REMOTE SENSING USING UAVS FOR DETECTING CROP DISEASES: AN OF MACHINE LEARNING AND DEEP LEARNING APPROACH

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ABSTRACT:

UAVs outfitted with remote sensing technologies present valuable options for detecting crop diseases in precision agriculture. reviewed the application of ML and DL techniques in conjunction with UAV-based remote sensing to improve the accuracy of crop disease identification. UAVs offer versatile coverage of agricultural fields and capture high-resolution images, which aid in the automated detection of diseases across various types of crops. UAVs gather data on crop features to assess disease levels by utilizing RGB, multispectral, and hyperspectral sensors. Earlier research has focused on using vegetation indices and extracting data at the plot level for disease evaluation. Recent advancements in UAV technology and sensor capabilities have made it possible to use ML & DL algorithms for more precise illness estimation. This paper assesses the benefits and drawbacks of current methods and highlights the significance of a thorough investigation of ML and DL techniques for agricultural disease detection with unmanned aerial vehicles (UAVs). The combination of UAV-based remote sensing with sophisticated data-driven techniques has the potential to significantly improve early disease detection, assist farmers in making timely decisions, and minimize yield losses in precision agriculture.

Keywords: UAV, Remote sensing, crop disease detection, machine learning, deep learning, precision agriculture, Unmanned Aerial Vehicle, Disease estimation, vegetation indices, plant phenotyping.

1. Introduction

Environmental stresses that reduce crop productivity are common and can be divided into two categories: biotic (such as pests and diseases like fungi, bacteria, and nematodes) and abiotic (such as drought, floods, and extremely high temperatures) causes [1]. Crop scouting has historically involved farm workers manually examining disease indicators, frequently with assistance from a plant pathologist or crop disease specialist [2]. Because it necessitates pathogen isolation, microscopy, and symptom observation, this approach takes time [3, 4]. UAVs, the Internet of Things (IoT), and artificial intelligence (AI) are examples of cutting-edge technology that present viable, easier-to-use, and quicker alternatives for disease detection [5]. Early diagnosis is essential for averting yield losses and inspiring researchers in precision agriculture to create novel, affordable remedies [6–8]. This difficulty can be successfully addressed by a multidisciplinary approach that makes use of drones, AI approaches, and remote sensing [9].

By using electromagnetic (EM) radiation as a transport of information, remote sensing offers a reliable and objective approach for measuring and monitoring illness [6]. The electromagnetic spectrum includes radio waves and gamma rays. Different spectrum sections are captured by sensors including RGB (visible), multispectral, and hyperspectral [10,11], with higher costs often corresponding to increased sensing ability [12]. Utilizing unmanned aerial vehicles (UAVs), remote sensing has been applied to precision agriculture (PA) applications, including disease identification [7], plant health monitoring [13], and yield estimations [14]. Because of their adaptable field coverage and capacity to obtain high-resolution images closer to plants than other airborne techniques, unmanned aerial vehicles (UAVs) are preferred in PA research [15]. With the help of these high-resolution photos, diseases like tomato spot wilt disease [17], peanut leaf wilt [S], and yellow rust in wheat [16] can be automatically detected in a variety of crops.

RGB, multispectral, and hyperspectral sensors have been utilized in numerous examinations to aggregate plants utilizing unmanned aerial vehicles. To predict yield and stress levels, these sensors gather data on crop attributes like covering thickness, biomass, and level. Furthermore, a couple of studies have confirmed the accuracy of UAV-based remote sensing in assessing disease. These investigations often extract plot-level data by counting pixels under a threshold to gauge sickness scores, or by working out the average worth of a vegetation index. For example, Patrick et al. [17] assessed tomato spot wilt sickness in peanuts utilizing multispectral picture derived indices like NDRE and NDVI. Utilizing a MicaSense RedEdge camera, they took multispectral pictures and applied a threshold to recognize healthy and unhealthy pixels. In the linear regression analysis, the disease percentage was the target variable and the number of pixels beneath or over this threshold was the predictor variable. However, the computerization of this technique is restricted by the need to physically set the best criteria for every vegetation index. Moreover, the utilization of the technique is convoluted by the way that certain vegetation indicators miss the mark on characterized threshold for differentiating among healthy and unhealthy plots.

Advances in UAV platforms and sensors, which have made image collection more frequent and inexpensive, have enhanced the accuracy of agricultural disease forecasting via predictive tactics, such as classical (ML) and (DL) approaches [19]. Hyperspectral remote sensing was used by Abdulridha et al. [20] to differentiate tomato disease using (VIs) and machine learning methods such as (ANN). Additionally, it was suggested to use machine learning and multispectral UAV images to identify wheat yellow rust [21]. Using a (RF) classifier trained at the pixel level, this method achieved an accuracy of 89.3% in classifying image pixels as either badly polluted, moderately infected, or healthy.

After carefully examining 100 publications on crop stress monitoring with unmanned aerial vehicles, Barbedo et al. [22] synthesized numerous studies on UAVs and sensors for plant stress monitoring. While the study offered suggestions for future research and tackled current issues, it did not fully address cutting-edge data-driven techniques like (ML) and (DL) for crop security with (UAVs).

Neupane et al.'s investigation [23] examined the sensors and techniques for employing UAV technology to automatically monitor and identify agricultural diseases. A thorough explanation of the ML and DL approaches and their assessment was absent from the survey, which instead focused on the benefits of using different UAVs and cameras, including RGB, multispectral, and hyperspectral, for precise crop disease identification.

The use of deep learning (DL) methods and unmanned aerial vehicle (UAV) footage for early disease diagnosis in agriculture was investigated by Bouguettaya et al. [24]. Still missing were details like a taxonomy for crop disease identification and comparisons of other UAV-based methods' effectiveness, as well as any discussion of competing strategies like traditional machine learning or techniques based on vegetation indices. Despite Bouguettaya et al.'s best efforts, a comprehensive taxonomy and literature review remain absent. [24] recently examined and compared the effectiveness of several deep learning approaches for exploiting UAV photos to detect crop diseases. Table 1 illustrates the key components, target areas, and limits of the most pertinent surveys that are currently available.

Table 1. Synopsis of Current Survey Research on Crop Disease Estimation Using UAV Images and Precision Agriculture

Ref	**Focused Area**	**Features and Highlights**	**Laminations and Gaps**
[22]	Monitoring plant stress	● Sensors and UAVs were discussed. ● A list of difficulties and	● Conventional machine learning methods were not addressed. ● Deep learning methods were not

		suggestions for UAVs in precision agriculture was provided. ● .	included.
[23]	Detecting crop diseases with UAVs	● Covered a range of sensors and UAV types. ● Featured various techniques for processing data. ● A brief discussion of deep learning techniques ● .	● The survey did not focus on ML and DL methods. ● It did not cover performance comparisons between conventional ML and DL methods.
[24]	Early identification of crop diseases	● Gave a summary on precision agriculture and UAVs. discussed some techniques for deep learning	● The survey did not include a taxonomy of crop disease detection. ● It was short and omitted any discussion of machine learning or other techniques.
[26]	UAVs for detecting plant and crop diseases	● A range of remote sensing and UAV methods. ● The ability of deep learning to detect agricultural diseases effectively. ● Obstacles and restrictions in using UAVs to detect agricultural diseases	● There was no taxonomy of crop diseases provided. ● The performance comparison of different machine learning and deep learning algorithms was not discussed. ● The literature was not the subject of a meta-analysis.
[9]	UAVs in precision agriculture	● Hyperspectral sensor overview. ● The overall method for detecting crop diseases using hyperspectral imaging. ● Crop disease detection	● It was not discussed how to use machine learning techniques. ● No discussion was held regarding a taxonomy of crop diseases. ● It did not address recent developments in deep learning

		using deep learning techniques	techniques.
[27]	Aerial hyperspectral imaging for crop disease detection	● Hyperspectral sensor overview. ● The overall method for detecting crop diseases using hyperspectral imaging. ● Deep learning methods for identifying agricultural diseases	● No mention of machine learning techniques was made. ● There was no discussion of a taxonomy of crop diseases. ● The most recent developments in deep learning techniques were overlooked.
[28]	Thermal UAV imaging for precision agriculture	● Generally, tasks related to precision agriculture were the main focus. ● Using thermal photography was one of the features	● Deep learning and machine learning techniques were not discussed. ● No taxonomy system was created.

This study addresses the current holes by providing a point by point scientific classification for assessing crop diseases utilizing UAV imagery. The principal contributions of this study are as per the following.

- Highlighting potential improvements to agricultural disease detection using various UAV platforms and sensors.
- Presenting a taxonomy for estimating agricultural diseases and delineating the main procedures for remote sensing pipelines utilizing UAVs.
- An examination and comparison of the practicality of deep learning (DL) and traditional machine learning methods for the identification of agricultural illnesses using information obtained by unmanned aerial vehicles (UAVs).
- Performing a meta-analysis of the literature to identify trends in the area and recommend directions for further research.
- A summary of the challenges, opportunities, and areas that require further study in UAV-based remote sensing for agricultural disease detection

The rest of this essay is structured as follows: Section 2 outlines the methodical process for locating pertinent research articles. Section 3 provides background information on remote sensing, vegetation indices, and ML/DL to facilitate the reader's understanding. In Section 4, we can see the proposed taxonomy for identifying crop diseases using UAV images. The results of the survey data synthesis and meta-analysis are presented in Section 5. In Section 6, we draw conclusions and offer recommendations for future research.

2. The Survey's Methodology

We tried to determine current research holes and explore the conceivable outcomes of machine learning and deep learning techniques in agricultural disease ID utilizing (UAV) remote sensing. To gather and incorporate research articles pertinent to the concerns of our review, we carried out a methodical review of the literature utilizing laid out procedures. PRISMA criteria [29] were continued in this review, and the purposeful strategy displayed in Figure 1 was used to track down relevant distributions.

