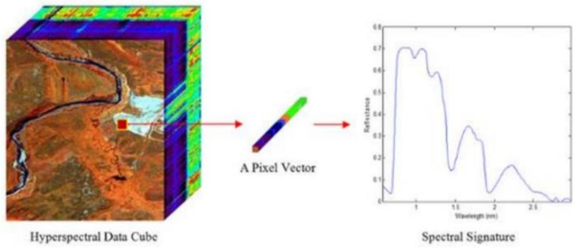

Fig Hyperspectral data cube, pixel vector, and spectral signature[26]

Dl-Based Architectural Proposal for Vineyard Disease Detection

Considering the key-knowledge that will extract relevant information from the acquired hyperspectral data, the remainder of this paper is dedicated to the proposal of a methodology - depicted in Figure 1 - that explores UASbased high-resolution spectroscopy for vineyard diseases early detection and further monitoring.

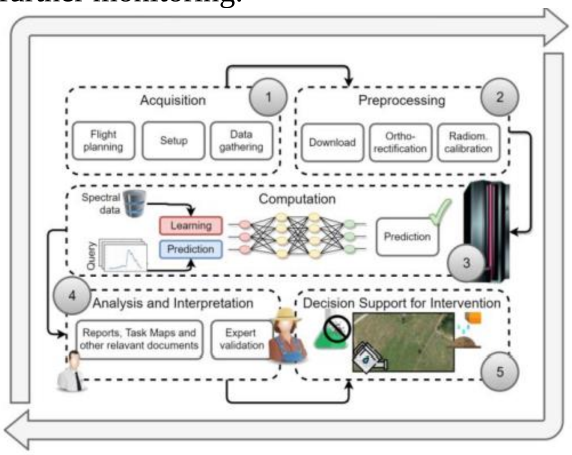

Fig Methodology proposal for a full-stack vineyard early disease detection and monitoring system.

The underlying processes rely on the following: (1) data acquisition, (2) pre-processing, (3) data computation (4) analysis and interpretation and (5) decision support for intervention. Data acquisition refers to the auto-pilot mode flight campaigns carried out with UAS to gather hyperspectral data with a lightweight push broom VNIR hyperspectral sensor with on-board data processing, data storage of 480GB, GPS and IMU for small UAV applications. Spectral range of the sensor is (400-1000 nm) with 270 bands. Next, acquired data must undergo a preprocessing step that usually consists of calibrating imagery regarding radiometry, atmospheric noise, etc., as well as performing orthorectification - required when a push broom sensor is used, as it is the case - for spatial correction purposes. Afterwards, data computation is responsible for highlighting the occurrence of diseases, using DL[27].

Convolution layer

The network is trained to differentiate the plant leaves from surroundings. The first layer of CNN obtains the features from an input leaf image. Using leaf input data to maintain the association among pixels by feature information of image. It holds image matrix and kernel as two inputs. An image in convolution layer executes the process like blur with different filters and edge detection. After the convolution layer the hidden layers generate the feature map. It shares the same weight and bias. The weights allow to be modifies during network training. The weights can be assigned based on the pixels by learning image features [28].

Deep Learning

The Deep learning algorithm is used for plant disease recognition and classification problems. The disease identification of plant has become a universal problem. The quality as well as quantity of the agriculture product can be reduced due to plant disease. The quick identification of disease is important for crop growth industry. The main task is to enhance the trait of farm production by the defect identification and disease classification of plant [29]. Traditionally with experience or training the humans carried out the crop inspection. In crop protection system early identification of plant disease and accurate result is important. Deep learning approach presents to detect the plant disease and classify the type of disease. Using continuous image capturing the autonomous agriculture vehicles accurately locate psychopathological problem in large cultivation field. The type of disease and disease harshness in plants can be identified by feature extraction and machine learning. The success of machine learning is train an algorithm by access the large amount of data and graphics processing unit (GPU) provides high computation power to achieve the parallelism in data computing [30].