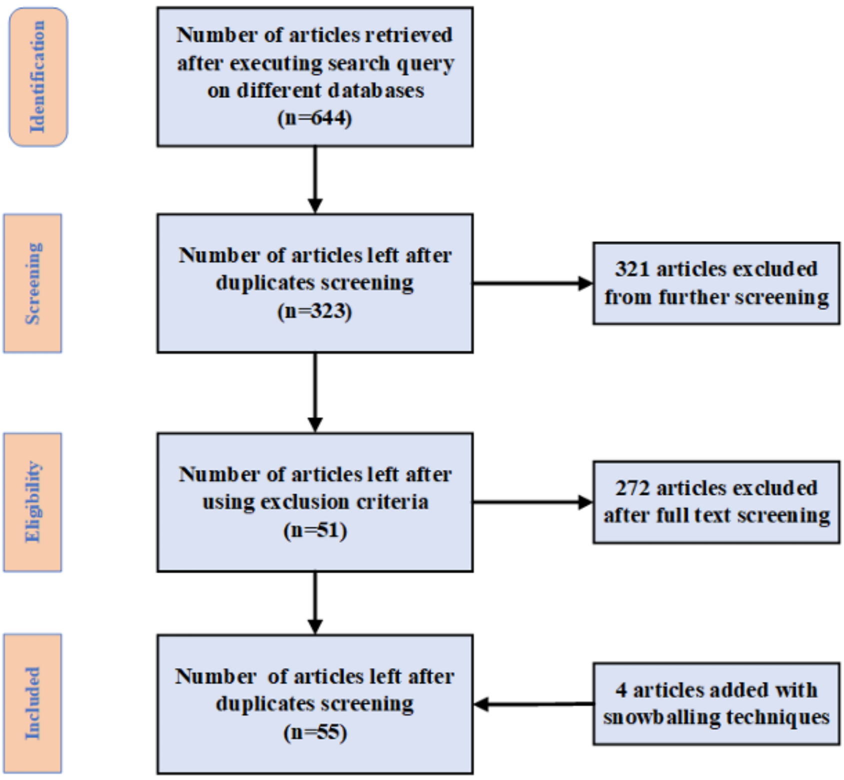


Figure 1. A methodical approach was utilized to obtain publications for the purpose of systematic review.

The following research questions served as our guide for creating this questionnaire:

RQ1: Which UAV systems and sensors are best suited to identify agricultural disease? This inquiry aims to determine which sensors—such as RGB, multispectral, and hyperspectral sensors—are most effective at detecting agricultural diseases when employed in various (UAVs).

RQ2: Which crop diseases have been investigated by data-driven approaches, such as (DL) and traditional (ML), and UAV-based remote sensing? The purpose of this question is to list the agricultural illnesses that are effectively detected by ML and DL approaches and are caused by fungi, bacteria, insect pests, and viruses.

RQ3: Based on statistics, which techniques are the most effective and precise for employing UAVs to identify crop diseases? This question, which evaluates the effectiveness of several data-driven techniques, including ML and DL, for UAV-based agricultural disease detection, demonstrates the significance of this study.

RQ3: Can you provide more context or clarify your questions? This will help me rephrase it more accurately.

To view as pertinent material, we first settled a tailored search strategy. We narrowed the search from general ideas like "ML" and "DL" to explicit phrases like "crop disease" and "UAV." The generated query string was as per the following: ("UAV" OR "unmanned aerial vehicle") + ("CD" + "ML" OR "DL"). Considering the tremendous progressions in machine learning and deep learning beginning around 2012, four databases were searched utilizing this query: IEEE Xplore, Scopus, Google Scholar, and MDPI. Titles and abstracts of articles published somewhere in the range of 2012 and 2022 were the primary accentuation (as cited in [30]).

Duplicate articles and non-peer-reviewed articles, like preprints, were eliminated during the article selection process. The following criteria were used to screen the entire texts, abstracts, titles, and keywords in order to eliminate irrelevant articles:

- Articles not in English.
- Publications related to agriculture that don't address crop disease estimation.
- Publications on crop diseases that don't utilize UAV-based remote sensing.

Following this procedure (Figure 1), we distinguished 55 publications for efficient analysis and combination to address the (RQ1-RQ4).

3. Background

3.1 UAVs and remote sensing:

Using energy that is reflected or transmitted from distant objects, remote sensing collects physical attribute data on an object without causing damage [31]. In active remote sensing, an object is interacted with, reflected energy is recorded, and the resulting images are transmitted, received, and analyzed. Precision agriculture (PA), which depends on precise temporal and geographical field data for sound decision-making, requires this method. Modern technologies are essential for managing PA, including networking, aerial sensors, and field-based sensors. Appropriate pesticide application [32], yield calculation [33], and irrigation management [34, 35] are just a few examples of PA operations where remote sensing has proven worthwhile. The three main ways these methods can be classified are field-based sensors, sensors based on satellites or airplanes, and sensors based on drones.

Large-scale data collection using field-based sensors necessitates frequent relocation, which raises labor and expense expenses [36]. Spectral imaging from satellites or airplanes is frequently costly and might not always be available [38]. On the other hand, drones, also known as unmanned aerial vehicles, are a relatively new addition to PA. When weather permits, (UAVs) can revisit fields and obtain high-resolution imagery while flying in close proximity to crops [39]. UAVs come in a variety of designs, such as parafoil, hybrid, fixed-wing, flapping, and rotary-wing [12]. Popular UAV models utilized in precision agriculture are shown in Figure 2 [12]. Fixed-wing UAVs are perfect for large-scale surveys because they can cover enormous regions quickly and with heavy payloads, but they need a lot of runway space. On the other hand, because of their versatility and ease of use, rotary-wing UAVs—which have the ability to take off and land vertically—are preferred. [40].

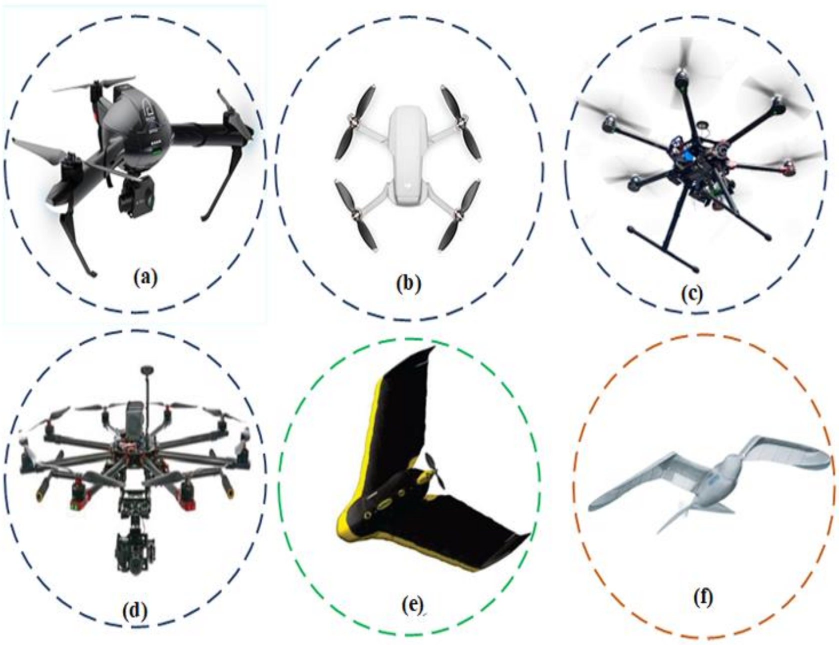


Figure 2. Certain popular (UAVs) that are utilized in precision agriculture are: (a) fixed wing (Ebee), (b) quadcopter, (c) hexa-copter, (d) octocopter, and (e) flapping wing (Smart Bird) [41].

(UAVs) are utilized in remote sensing to gather light spectrum reflections off diverse objects, including plants, soil, and water. Data on reflectance are fundamental for tracking crop growth [42]. Vegetation index (VI) pictures are pixel-level estimations that include algebraic operations on various spectral bands to generate differentiated information. Whether a VI image is (a) RGB-based, (b) multispectral, or (c) hyperspectral depends on the kind of sensor [43]. To detect plant illnesses, vegetation indices primarily use red and near-infrared bands from hyperspectral and multispectral sensors; however, they also use RGB-based VIs in combination with these types of VIs. For Table 2, where the spectral bands denoted by the letters "R," "G," "B," "NIR," and "RE" are red, green, blue, near-infrared, and red edge, respectively, the commonly used VI and their derived formulae are remembered.

Ref.	Vegetation Index	Formula
[44]	Normalized difference VI (NDVI)	$\frac{(NIR-R)}{(NIR+R)}$
[45]	Normalized difference red edge VI (NDRE)	$\frac{(NIR-RE)}{(NIR+RE)}$
[46]	Green VI (GVI)	$\frac{(G-R)}{(G+R)}$
[47]	Difference VI (DVI)	NIR-R
[48]	Excess Green (ExG) VI	2*G-R-B
[49]	Green normalized difference VI (GNDVI)	$\frac{(NIR-G)}{(NIR+G)}$
[49]	Soil adjusted VI (SAVI)	$\frac{(1.5(NIR-R))}{(NIR+R+0.5)}$
[17]	Simple ratio (SR)	$\frac{NIR}{(RE)}$
[16]	Plant senescence reflectance index (PSRI)	$\frac{(R-G)}{(RE)}$
[50]	Chlorophyll Index (CI)	$\frac{(NIR)}{G}-1$
[51]	Green leaf index (GLI)	$\frac{(2*G-R-B)}{2*G+R+B}$

3.2 Machine Learning

Recent advances in machine learning and data examination have had a huge effect across various fields, including stock market prediction, computer vision, text mining, biomedical picture analysis, and precision agriculture. The strength of ML lies in its capacity to extract bits of knowledge from large datasets. In agriculture, how much data has increased dramatically with the introduction of sensors, GPS, and the Internet of Things. This has prompted a greater demand for thorough data analysis. In order to help choices for disease detection, crop monitoring, irrigation for executives, and yield prediction, these data may be examined under the guidance of machine learning [40].

ML methods apply rules or patterns found in training data to fresh data by using supervised or unsupervised learning procedures. Supervised learning approaches that are often used include support vector machines (SVM), decision trees (DT), random forests (RF), multi-layer perceptron (MLP) neural networks, and Naive Bayes (NB) [56–59]. These methods need manually labeling the contaminated regions in UAV photos in order to train the model [60]. Once trained, the model can identify if an ailment is present in another crop-field image [57].

In contrast, unsupervised machine-learning models work with unlabeled data and can uncover patterns without human intervention [61]. For example, Wang et al. used the k-means clustering method to detect cotton root diseases by grouping image pixels based on their similarities. This approach successfully differentiated between healthy and diseased pixels by clustering them into separate groups [62].

3.3 Deep Learning

DL has advanced dramatically over the last ten years, revolutionizing data analysis and pattern identification in domains such as CV [19], SP [63], and PA [55]. Deep Learning (DL) is an extension of neural networks that uses layered architectures to learn the hierarchical characteristics. Convolutional neural networks (CNNs), as shown in Figure 3, are widely used in computer vision applications, such as image recognition and organization [64]. Plans such as VGG [65], DenseNet [66], ResNet [67], and GoogleNet [68] use convolution, pooling, and actuation to extract higher-order semantic information. Consequently, CNNs have shown outstanding performance in remote sensing [40,70], wellness informatics [54-69], and natural language processing [71].

Precision farming has made use of DL. For instance, Zhang et al. [72] developed a DL framework to identify wheat yellow rust sickness using UAV aerial pictures. With Inception-v3 [73], ResNet50 [74], VGG [65], and Xception [75] as their architectures, they were able to achieve an astounding 99.04% accuracy rate with RGB images captured at a 2-meter level. This features the chance of accurately assessing disease utilizing refined DL models. However, these models require high-resolution pictures from low elevations, which can be impractical attributable to legitimate and operational constraints including battery life restrictions. Moreover, lower flight elevations reduce the coverage area of the UAV.

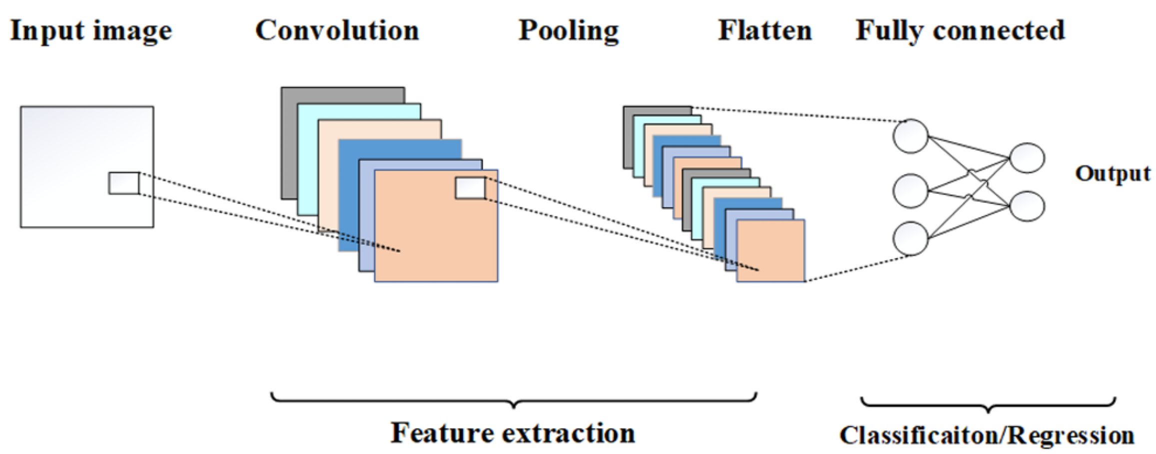


Figure 3. Example of a standard (CNN).

3.4. Assessment Matrix

To help with comparing the models in the parts that follow, this section gives an outline of the assessment metrics used to assess approaches for crop disease detection. The coefficient of determination (R^2), as outlined in Equation (1), is commonly used to assess methods that estimate diseases using continuous dependent variables, such as disease scores or percentages.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - z_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (1)$$

The primary approaches for evaluating disease estimating techniques where the dependent variable is discrete, such class or category representations, are precision (Equation (2)), recall (Equation (3)), I-score (Equation (4)), and accuracy (Equation (3)).

$$P = \frac{T_P}{T_P + F_P} \quad (2)$$

$$R = \frac{T_P}{T_P + F_n} \quad (3)$$

$$F = \frac{P \times R}{P + R} \quad (4)$$

$$A = \frac{T_P + T_n}{T_P + T_n + F_P + F_n} \quad (5)$$

Here, T_P 〖,T〗_n,F_P and F_n represent, in a specific order, true certain, true regrettable, bogus positive, and misleading negative qualities. Furthermore, P, R, F, and A stand for accuracy, recall, f-score, and precision, respectively.

4. Classification of Crop Disease Assessment Using UAV Imagery

We divided the current techniques for identifying agricultural diseases using UAV data into three main categories. Statistical techniques leverage a variety of (VIs) to extract agricultural attributes and apply regression and correlation studies to build linear correlations between disease and spectral data from UAV imagery. Second, classic (ML) approaches construct disease estimation models by utilizing vegetation indexes as input characteristics and applying conventional supervised or unsupervised procedures. Lastly, deep learning techniques train end-to-end models for illness recognition employing UAVs using raw photos and other characteristics.

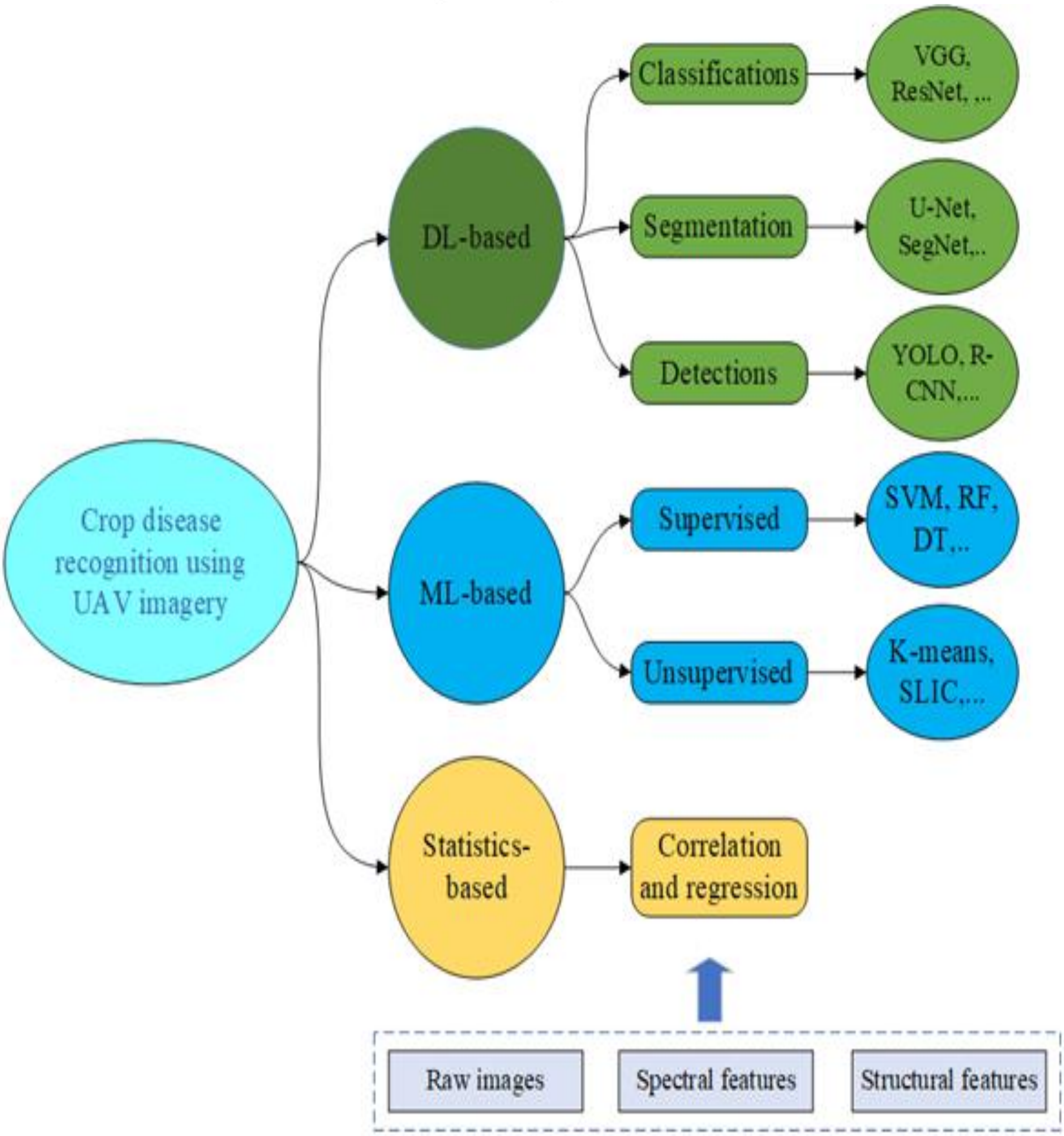


Figure 4. A classification system for assessing agricultural illnesses by unmanned aerial vehicle remote sensing. The visual components used in one or more branches are represented by the items within the dotted box.

4.1. Methods Based on Statistics

Crop-related features from UAV data are utilized as the autonomous variables in language model-based approaches to appraise crop illnesses, with the disease score serving as the target variable. The connection between these variables is determined by the strength of the correlation between them. Preprocessing UAV pictures, creating a vegetation index, and statistical analysis are the three processes in the procedure. To produce spatial data products that assist with extracting agricultural features at the plot or field level, such reflectance maps and advanced surface models, pre-processing is fundamental. The unmistakable spectral bands are used to create different vegetation indices after the reflectance map has been created. The current literature on crop disease estimation frequently utilize these indices as free variables in regression and correlation examinations. One productive technique to evaluate shelter cover, growth, and vigor is by means of (VIs), which can be acquired utilizing remote sensing platforms, for example, satellites and UAVs [36]. Covering data from VIs is utilized to evaluate crop traits like water stress, yield, and leaf area index [76]. Researchers have used a variety of vegetation indicators derived from UAV-based sensing frameworks to assess agricultural illnesses [56, 57]. An essential pipeline for disease evaluation utilizing viability indices (VIs) starts with extracting VIs from crop field pictures. Then, the illness score is utilized as the reliant variable and VIs as the free variables in a regression and correlation study [8, 16, 17].