Algorithms

Naive Bayes (NB)

Naive Bayes classifier is a “probabilistic classifier”. On the basis of Baye’s theorem, Naive Bayes classifier is implemented with the independence presumption among the features. It presumes that the prior probabilities of the patterns are well-known and the posterior probabilities are assigned to the class labels. With these hypotheses, the posterior probability is computed with highest probability which belongs to a specific class label. Though these hypotheses usually do not hold in the real-life environment, it is quite doing well in many classification applications [31].

K-Nearest Neighbors (KNN)

KNN classifier makes the categorization of unidentified instances based on a similarity measures or distance function. It is a supervised ML, lazy learning and nonparametric model. Normally, it uses in pattern recognition. It is based on the principle of nearest neighbor rule. For model generation, this classifier does not require any training pattern. All training patterns are utilised in testing phase to classify the test pattern dependent on similarity function. It behaves as a kind of instance-based learning where the functions are locally estimated and all the calculations have varied until the completion of classification method. The result of the KNN classifier is a class membership value that it belongs to [32].

Decision Tree

It is a supervised classification and regression model. In supervised learning, which constructs the classifiers, divided the data into numerous smaller trees and sub-tree structures dependent on the division to construct the higher inconsistency. The attribute selection measures such as Gini index, entropy are usually employed as disparity measures. For implementers, evaluation of the results using this model will be easy. If the tree had learned with no restriction of tree depth, then DT would have generate minimum training error. Several types of decision trees like CART, C4.5 and ID3 are most commonly used in ML and data mining applications[33].

Random Forest (RF)

It is an ensemble model of randomized DT classifiers. At the training time, multiple DTs are constructed. The testing dataset’s class labels are determined by the voting of all classification trees, which becomes the result of this classifier. While building of each individual tree, this classifier model uses bagging and random features. This model endeavors to make an unrelated forest of trees. The prediction of forest of tree’s performance will be more accurate than the individual tree [34].

Artificial neural networks

Deep learning is a subset of machine learning, a subset of artificial intelligence. Deep learning relies on deep artificial neural networks to learn patterns and draw inferences from provided data. There are three different deep learning and more generally machine learning approaches based on the availability of labeled data, namely supervised learning, where all the training data is labeled, semi-supervised learning, where part of the training data is labeled, and unsupervised learning, where only unlabeled data is provided [35].

Using deep learning techniques, plant disease identification has proven to be a promising approach as convolutional layers have been successfully used to automatically identify important plant features, including the colors and textures of lesions. Furthermore, similar performance was attainable while removing 75% of the parameters, further emphasizing the usefulness and practicality of deep learning. CNNs can also identify the features within images and perform classification concurrently. However,

this approach is limited and time-intensive due to the need for large datasets. More researchers are starting to adopt these techniques as more authors are beginning to provide their datasets for public use and push research further [9,46,107] [36].
Deep learning is being promoted in precision agriculture and phenotyping as it holds a lot of promise for developing the research area. However, one limitation of deep learning-based solutions for plant disease identification is the interpretability of the results. Therefore, a thorough review of deep learning-based plant disease identification studies is crucial for understanding the techniques, the ability to derive useful information from the results, and the importance of different evaluation metrics [37].
A typical convolutional neural network consists of an input layer, hidden layers, convolutional layers, pooling layers, fully connected layers, and an output layer cost function used during training. In addition, different activation functions are used and, in some cases, dropout layers as a regularization technique [38].

HSI datasets for agriculture analysis

The advent of HSI cameras has ushered in a new era in agricultural research and applications, leading to the collection and labelling of extensive datasets for Agricultural analysis using HSI data. These datasets have significantly expanded the possibilities for machine learning techniques, particularly DL, which requires considerable data for training and evaluation. Table 1 serves as a concise summarization of the available HSI datasets, in which the details of each dataset are highlighted. This table presents crucial details about each dataset, such as its size, spatial resolution, spectral channels, and the number of distinct classes it encompasses [39].