Separating the crop fields into individual plots is the underlying move toward extracting the vegetation index (VI). Vegetation extraction at the plot level was in this manner performed utilizing the average vegetation index esteem across all plots. The approach embraced by Patrick et al. [17] was based on thresholds. They concocted a lot of vegetation indices, as NDRE, NDVI, and DVI, to tell healthy pixels from wiped out ones. The number of pixels was thereafter utilized as a reliant variable, whereas the disease score was used as a free variable. Yet, it's not generally simple to tell healthy plots from sick ones utilizing a particular threshold, particularly on the off chance that the index in question doesn't have a clear segmentation threshold. An alternative technique proposed by Shahi et al. [77] utilizes a measurement index or coefficient of variance.

When comparing manual sickness assessments to UAV-gathered vegetation indices such as NDRE, NRRE, GDVI, and other indicators of nut wilt disease, Table 3 demonstrates the strongest connection (0.73). The most precise findings, according to Chang et al. [50], were obtained by calculating NDRE using UAV photos taken 120 days after planting. Four VIs (NDVI, MSAVI, NDRE, and CI) were prepared to distinguish between healthy and sick citrus fruits at a 5% importance level in instances of greening disease. Sugiura et al. [78] achieved a commendable R2 of 0.73 for UAV-based potato blight surveillance by using a similar VI technique. Ye et al. [79] achieved a very enhanced accuracy of 91.7% by using CI, NDVI, and NDRE to identify Fusarium wilt in bananas. Guo et al. [16] used hyperspectral indices and VI and texture integration with partial least square regression (PLSR) to monitor wheat yellow rot. Using VIs produced by RGB sensors, Bhandari et al. [51] examined wheat foliar disease and found a correlation with the coefficient of infection (CI). They assessed wheat leaf and stripe rust using RGB-based VIs such SRI and LRI, and by using the GUI index, they were able to get the highest R2 of 0.79. They found a correlation of 0.92 and 0.96, respectively, for the severity of white leaf rust and stripe rust (R2 = 0.81). This study illustrated how

RGB sensors might be useful for estimating agricultural diseases using unmanned aerial vehicles.

Multispectral sensors were used in six of the eleven research that were reviewed, whilst RGB and hyperspectral sensors were utilized in three and two of the studies, respectively. This distribution may depend on the spectral resolution and cost of the sensors. Despite their exorbitant cost, hyperspectral sensors cover over a hundred spectral bands and provide substantial canopy information. Multispectral sensors record a larger spectrum, including wavelengths that are invisible to the human eye, but at a greater cost. In terms of price and spectral resolution, they are situated between RGB and hyperspectral sensors. Due to their limited spectrum range of detection, RGB sensors—which are widely accessible and reasonably priced—may overlook important crop disease data. Thermal sensors have been investigated in a few research [80,81] to evaluate abiotic stress in crops.

Table 3. An overview of ST-based methods for utilizing UAV photos to estimate agricultural diseases is provided. WD, FD, GD, LB, FW, WLD, LR, SR, VW, and YR are some examples of disease acronyms. Additional symbols consist of OA, RGB, MS, HS, and R2 (coefficient of determination).

Ref.	Crop	Disease	Sensors	Vis	Eval. Metrics	Remarks
[80]	Olive	VW	HS and Thermal	CWSI, PRI	R^2=0.83	The use of the CWSI index allowed for the successful early detection of disease, which demonstrated a strong correlation.
[82]	Potato	LB	MS	NDVI	-	The NDVI map was utilized to visually represent the affected regions of the illness.
[83]	Grape	Leaf stripe	MS	NDVI	-	The aim of the statistical study was to distinguish between vines that were healthy and those that weren't.
[17]	Peanuts	WD	MS	GDVI, GNDVI, NDRE, NRRE, , Etc	R^2=0.82	Using UAV photos taken 120 days after seed sowing, the NDRE approach showed the highest association with manual illness scores, indicating that it was the most effective in estimating wilt disease.
[51]	Wheat	FD	RGB	NDI, GLI and GI	R^2=0.79	The greatest R2 value was obtained with the GLI index after researchers computed three values for VIs and correlated them with the coefficient of infection (CI) for foliar disease on wheat.
[50]	Citrus	GD	MS	MSAVI, NDRE, NDVI and CI	R^2=0.90	The four Vis can differentiate between the healthy and diseased citrus groups at a 5% level of significance, according to a two-sample t-test.
[78]	Potato	LB	RGB	HSV	R^2=0.73	They used the HSV color space to distinguish between crops that were sick and those that weren't.
[79]	Banana	FW	MS	NDVI, NDRE and CI	OA=0.91	The pixels were classified as either healthy or unhealthy using the binary logistic regression in conjunction with the VIs.
[45]	Sugarcane	WLD	MS	NDRE, NDVI, GNDVI, RVI, OSAVI, etc.		The two groups differed significantly in the NDRE and GNDVI, with a range of 49–88%.
[84]	Wheat	LR and SR	RGB	LRI and SRI	R^2=0.81	For white stripe rust severity, the correlation coefficient (r) was 0.96 and for white leaf rust severity, it was 0.92 (R2=0.81).
[16]	Wheat	YR	HS	TCARI, SIPI, YRI GI, etc.	R^2=0.88	Vibration and textural characteristics were evaluated for PLSR-based yellow rust detection. The combination of these characteristics produced the best accuracy during the later stages of infection (R2=0.88).

4.2 Conventional ML Based Method

Using (UAV) footage, traditional ML techniques like (SVMs), (RFs), and (ANNs) have been used to detect crop disease and stress by identifying patterns in the data [53]. Supervised and unsupervised machine learning are two prominent classifications for it. While unsupervised learning looks for hidden patterns in unlabeled data, supervised learning makes use of labeled input-output data pairs. Using training data, supervised learning algorithms like SVM, RF, and decision trees (DT) create rules for categorizing or forecasting test data. On the other hand, without outside supervision, unsupervised learning algorithms like K-means and SLIC uncover latent patterns [40].

Typically, feature extraction, model creation, and data collecting are steps in the machine-learning process [63]. Using UAV photography, crop disease detection involves gathering data, pre-processing it, extracting features, and creating a model. Drone-captured photos are pre-processed by stitching and adjustments to create Orth mosaic images [40]. Then, utilizing feature extraction methods like canopy characteristics and vegetation indices, pertinent data is taken out of these pictures. Ultimately, the model was implemented, verified, and trained.

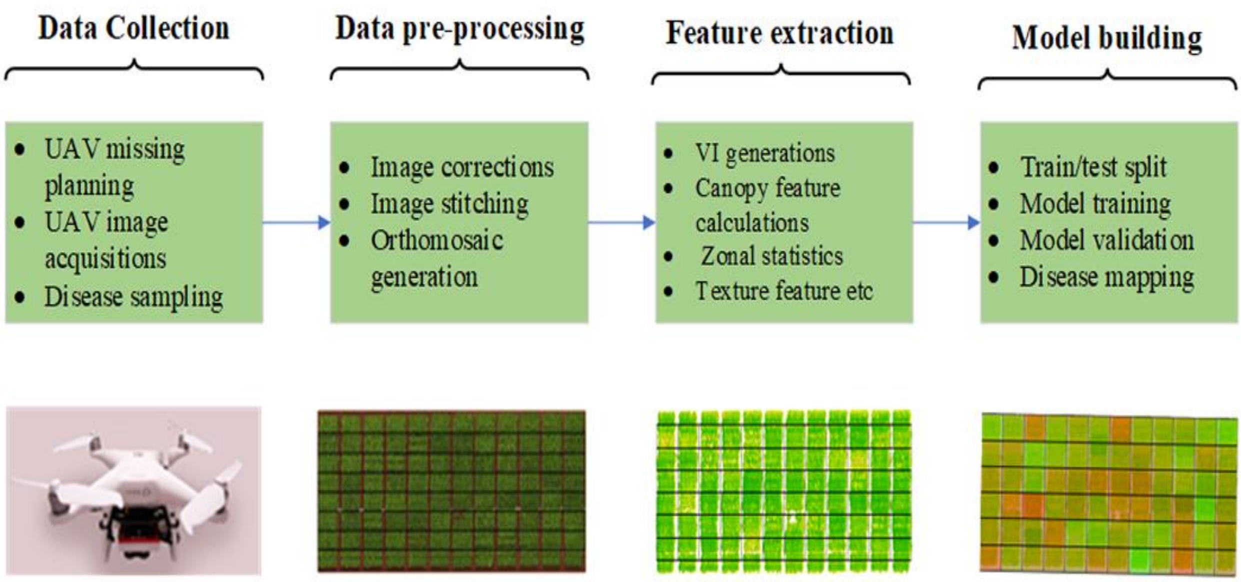


Figure 5. Standard process for employing Conventional ML in crop disease detection using aerial imagery captured by drones.

The traditional approach to crop disease estimation with (ML) entails extracting features like structural canopy characteristics (e.g., crop height and volume), zonal statistics, and texture features. This goes beyond data collection and preprocessing in ST-based methods. Afterwards, ML models were constructed using these attributes to estimate crop illnesses. Conventional (ML)-based studies can be broadly classified as either supervised or unsupervised, as seen in Figure 5. Depending on how the crop disease variable is handled, supervised methods can be further subdivided into approaches based on classification and regression.