Table 1 Comparison of different HSI agricultural datasets with Source, Spatial Dimensions (SD), Spectral Bands(SB), Wavelength (WL), Spatial Resolution (SR).

Dataset	Year	Source	SD (pixels)	SBWL (nm)	Samples	Classes	SR (m)
Indian Pines	1992	NASA AVIRIS	145 x 145	220-2500	10,249	16	20
Salinas	1998	NASA AVIRIS	512 x 217	224-2500	54,129	16	3.7
Pavia University	2001	ROSIS-03 sensor	610 x 610	115-860	42,776	9	1.3
Botswana	2004	NASA EO-1	1496 x 256	242-2500	32,481	4	30
Chikusei	2014	Headwall Hyperspec-VNIR-C imaging sensor	2517 x 2335	128-1018	75,921	9	2.5
WHU-Hi-HanChuan	2016	Headwall Nano-Hyperspec imaging sensor	1217 x 3032	744-1000	25,753	10	160.1
WHU-Hi-HongHu	2017	Headwall Nano-Hyperspec imaging sensor	940 x 475	704-1000	38,669	3	220
WHU-Hi-LongKou	2018	Headwall Nano-Hyperspec imaging sensor	550 x 400	704-1000	20,454	2	90.5

Table 2. Summary of Recent Works

Author(s) & Year	Title/Focus	Key Points	Techniques/Algorithms
[40] (2022)	UAV-Borne Hyperspectral Imaging for Plant Disease Detection	Overview of using UAVs and deep learning for disease detection.	Deep learning, Hyperspectral Remote Sensing (HRS)
[41] (2024)	Hyperspectral Image Analysis and Machine Learning Techniques for Crop Disease Detection	Reviews applications of hyperspectral imaging and machine learning in agriculture.	Machine learning, Deep learning
[42] (2023)	Hyperspectral Imaging for Early Plant Disease Detection	Provides an overview of hyperspectral sensors and disease detection.	Hyperspectral imaging, Disease detection
[43] (2022)	Hyperspectral Imaging and Machine Learning in Agriculture	Reviews datasets and algorithms for agricultural applications.	CNN, SVM, Random Forest
[44] (2021)	Hyperspectral Detection of Grapevine Viral Diseases	Examines using hyperspectral imaging for classifying grapevine diseases.	SVM, RF, 3D-CNN, Vegetation indices
[45] (2019)	Detection of Yellow Rust in Winter Wheat Using UAV Hyperspectral Imaging	Proposes deep learning for yellow rust detection in wheat.	DCNN, Random Forest
[46] (2022)	Hyperspectral and Deep Learning for Basal Stem Rot (BSR) Detection in Oil Palm	Uses deep learning and hyperspectral imaging to detect BSR disease in oil palm.	VGG16 CNN, Mask RCNN

Materials And Methods

A dataset comprising 54,343 photos of diverse plant species, including pictures of healthy and sick plants as well as pictures of different fruits and vegetable crops, was collected for this suggested method.

Three sets of the dataset were created: the training set, the validation set, and the testing set. Training is carried out by fine-tuning the final network layers using the pre-trained model Inception V3[47]. Transfer learning architectures now contain four additional unique convolutional and max-pooling layers. Finally, two thick layers containing 64 neutrons and 2 neurones each were used[48]. Softmax is the activation function used for classification in the last layer. The model was trained using 20 epochs, or iterations, in which different parameters such as batch size, optimiser, pre-trained weights, and learning rate were changed. to minimise overfitting between ideals. Along with a few data generators for training and testing data[49], the model also used the assessment measure known as Multi-Class Log Loss. These generators assist in converting the batches into training data and training models and assist in loading the necessary quantity of data straight from the source folders with batch sizes according to the detection requirements. An effort has been made to standardise hyper-parameters throughout all experiments and studies in order to conduct a fair comparison of the outcomes of all trials. 30% dropouts were used in conjunction with batch normalisation and several layers to lessen the internal covariate shift, which actually aids the model in avoiding being trapped in the local[49].

Model preprocessing and training: The first thing that is done to the photographs is pre-processing. This stage involves pre-processing the database, which includes reshaping, resizing, and converting images into array form (Fig. 1). The test photos are likewise pre-processed in the same manner. There are 54,343 photos of various plant species in the database, and any photo may be used as a test picture [50]. In addition to helping to identify the test picture and its ailment, the database is utilised to train the dataset using the Inception V3 model. The program can identify plant illnesses that have previously been recorded in the database after the model has been trained. The assessment between the test and trained model to forecast the illness is carried out after the completion of training and pre-processing [51].

Database Collection: The first stage of any project involving image processing is obtaining a legitimate database collection. There are several approaches to creating the database, such as storing every picture or gathering photographs from various sources and creating your own database for processing.

The current research made use of the Kaggle Plant Village Dataset database[52]. Prior to image processing, the data was first cleaned and labelled. To guarantee a high-accuracy algorithm identification system, photos with excellent resolution and angles were chosen for image processing. A thorough understanding of various plants and their illnesses was acquired after the selection of every photograph from the database. This processing method was used to study various plant disease kinds and their symptoms. Following the thorough and in-depth analysis, picture segregation was carried out to label the photographs, and the further actions were taken[53]:

- Pre-processing was carried out in accordance with the acquisition of the input test picture. Following pre-processing, the picture was transformed into an array format for analysis.
- After that, the dataset was divided up and pre-processed.
- Following pre-processing, the dataset was trained using the Inception V3 model, and further classification was finished.
- The test and training models were compared in the next stage, and the final findings were generated based on system inputs.
- The program indicated whether the plant was healthy or unhealthy in the last stage[54].

Classification Models: To classify datasets, two models were used: SRCNN (Super-Resolution Convolutional Neural Network) Model and Bicubic Model [55].

A neural network, or CNN, is used to classify images. Recovering high-resolution pictures from low-resolution photographs is the aim of Super-Resolution (SR). Reconstruction, non-linear mapping, feature extraction, and pre-processing are the four primary functions of the SRCNN network [56].

- Upscaling low-resolution photos to high-resolution is known as pre-processing.
- The collection of feature maps is extracted from the upscaled low-resolution picture in the feature extraction process.
- Mapping feature maps representing low-resolution to high-resolution patches is known as non-linear mapping.
- Reconstruction: Using high-resolution patches, the high-resolution picture is created or rebuilt.

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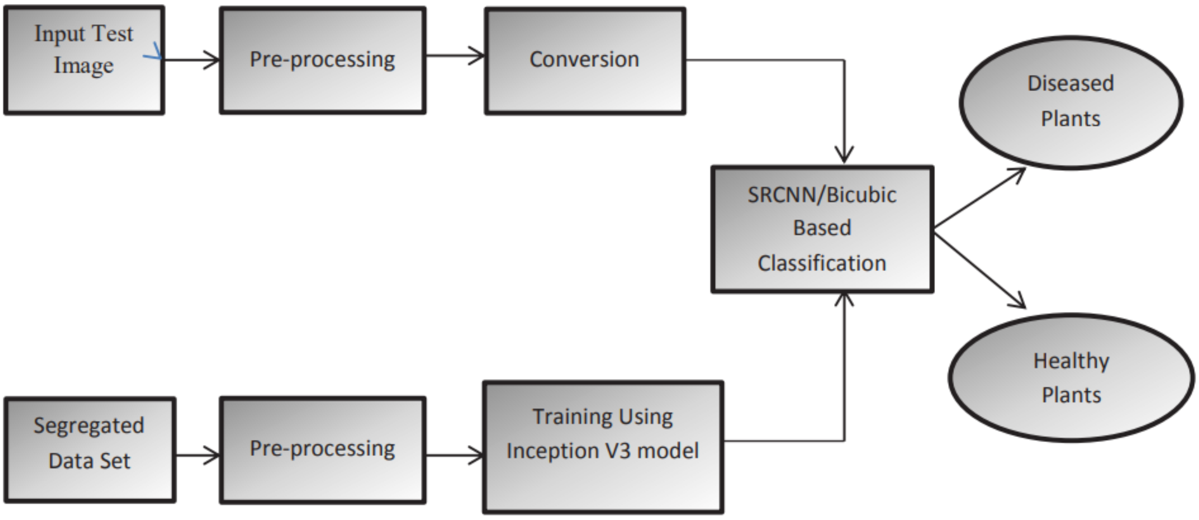