As indicated by Table 4, crop disease detection is usually approached by researchers as a regression problem or as a classification challenge. When it comes to classification, illnesses are viewed as discrete variables, and the number of correctly identified pixels serves as a performance indicator. For example, Xavier et al. [86] used three spectral bands (NIR, red, and green) for SVM, MLR, and RF classifiers, and discovered that SVM was the most successful in detecting leaf blight in cotton. A similar evaluation of SVM, RF, and ANN for FW detection in bananas utilizing spectral bands was done by Ye et al. [58]. SVM produced an accuracy of 91.40%.

Researchers have used spectral bands and multispectral images (VIs) as features in machine learning (ML) models to detect agricultural diseases. Rodriguez et al. [87] identified potato late blight with an accuracy of 87% by utilizing visual aids and (ML) models with GBM, (SVC), (RF), and (KNN). A corn army-worm disease detection model was developed by Tao et al. [56] with spectral bands, the normalized difference vegetation index (NDVI), (RENDVI), (DSM), and RF. The model achieved 98.50% accuracy. Liu et al. [59] used a (BPNN) and simulated annealing to identify Fusarium head blight in wheat with 98.00% accuracy by utilizing spectral bands, hyperspectral VI, and textural features.

In a research by [SS], Fusarium wilt (FW) in potatoes was detected with an accuracy of 84.0 % using the mean VI and crop height in conjunction with GBM. The variance in (ML) model accuracy between crops underscores the intricacy of comparing performance, stressing the importance of taking climate, agricultural terrain, and crop varieties into account when choosing models.

Researchers have used classification models and regression mapping techniques to estimate agricultural diseases. Zhu et al., for instance, employed (BPNN), (SVR), and (PLSR) on UAV multispectral imagery to estimate wheat scab (WS). They obtained the lowest RMSE of 3.35 and the highest R2 of 0.83 using various VIs and texture attributes.

Bohnenkamp et al.'s hyperspectral sensor and SVM investigation of yellow rust (YR) on wheat produced an R2 of 0.63 by employing VIs as input features. At a height of 60 meters, the findings revealed a strong correlation (R2 = 0.88) between image-derived and manual sickness ratings. Additionally, an SVM was used to enhance the wavelet features, spectral bands, and UAV-based hyperspectral vegetation index for wheat (FHB) identification. These findings suggest that hyperspectral imagery from unmanned aerial vehicles has considerable potential for rapid and unbiased agricultural disease surveillance.

However, few studies have used unsupervised methods to assess agricultural illnesses using UAV data. Wang et al. used an SVM together with a combination of red, green, and NIR spectral bands to apply K-means for (CRR) detection, achieving 88.50% accuracy. Zhang et al. used supervised machine learning models such as SVM, BPNN, LR, and RF in combination with the (ISODATA) to identify (FW) in banana harvests. In contrast to K-means, which employs a set number of clusters, ISODATA assigns pixels to clusters and refines them via an iterative process.

Table 4. An overview of the traditional machine-learning methods used to estimate crop diseases. The following are the abbreviations for the diseases: FHB, FW, LB stands for late blight. WS; YR WLD, CCD, BRR, CRR, and AW. Other pertinent techniques are represented by the acronyms listed below: DSM, WV, TF, HA, and SB.

Ref	Crop	Disease	Sensors	Features	ML Methods	Evaluation Metrics
[86]	Cotton	Leaf blight	MS	NIR, GRE AND RED	RF, MLR and SVM	A=79.00
[57]	Banana	FW	MS	WDRVI, NDVI and TDVI	SVM, RF, BPNN, LR, ISODATA, HA	A=97.28
[58]	Banana	FW	MS	SBs	RF, SVM, and ANN	A=91.40
[59]	Wheat	FW	HS	SBs, TF and VI	BP with SA	A=98.00
[88]	Potato	FW	MS	Mean, VI and Heights	GBM	A=84.00
[85]	Wheat	FHB	HS	SBs, VIs and WFs	SVM	R^2=0.88
[87]	Potato	LB	MS	VI and SBs	RF, GBM, SVC and KNN	A=87.80
[89]	Wheat	WS	MS	TF and VI	PLSR, SVR, and BPNN	R^2=83.00
[90]	Wheat	YR	HS	VIs	SVM	R^2=63.00
[91]	Sugarcane	WLD	MS	VIs	XGB, RF, KNN, and DT	A=92.00
[92]	Citrus	CGD	MS	VIs	SVM	A=81.75
[62]	Cotton	CRR	MS	GRE, NIR and RED	K-Mean, SVM	A=88.50
[93]	Pam Oil	BSR	MS	GRE, NIR and RED	ANN	A=72.73
[56]	Corn	AW	MS	NDVI, RENDVI, DSM, Red, Green, RE and NIR	RF, MLP, NB and SVM	A=98.50

4.3 Deep Learning (DL)-Based Methods

Crop disease estimate often uses deep learning (DL) methods such as U-Net, SegNet, YOLO, Faster R-CNN, VGG, and ResNet using (UAV) images. The essential components of these methods are CNN. Gathering, preparing, collecting, and assessing data are the usual steps in the process of predicting agricultural disease using UAV photography. However, certain data preparation techniques like picture stitching, tiling, and annotation are needed in order to build a crop disease identification model.

As shown in Figure 4, there are three types of deep learning models available for crop disease estimate using UAV imagery: classification-based, segmentation-based, and detection-based. Segmentation methods identify each pixel as healthy or sick, while classification models evaluate the whole picture to categorize it into predetermined illness categories. On the other hand, detection models build bounding boxes around items of interest and label them (for example, "healthy" or "diseased," as shown in Figure 6). While the evaluation criteria used for these procedures vary, prominent metrics include IoU, recall, accuracy, precision, and mean average precision (mAP). Crop and disease categories, sensors, flying heights, and detailed performance information are included for each approach in Tables 5-7.

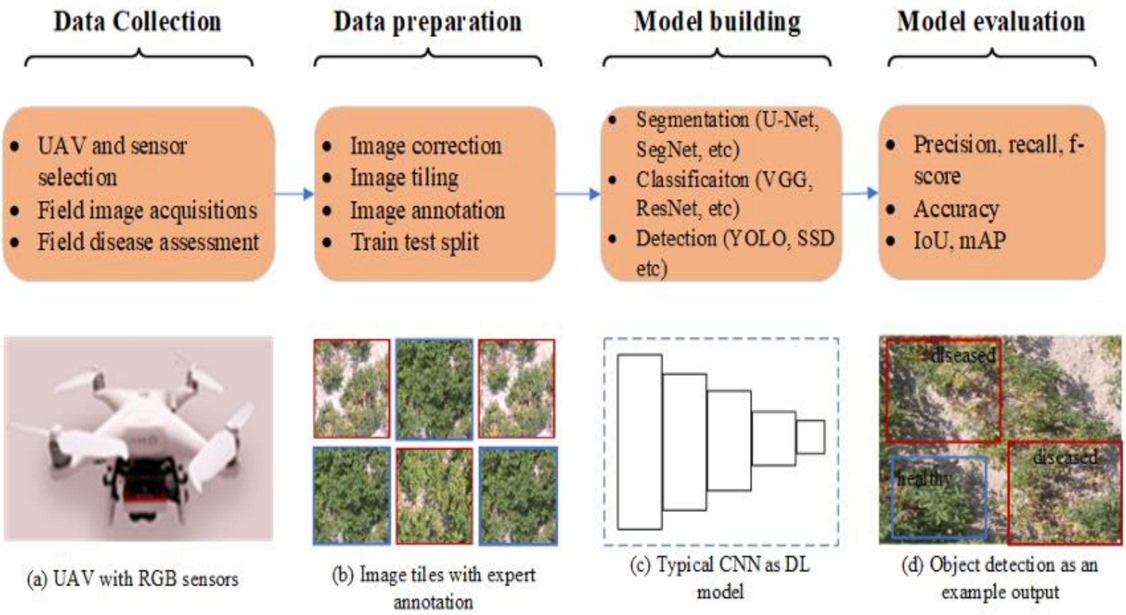


Figure 6. The standard process for detecting crop diseases using drone-based imagery relies on deep-learning techniques.

4.3.1 Pixel-Based Segmentation Models

The picture classification model divides the image's pixels into distinct sections. Pixels are clustered using iterative methods such as K-means or ISODATA in conventional segmentation procedures. Deep learning methods make use of an encoder-decoder architecture, in which the encoder uses convolutions and down-examining to arrange the information image into a latent space, and the decoder spends inspecting procedures to reconstruct the segmentation map. A selection of the widely used encoder-decoder schemes for image segmentation using UAV images are shown in Table 5: U-Net [94], PSPNet [99], SegNet [95], and others [100].

Most studies [94, 101, 102] on crop disease segmentation in UAV data have used U-Net [103], a well-known deep learning model for semantic segmentation. Su et al.'s [94] UAV imagery monitoring of wheat yellow rot revealed that a five-band input combination outperformed RGB alone and VIs. Oliveira et al. [101] used U-Net with RGB photos taken at a 10-meter flying height to locate coffee nematodes. They also trained PSPNet using various coffee picture resolutions, and found that

U-Net outperformed PSPNet with an accuracy of 69.00%.

Zhang et al. [102] enhanced the architecture of a modified U-Net for wheat yellow rust detection using RGB aerial images by including irregular encoder and decoder modules as well as a channel-wise re-weight module. This resulted in a 97.13% accuracy rate using five-band input pictures. A separate study [104] reported 96.3% accuracy in separating wheat yellow rust using multispectral images and U-Net. These findings highlight the value of high-resolution images obtained at less than 30 meters above the ground and demonstrate the suitability of U-Net for crop disease segmentation using aerial images from RGB or multispectral sensors.