Agricultural Big Data using Hyperspectral Analytical Tools

A number of exemplary studies for the use of big data and hyperspectral analytics in agriculture are included in this subsection. Table 2 provides an overview of the representative works. For agriculture to produce high-quality crops and pastures, good soils are essential. The field of soil spectroscopy, which seeks to discover and create soil spectral libraries (SSLs) and signatures, is where one of the real-world Big Data issues starts [57]. An evolving fuzzy rule-based system was put out by the authors in and used with actual agricultural big data. Large datasets from the field of soil spectroscopy (GEO-GRADLE and LUCAS SSL libraries) were used in their study. The authors of this paper suggested a two-phase MapReduce framework along with a number of modifications for handling large amounts of data [58]. Their method modified DECO3RUM, an innovative fuzzy rule-based technique for big data. Their experimental effort combined hyperspectral information from the field of soil spectroscopy with real-world Big data. A wide range of soil and land cover types were included in the data samples. Eight virtual servers running a hardware setup with two Intel Xeon processors and 128GB of RAM were used to simulate the model and assess it in a Hadoop cluster [59].

At the regional and farm levels, the FLTL structure provides a framework for managing big data and remote sensing for precision agriculture. The creation of crop maps is necessary for both crop identification and categorisation. The enormous amount of input data and the spectrum similarity provide two difficulties for crop identification and classification. To solve the spectral similarity problem for Big data in agriculture, a crop classification method that combines many characteristics (spectral, spatial, and vegetation index features) [60]. Using PCA (principal component analysis) and MNF (minimal noise transform) in the first step, their method reduces dimensionality before moving on to support vector machine (SVM) supervised classification. Six crops were employed in their study to conduct the experimental evaluation: potatoes, winter wheat, cucumbers, onions, maize silage, and sugar beets.

According to their findings, the classification accuracy increased to 98% when the vegetation index characteristics were combined with the spectral and spatial information. For a research conducted in Florida using unsupervised learning for hyperspectral agricultural photos, the authors in suggested an image classification method called ISODATA (Iterative Self-organising Data Analysis Technique Algorithm) [61]. The ENVI (Environment of Visualising Images) program for geographic images was used in their experimental work. Following PCA, the hyperspectral images were classified using the ISODATA method for several class types (Water, Shadow, Wet, Fertile Soil, Land, and Forest). After performance evaluation, the classification process's total accuracy came out to be 75.6%. For dimensionality reduction, the authors of another work in [80] suggested a graph-based learning strategy called local geometric structure Fisher analysis (LGSFA). The authors' experimental findings provided classification results similar to other state-of-the-art approaches, and they proved that their methodology was successful in exposing the manifold structure for high-dimensional hyperspectral data.

The authors' survey work from has further details on graph-based learning strategies for hyperspectral data [62].

Methods of Machine Learning for Agricultural Hyperspectral Data Analysis

In the field of agricultural remote sensing, hyperspectral image classification has become an important topic [63]. Hyperspectral data have complex characteristics and a nonlinear relationship amongst the spectral bands and its various component materials. This makes the accurate classification of the sensed scene a challenging task. This subsection presents a review of more recent works on machine learning techniques for multispectral and hyperspectral data analytics in agriculture [63].