Several DL models aimed to using UAV images to detect agricultural diseases are shown in Table 5. Sheath rust (SR), northern leaf blight (NLB), vine mildew (VD), yellow rust (YR), Cercospora leaf spot (CLS), and nutrient-related chlorosis (NM) are among these illnesses. Veil R-CNN[105], SegNet[95], pixel-wise segmentation networks (PSPNet)[99], fully convolutional networks (FCN)[106], DeepLabV3[100], CropDocNet[107], and VddNet[108] are a few examples of these models. Cover R-CNN was used in a review led by Stewart et al. [105] to detect NLB in maize. The results showed an intersection over union (IOU) of 0.50 and an average accuracy of 0.96. The findings of this research suggest that deep learning-based occurrence segmentation may be used to identify plant diseases using UAV data. To distinguish mildew in vines, Kerkech et al. [95] utilized multispectral pictures with SegNet [109] to categorize pixels into shadow, ground, healthy, or mildew layers. Accuracy in detection was 92% on grapevines and 87% on leaves. Similar to how a FCN [101] trained on DenseNet [66] could identify Cercospora leaf spot (CLS) on sugar beets, it could likewise distinguish healthy and background pixels. In different field settings, their technique yielded f-scores of 44.48% for background pixels, 88.26% for healthy pixels, and 93.90% for CLS, respectively.

Ref.	Crop	Disease	Sensors	Height	DL Methods	B	Recall	F-Score	Acc.
[105]	Maize	NLB	RGB	6m	Mak R-CNN	96.00	-	-	-
[95]	Grape	VD	RGB & NIR	-	SegNet	84.04	90.47	87.12	-
[106]	Sugar	CLS	RGB	-	FCN	74.81	80.25	75.55	-
[99]	Wheat	YR	RGB	-	PSPNet	-	-	-	94.00
[94]	Wheat	YR	MS	20m	U-Net	91.30	92.60	92.00	-
[101]	Coffee	NM	RGB	10m	U-Net & PSP-Net	-	-	69.00	-
[100]	Wheat	SR	RGB	50m	DeepLabv3+	-	-	81.00	-
[102]	Wheat	YR	RGB	-	Ir-UNet	-	-	-	97.13
[107]	Potato	LB	HS	30m	CtopdocNet	-	-	-	95.75
[105]	Maize	NLB	RGB	6m	Mask R-CNN	96.00	-	-	-
[106]	Sugar	CLS	RGB	-	CNN	74.81	80.25	75.55	-
[108]	Vine	VD	RGB-NIR-D	25m	VddNet	-	-	-	93.72
[104]	Wheat	YR	MS	20m	UNet, DF-UNet	-	-	-	96.93

4.3.2. Models of Object-Level Classification

Characterizing an information picture into predetermined classes is the first move toward object grouping. A solitary field map was created by sewing together overlapping tiles from UAV photographs of agricultural areas. In order to train a deep learning model to classify picture tiles as healthy or unhealthy, the crop field area may be divided into small object-level tiles. The results are combined during post-processing to produce a new field map that includes the locations of the contaminated and healthy zones. Two deep learning approaches were used for crop disease arrangement using UAV imagery: pre-trained architectures such as ResNet, Inception-v3, VGG, DenseNet, MobileNet, and GoogleNet, which are reasonable for transfer learning and often trained on ImageNet, and handcrafted CNNs that should be trained from scratch for specific tasks.

Wu et al. [98] utilized a transfer learning strategy involving ResNet for sore recognizable proof on maize utilizing high-resolution RGB UAV data that was gotten in two phases from a drone operating six meters over the ground. At first, they randomly cropped 500 x 500 pixel sub-pictures to train a spine CNN (ResNet). After pre-training on ImageNet, ResNet-34 was utilized to apply transfer learning. The result of the trained CNN was utilized to create an intensity guide of diseases, and sliding windows were utilized to create taking care of patches over the original UAV photographs. Similar to this, Tetila et al. [110] utilized RGB pictures and a transfer learning strategy with many deep learning architectures already being used, including VGG, ResNet, Inception, and Xception, to characterize soybean leaf diseases.

Their framework included three stages:

To improve the quality and clarity of the given sentence while preserving its original meaning, the sentence has been rephrased as follows.

Researchers have utilized various deep-learning strategies to order crop diseases utilizing UAV pictures. These techniques incorporate acquiring pictures, fragmenting leaves utilizing SLIC, and characterizing leaves into different disease levels. The Inception network accomplished the most noteworthy accuracy of 99.04%, outperforming the other models. Similarly, Zhang et al. utilized an Inception ResNet to identify yellow rust in wheat utilizing hyperspectral imagery, accomplishing 85.00% accuracy utilizing a sliding window technique. The post-processing visualizes the rust guide. Custom CNNs have been created for explicit crop diseases. In order to classify RGB images of sliding windows into four groups—ground, healthy, slightly diseased, and sick—Kerkech et al. designed a CNN that was influenced by LeNet-5. 95.8% accuracy was achieved by this method after postprocessing. Similar LeNet-5 CNN was developed by Huang et al. using RGB images for HLB order on wheat, achieving 91.43% accuracy and outperforming SVM's 90.00% accuracy using features including LBP, histograms, and VIs.

Table 6 gives an overview of the DL models based on object-level order that are utilized to identify agricultural diseases utilizing UAV data. The accompanying abbreviations are utilized in the table: FW (Fusarium wilt), JV (vine disease), Compact disc (corn disease), BD (banana diseases), HLB (Helminthophobia leaf blotch), YR (yellow rust), and NLB (northern late blight).

Ref	Crop	Disease	Sensors	Height	DL Methods	Acc.(%)
[118]	Potato	Virus	RGB	10 m	CNN	84.00
[98]	Maize	NLB	RGB	6 m	ResNet-34	95.10
[72]	Wheat	YR	HS	30m	Inception-ResNet	85.00
[110]	Soyabean	SD	RGB	2m	Inception-v3, ResNet50, VGG-19, Exception	99.04
[74]	Radish	FW	RGB	-	VGG	93.30
[111]	Corn	CD	RGB	12 m	VGG, ResNet, Inception, DenseNet169	100.00
[113]	Radish	FW	RGB	10m	GoogleNet	90.00
[119]	Banana	BD	RGB	50m	VGG and CNN	92.00
[112]	Maize	FAW	RGB	5m	VGG16, VGG19, Inception-v3 and MobileNet	100.00
[115]	Grape	VD	RGB	25m	CNN	95.80
[117]	Wheat	HLB	RGB	80m	CNN	91.43

4.3.3. Object Detection Based Models

A prominent area of study in computer vision is object detection [120], which is more complex than image classification tasks [96], which just give a class to an image. Object detection requires both object classification and localization. Bounding boxes are created around objects and labels are applied to them in object detection [96].

There are two primary categories of object detection methods: single-stage and two-stage. Initially, an algorithm like selective search is used by two-stage detectors, such R-CNN [121], to suggest areas of interest (ROIs). After that, a linear support vector machine (SVM) is used for classification and a deep learning architecture like VGG [65] is used to extract features from these candidate areas. On the other hand, one-stage detectors use a deep learning model to evaluate incoming photos and predict item bounding boxes. Table 7 demonstrates that most studies choose one-stage detectors such as YOLO [96], RetinaNet [122], and CenterNet [123][121] [97], whereas fewer studies utilize two-stage detectors such as Faster R-CNN.

Table 7. Here, is a rephrased version of the sentence.

The following is a summary of the use of UAV imagery for detecting crop diseases using object detection, including the abbreviations for diseases (CRR, WW, WLD, DS, and TLB).

Ref	Crop	Disease	Sensors	Height	Methods	Metrics(%)
[96]	Cotton	CRR	MS	120m	YOLOV5	A=70.00
[123]	Brassica chinensis	WW	RGB	2 m	CenterNet	A=87.20
[97]	Sugar	WLD	RGB	20 m	YOLOV5, Faster R-CNN, DETR	P=95.00
[112]	Potato	DS	RGB	-	RetinaNet-Ag	P=74.00
[124]	Tea	TLB	RGB	5 m	DDMA-YOLO	P=73.80

Figure 7 illustrates the distribution of studies based on the given taxonomy, with 55% utilizing deep learning techniques, 25% employing machine learning, and the fewest using statistics-based methods. This indicates that when assessing agricultural diseases utilizing UAVs and remote sensing technologies, deep learning is strongly preferred by precision agriculture experts.

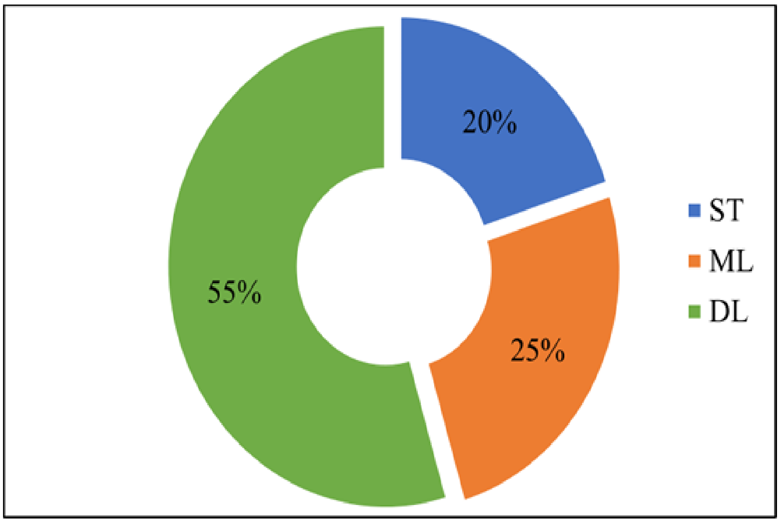


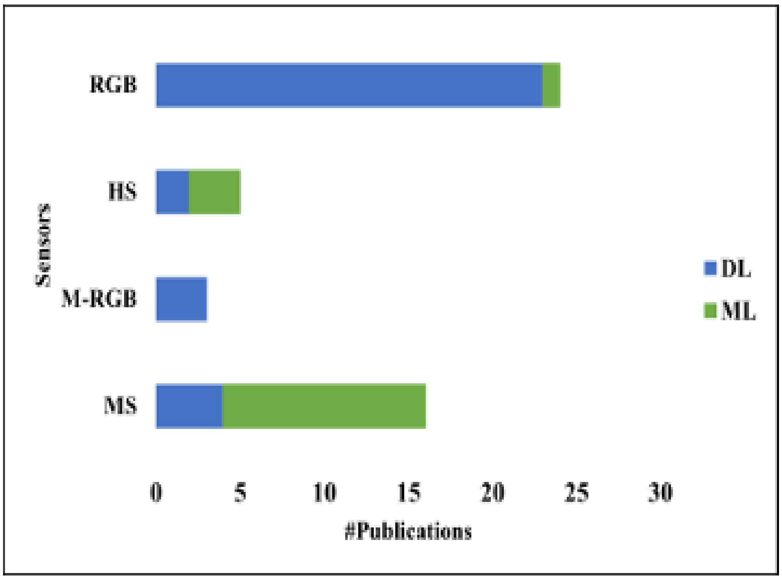
Figure 7. A review of 55 previous studies on estimating crop diseases using UAV imagery was organized according to the techniques used. "ST," "ML," and "DL" refer to statistical, conventional machine learning, and deep learning approaches, respectively.