A large-scale crop mapping using Google Earth Engine and multisource remote sensing pictures. Their method is divided into three phases: (1) using spectral characteristics from satellites (Landsat-8 and Sentinel-2) in conjunction with NDVI data for harmonic analysis; (2) using previous crop distribution and dominance limitations; and (3) using Google Earth Engine for information processing[64]. Three crop types—wheat, rapeseed, and corn—were employed in their studies to assess their regression tree classification methodology. They showed an overall accuracy of 84.25% in their findings. Their research also shown that the terrain, agricultural climate, and cultivation methods all had an impact on the distribution of the crops in the studied area [65]. the authors presented a method for using spatial, spectral, and temporal S2-SITS data to analyse the development of agricultural fields. Their methodology was divided into three main steps: (1) creating a vegetation map by fusing temporal NDVI data with spatial and spectral data[66]; (2) building an NDVI time series for a crop field and establishing an adaptive regression model using a multilayer perceptron neural network (MLP-NN); and (3) extracting and analysing the spatial-temporal information from the NDVI time series. Experiments using S2-SITS data collected across a region near Barrax, Spain, confirmed the effectiveness of their methodology [67].

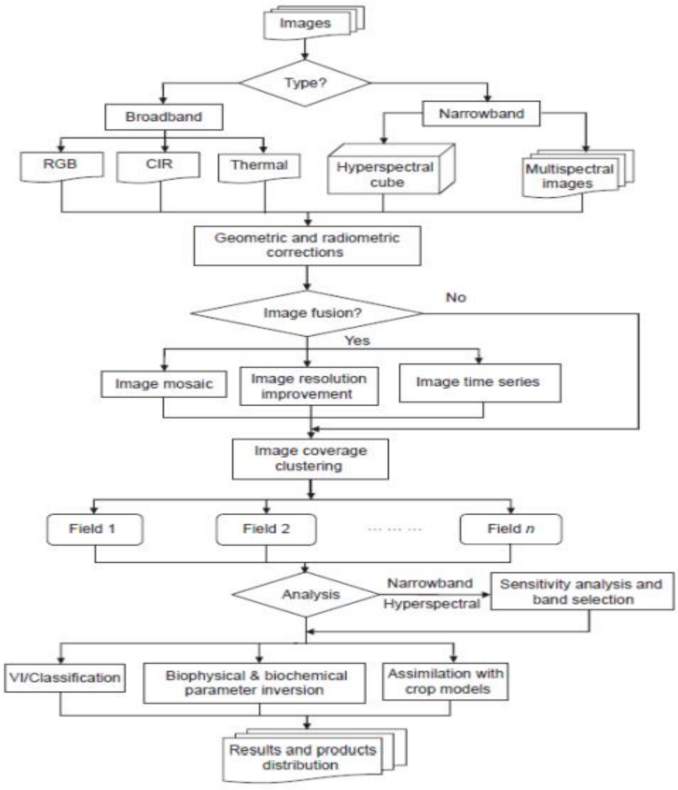
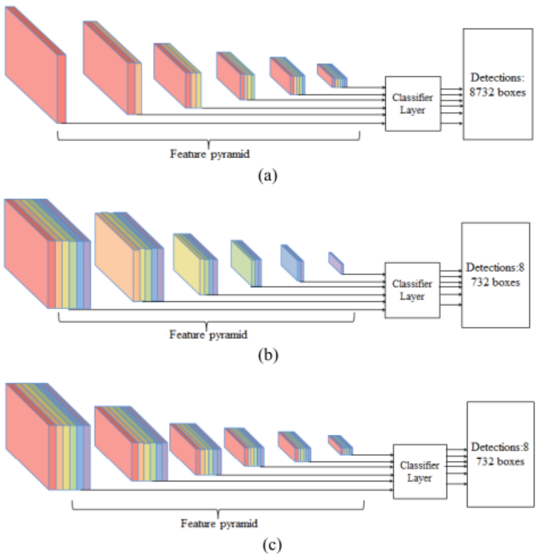


Fig Framework for FLTL remote sensing data management.