5. Results and Discussion

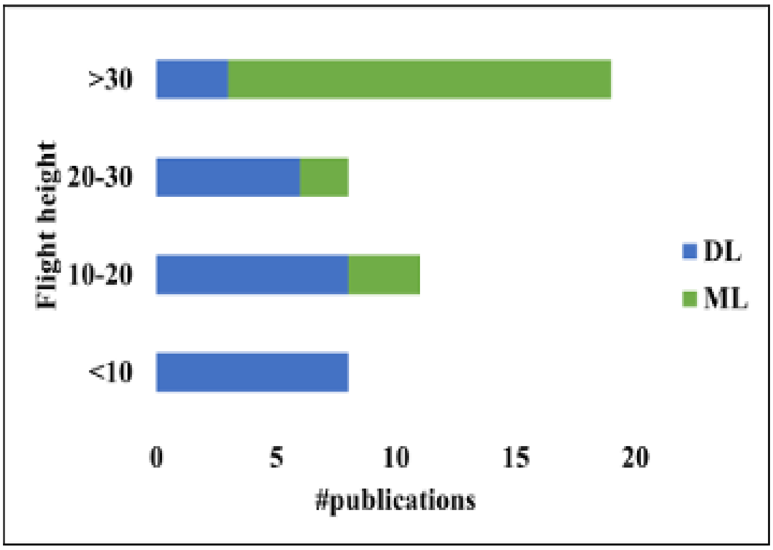
By responding to the review questions, this section offers an overview of the material examined in section 2. The first section covers different UAV platforms and sensors, along with configurations like flying height. Next, we look at how these platforms affect the taxonomy's crop disease estimation techniques. The most successful vegetation indices and how well they can identify particular crop diseases are then determined. It also assesses the effectiveness of several variables, such as vegetation indices, in conjunction with sophisticated data-driven crop disease estimating techniques, such traditional ML and DL. This section concludes by outlining the shortcomings, difficulties, and potential future developments of the UAV-based crop disease assessment system.

5.1. UAV Sensing Systems

In the last several years, UAV sensing systems have developed to such an extent that they are now essential tools for monitoring crop health, spotting diseases early on, and helping to limit crop disease outbreaks [40]. Using RGB, multispectral, and hyperspectral sensors, rotating-wing (UAVs) have become popular and effective platforms for answering Research Question 1 (RQ1) in Section 2. RGB sensors are typically employed in conjunction with DL methods for comparing (ML) and (DL) approaches for crop disease assessment, although multispectral (MS) sensors are more frequently used in conjunction with ML methods (see Figure ff). This implies that high detail images are needed for DL techniques, and RGB sensors can provide these images at closer ranges. However, due to their high cost and complicated data processing, hyperspectral sensors are used less in both ML and DL techniques (Figure S). Crop disease modeling techniques are correlated with the altitude at which UAVs fly. Most studies using the NIL framework have been conducted at altitudes exceeding 10 m, and several have gone up to 30 m. In contrast, DL-based studies primarily used altitudes below 20 m, with few studies using altitudes above 30 m (Figure S). This indicates that RGB sensors at lower altitudes are sufficient for high-resolution imagery required by DL methods.



(a)



(b)

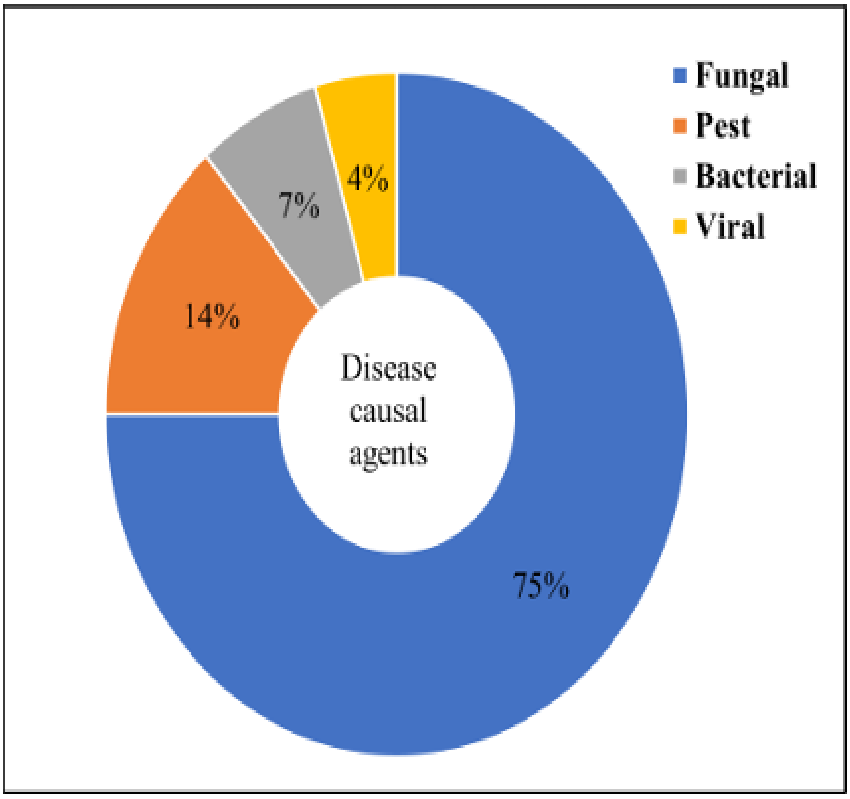
Figure 8. Please provide the sentence you would like me to rephrase for better language quality and clarity. I am unable to generate a response without a specific sentence to work with.

5.2 Type of Crops and Diseases

Crop illnesses brought on by bacteria, fungus, and viruses may significantly reduce crop production and need efficient preventative measures to stop them from spreading widely. These diseases' symptoms, which include color and form alterations like leaf spots and yellowing, often show up on leaves. These visual signs are crucial for manual illness evaluation, and they might change based on the kind of disease and the pathogen involved. For instance, leaf rust, yellowing, leaf spots, white mold, and stem rust are common indications of fungal infections.

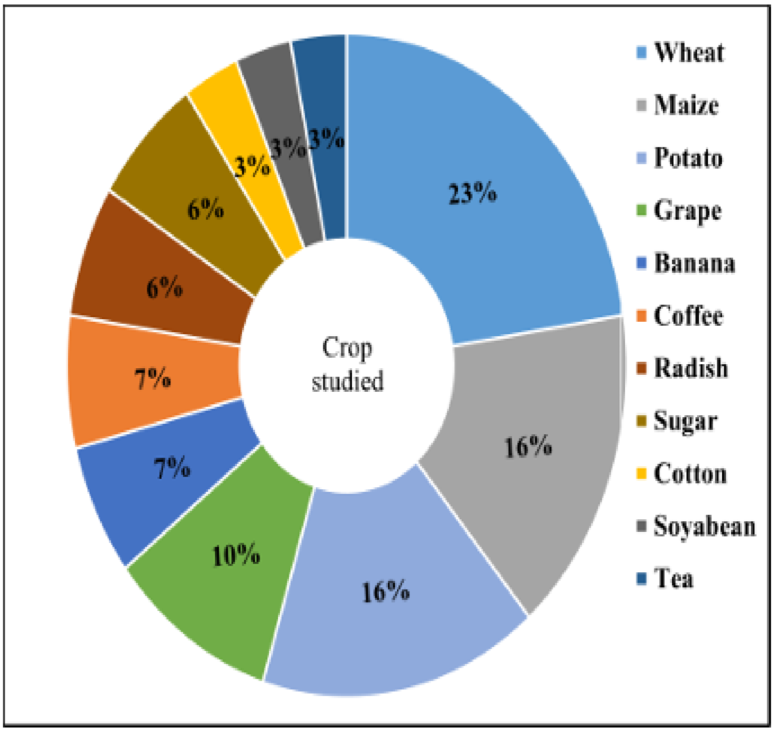
Insect pests and bacterial, viral, and fungal diseases are the four main categories into which this study divides research on crop diseases utilizing UAV imaging. The spread of these disease groups and the crop kinds that are afflicted are shown in Figure 9. Notably, 75% of the papers in the study were on fungal illnesses, which made up the bulk of the topics. This might be explained by the fact that, in deep learning-based methods, fungal illnesses are more prevalent and simpler to visually identify using RGB pictures (Figure 10).

Regarding particular crop diseases, the identification of wheat disease is a major focus in 23 percent of the research, with maize and potato coming in at 16 percent apiece. A fungus that is extensively researched in wheat is fusarium wilt. Deep learning and machine learning, along with UAV imagery, are common methods for detecting and monitoring this disease.