Rainbow Concatenation

The original SSD algorithm has two main drawbacks: One is that the same object can be detected in multiple scales of feature maps because each layer in the feature pyramid is used independently as an input to the classifier network. The other is that the performance of SSD in detecting small objects is limited. Thus, an algorithm that is dedicated to solving these two problems, namely, R-SSD, is proposed, which applies Rainbow concatenation to the SSD algorithm [68]. The methodology of Rainbow concatenation, which is implemented in R-SSD, is applied to further improve the detection accuracy for small objects that correspond to apple leaf diseases. Figure 7 presents three approaches to increasing the number of feature maps to take advantage of the relationships among the layers in the feature pyramid. feature maps in the upper layers are concatenated to those of the lower layers via deconvolution. However, using pooling or deconvolution separately only allows the contextual information to flow in one direction. Therefore, in R-SSD, these two methods are both applied to produce an explicit relationship of feature maps among layers. By using Rainbow concatenation, the detection precision of small objects is substantially improved [69].



Data Augmentation Comparison Experiments

Several techniques have been used in this research to avoid overfitting. Initially, the sick apple leaves were photographed in a range of settings and climates.
A small number of infected apple photos with homogeneous backgrounds were taken in a lab setting, while the majority of diseased apple photos with intricate backgrounds were gathered in the apple orchard [70]. The generalisation of the suggested model may be guaranteed by using different shooting backgrounds, which lowers the likelihood of overfitting. Second, to replicate the real acquisition environment and boost the variety and quantity of apple leaf training images, a variety of digital image processing technologies, including rotation transformations, mirror symmetry, and intensity disturbance, were applied to the natural training images. This can help avoid overfitting and enhance the suggested model's generalisation performance throughout the training process [71].

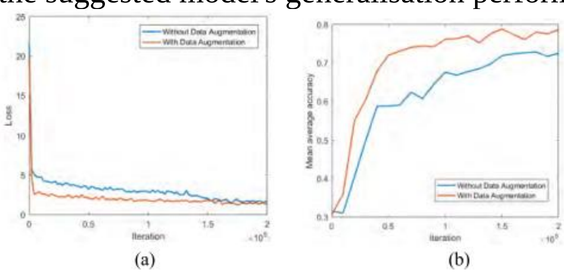


Fig Influence of the expanded dataset. (a) Training loss. (b) Test accuracy [72].

Data augmentation is a satisfactory option when the training dataset is insufficient or to prevent overfitting to make the model more robust. This paper performed two sets of experiments to estimate the performance of the dataset for the proposed model, which was trained separately before and after the expansion of the dataset. without data augmentation, the training process has high loss and low accuracy and finally reaches 71.89% mAP. However, the proposed model with data augmentation realizes 78.80% mAP, which corresponds to a detection precision improvement of 6.91% over the dataset without data augmentation [73].

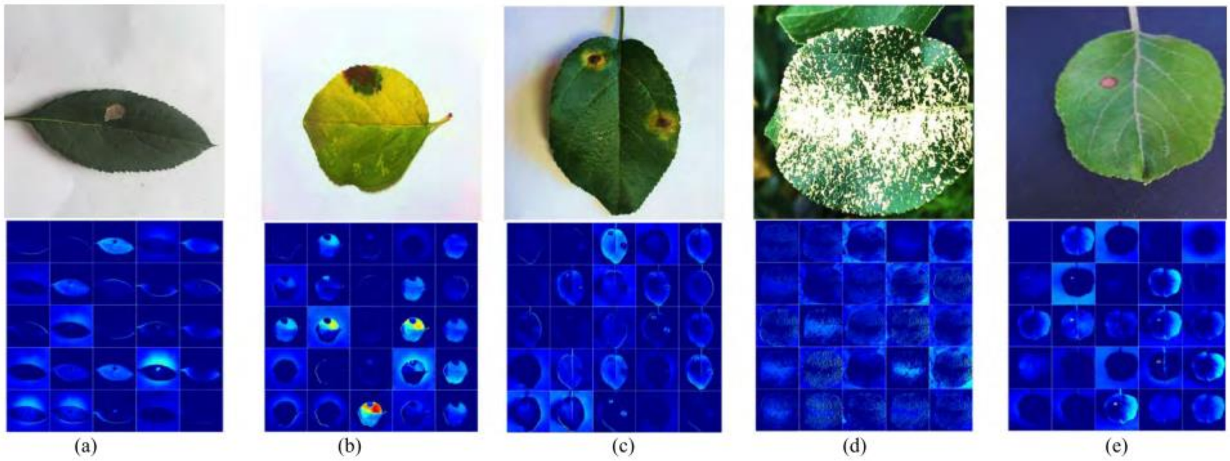


Fig Activation visualization results. (a) Grey spot. (b) Brown spot. (c) Rust. (d) Mosaic. (e) Alternaria leaf spot [74].

Feature Visualization Process

The weak explanatory ability of the CNN makes it a ''black box'' model. Other factors, such as its multi-layer hidden structure and massive number of parameters, also defy understanding. To determine how CNNs learn features for distinguishing among classes, visualization techniques are used to reveal CNN feature maps [75]. Through this experiment, the differences among the feature maps that are extracted from various diseased apple images can be better understood. Alternaria leaf spot is rounder and smaller than Grey spot. In this experiment, the activation visualization results for various apple leaf diseases demonstrate the strong performance of the proposed model in detecting diseases and clarify how CNNs learn features for distinguishing among classes [76].

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Fig Types of detection results. (a) Single object of a single class. (b) Multiple objects of a single class. (c) Multiple objects of multiple classes.

Plant Leaf Recognition Based On Deep Learning

Image recognition technology is an important field of artificial intelligence. Image recognition technology is based on the main features of images. In-deep learning is the result of recent outstanding performance to solve the perception, planning, positioning, and control of various robot task areas. Learning its excellent ability indicates that the real environment of complex data acquisition makes it very suitable for various autonomous robot applications. The essence of leaf image segmentation is to classify pixels and use machine vision and image processing technology to segment plant leaves from the background. In feature preprocessing, we focus on the possible problems of non-uniform dimension, redundancy of information [77], non-acceptance of qualitative features by machine learning algorithms and models, lack of features and low utilization rate of information existing in unprocessed original features, and study the dimensionless and standardized features. If the degree of reflection exceeds the threshold of this kind of neuron, the neuron will only reflect, thus leading to the next neuron. People use functions that can take values continuously. The key to a general classification problem based on image sets is to consider how to model the image sets, and how to define the distance or similarity between the image sets to achieve classification [78].

When choosing the parameters outside the model, such as learning rate and iteration number, the training set is subdivided into actual training set and cross-validation set by using multi-fold cross-validation method. By observing the different effects of various parameters. The deep model is also very convenient to adjust. The model can be changed only by modifying the parameters [79]. It can meet different input and classification requirements and has strong flexibility and growth. In the actual deep learning model, some information will be lost for each layer, so the system parameters need to be adjusted continuously to make the errors between images as small as possible. After the noise is removed, the focused part can be marked out for subsequent processing, instead of dividing the whole blade. A large amount of plant digital image information is collected, whether in the training or testing stage, multiple plant digital images can be used to replace the traditional research on identification and classification methods of single plant images [80], that is, plant classification based on image sets. The detected patterns are combined to form a larger pattern, and subsequent layers detect objects that combine these patterns. Compared with traditional feature engineering, deep learning has changed the way of obtaining features. Because the image is high-dimensional and includes all kinds of huge changes. Even if the model has used convolution and pooling techniques to keep some of the comments unchanged, the operation of translating a few pixels along each direction of the training image can usually greatly improve generalization[81].

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