(a)

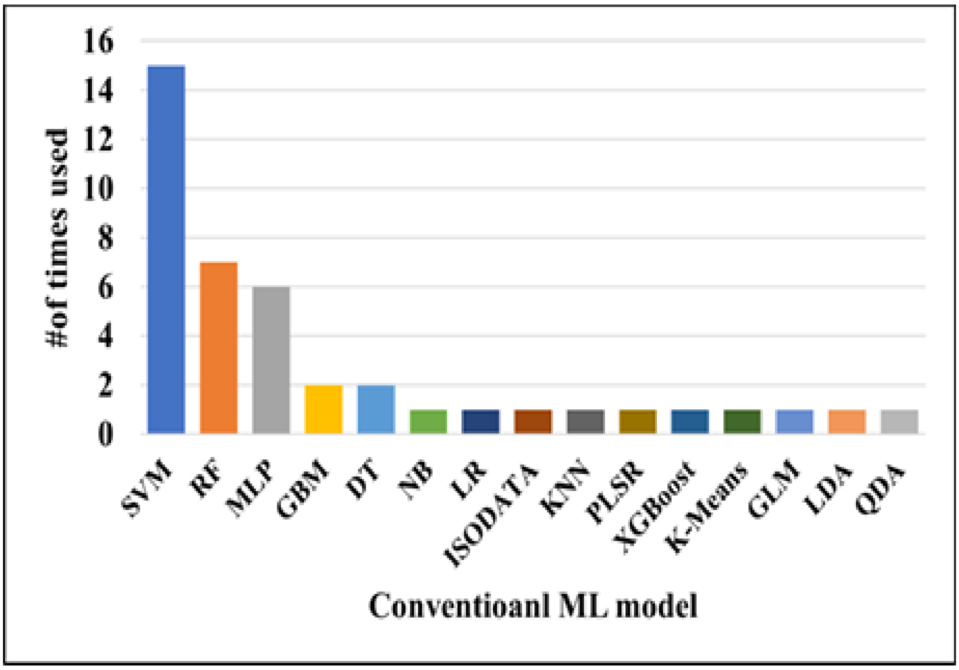
Figure 9



(b)

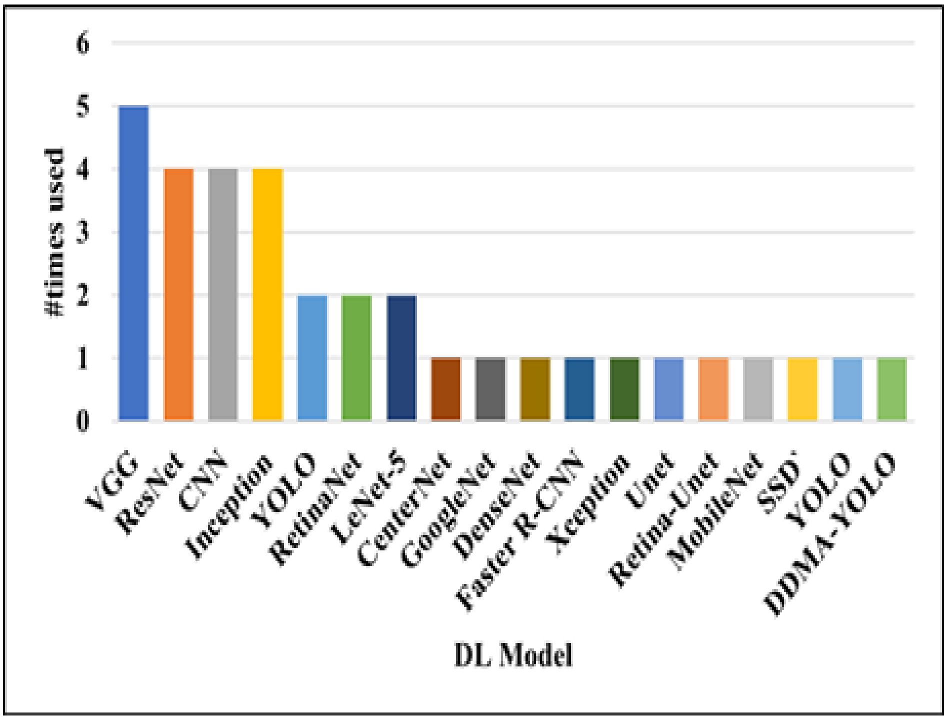
Figure 9. The organization of prior research into two categories: (a) the pathogens responsible for

crop diseases and (b) the specific crops under investigation.



(a)

Ficure 10



(b)

Figure 10. Existing studies are categorized into two groups: those using conventional machine learning-based techniques and those employing deep learning-based methods.

5.3. Conventional DL and ML Methods

The volume of data collected by UAVs and other image sensors has made data-driven methods—like standard ML and DL—outperform classical statistical techniques in the estimate of crop diseases. However, all approaches need expert-annotated data before the model can be trained. Figure 10 shows the frequency of study using ML and DL models. The classic ML models (SVM), (RF), (MLP), and (GBM) are most often employed for agricultural disease assessment utilizing UAVs. The visual geometry group (VGG) is the most widely used model when it comes to (DL), closely followed by ResNet, CNN, and Inception.

Table 4 shows the crop disease estimation accuracy of traditional machine learning models, with classification accuracy ranging from 72% to 98% and coefficients of determination from 63% to 88%. The identification of Fusarium wilt in bananas had the highest accuracy rate (98%) while the detection of cotton rot roots had the lowest (72.73%). One cannot simply propose one machine learning method over another because different aspects affect the performance of these models, including sensor type, crop and disease type, and UAV flight height. However, ML techniques tend to outperform RGB sensors when used with multispectral and hyperspectral sensors.

ML and statistical (ST) approaches are surpassed by (DL) models, which get crop disease segmentation accuracies between 93% and 97% and classification accuracies between 85% and 100%. But in order to create illness maps, DL techniques are more involved and frequently call for pre- and postprocessing of UAV photos. (Picture 6).

5.4 Summary of Findings

Here's a possible rephrased version:

i. We summarize our findings from a survey conducted on UAV-based crop disease estimation, highlighting the following aspects: (a) strengths and current research focus, (b) emerging trends in research and technology, and (c) challenges and potential solutions. Rapid advancements in UAV platforms and sensors have significantly affected crop disease detection owing to machine learning and deep learning methods. The survey results indicate a preference for RGB sensors combined with deep learning techniques, which suggests a shift towards cost-effective sensors, such as RGB sensors, instead of more expensive ones, such as hyperspectral and multispectral sensors. Notably, deep learning techniques have been proven to enhance the accuracy of crop disease estimation compared to traditional statistical and machine learning approaches.

ii. Compared to diseases brought on by bacteria, viruses, and pests, our meta-analysis showed that fungal diseases have been researched the most using UAV-based remote sensing. Given the effectiveness of sophisticated deep learning models when combined with unmanned aerial vehicles, we suggest addressing the following issues and approaches for further study:

iii. Factors such as flight altitude, payloads, and sensors affect the effectiveness of UAV sensing systems for crop disease estimation. To address this, it is necessary to develop cost-effective, high-payload sensing technologies for small UAVs, which are limited in their payload capacity. Additionally, image resolution is crucial for deep learning models, and can be achieved through low-altitude flights or up-sampling techniques.

iv. A significant challenge in the field is the lack of labeled data, as labeling requires expensive expert involvement. Future research should focus on unsupervised and semi-supervised techniques to mitigate this issue. Furthermore, because different studies' accuracy varies, choosing between deep learning models and traditional machine learning is challenging. To compare performance, a benchmark dataset for various agricultural diseases must be created. To overcome the high computational resource needs, lightweight deep learning models appropriate for edge computing platforms, like IoT, should be developed.

6. Conclusions

The overflow of data acquired by various imaging sensors and UAVs has driven data-driven approaches, like deep learning (DL) and conventional machine learning (ML), to outperform traditional statistical strategies in crop disease estimation. However, these strategies require data that has been clarified by experts to start training the model. Figure 10 displays the frequency of study using ML and DL models. Support vector machine (SVM), random forest (RF), multilayer perceptron (MLP), and gradient boosting machine (GBM) are the most often used classical ML models for agricultural disease assessment using UAVs. The visual geometry group (VGG) is the most widely used model in deep learning (DL), closely followed by ResNet, CNN, and Inception.

The goals of various UAV platforms, sensors, and data processing methods for remote agricultural disease monitoring are made clear by this comprehensive evaluation. It covers the challenges, potential results, and potential research directions in drone-based remote sensing for crop disease prediction in addition to offering a comprehensive scientific classification and meta-analysis of the available literature. Surprisingly, deep learning-based models outperform machine learning and statistical methodologies in UAV-based agricultural disease measurement. However, since these models often function as "secret elements," it is required to increase their receptiveness and restrict with regard to clarity in order to promote certainty and steadfastness. It takes a lot of work to investigate the best strategies to combine several remote sensing data modalities for crop disease diagnosis. Another intriguing path is to develop deep learning models that are small and suitable for edge computing platforms such as the Internet of Things. Every author contributed to the ideation, writing, method, data curation, and visualization of the paper. After T.B.S. took the lead in writing the first draft, A.N., C.-Y.X., and W.G. evaluated and revised the work.

Funding: This research received no external funding.

Acknowledgments: The authors acknowledge the support and resources they received from CQUni and the Australian Government's RTP scholarship. Also acknowledged is Ram Khadka, a Plant Pathology Scientist at the Nepal Agricultural Research Council, who provided insightful commentary on crop diseases.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

ANN	=	Artificial neural network
BPNN	=	Back propagation neural network
CNN	=	Convolutional neural network
DL	=	Deep learning
DT	=	Decision tree
DSM	=	Digital surface model
DCNN	=	Deep convolution neural network
FCN	=	Fully connected neural network
GPS	=	Geographical positioning system
GBM	=	Gradient boosting machine
GLM	=	Generalized linear models
ISODATA	=	Iterative self organizing data analysis technique
IoT	=	Internet of things
IoU	=	Intersection of union
KNN	=	K-nearest neighbor Linear regression
LR	=	Linear discriminant analysis
mAP	=	Mean average precision
MLP	=	Multi-layer perceptron
ML	=	Machine learning
MLR	=	Multiple linear regression
NB	=	Naive Bayes
PLSR	=	Partial least square regression
PA	=	Precision agriculture
QDA	=	Quadratic discriminant analysis

RF = Random forest

ROI = Region of interest

SVM = Support vector machine

UAV = Unmanned aerial vehicle

VI = Vegetation index

VGG = Visual geometry group

XGBoost = eXtreme gradient boosting

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